LUCKAS SABIONI LOPES

MUDANÇAS RECENTES NOS CICLOS DE NEGÓCIOS BRASILEIROS

Tese apresentada à Universidade Federal de Viçosa, como parte das exigências do Programa de Pós-Graduação em Economia Aplicada, para obtenção do título de *Doctor Scientiae*.

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Aprovada em: 24 de fevereiro de 2014

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À minha esposa, Letícia, minha filha, Maria Clara, e meu filho, Murilo.

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BIOGRAFIA

Luckas Sabioni Lopes, filho de Henrique Cavalcanti Moreira Lopes e Mônica Sabioni, nasceu na cidade de Visconde do Rio Branco, interior da Zona da Mata Mineira, em 7 de julho de 1984.

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É casado com Letícia Ribeiro Oliveira Sabioni e pai de uma criança, Maria Clara, e espera o nascimento de outra, o Murilo.

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LOPES, Luckas Sabioni, D.Sc., Universidade Federal de Viçosa, fevereiro de 2014. **Mudanças recentes nos ciclos de negócios brasileiros**. Orientador: João Eustáquio de Lima. Coorientadores: Marcelle Chauvet e Marcelo José Braga.

A presente tese contém dois artigos. No primeiro novos fatos sobre os ciclos de negócios ocorridos no Brasil entre 1947 e 2012 são oferecidos. Utiliza-se um método de extração do componente cíclico do produto interno bruto (PIB) que combina o resultado de diversos filtros Hodrick-Prescott, criando um conjunto de informações que é robusto aos problemas de quebras estruturais e de seleção de filtros. As principais conclusões do artigo são que os ciclos econômicos no país são assimétricos, com expansões mais longas que recessões; a tendência de crescimento da economia tornou-se visivelmente mais suave após os anos 1980; e, há uma quebra na volatilidade do PIB ocorrendo aproximadamente nos anos de 1996 ou 1997, quando o país se tornou mais estável. Foi também verificado que a taxa de crescimento de longo prazo da economia reduziu-se em 50%, de um valor de 8% ao ano no período de 1947 a 1980, a 4% no período seguinte. O segundo capítulo estuda profundamente a questão da Grande Moderação aplicada ao caso brasileiro, investigando quais fatores geraram a queda observada na volatilidade da inflação e do produto no país. Para tanto, estima-se um modelo dinâmico de equilíbrio geral estocástico (DSGE) Novo Keynesiano, através de técnicas bayesianas, ao longo de diferentes amostras para o período de 1975 a 2012. De acordo com os resultados obtidos, a Grande Moderação Brasileira começou no ano de 1995, quando a volatilidade da inflação e do Produto Interno Bruto (PIB) caiu significativamente. Detectaram-se também instabilidades nos parâmetros que descrevem o setor privado, a política monetária e a variância dos choques exógenos. Com respeito às causas desse fenômeno, mudanças na política monetária e nos choques explicam a redução na volatilidade da inflação (aproximadamente 50% cada, de acordo com algumas especificações). Entretanto, nas estimações em primeira diferença, percebeu-se que alterações na inclinação da curva de Phillips também foram importantes para a

estabilização da inflação. Em relação ao PIB, a redução da variância dos choques foi o único fator por trás de sua maior estabilidade. A Grande Moderação no Brasil é, portanto, fruto de um misto de política monetária efetiva, de mudanças no setor privado e de um ambiente macroeconômico favorável.

ABSTRACT

LOPES, Luckas Sabioni, D.Sc., Universidade Federal de Viçosa, February, 2014. **Recent changes in the Brazilian business cycles**. Adviser: João Eustáquio de Lima. Co-adivisers: Marcelle Chauvet and Marcelo José Braga.

The present research work has two chapters. The first one provides new information about the Brazilian business cycle from 1947 to 2012, using a quarterly and seasonally adjusted real GDP time series. Our method averages over a variety of HP-filters and creates a set of information which is robust for structural breaks and filter selection. The main findings are that Brazilian business cycle is asymmetric, with expansions lasting longer than recessions; the country's long-term trend presented a noticeable flatter slope after the 1980s; and, volatility decreased after 1996-1997, when a statistically significant structural break occurred. We also found that Brazilian real long-term growth rate decreased by 50%, from 8% per year, in the period between 1947 and 1980, to 4% per year after that. The second one evaluates the Great Moderation issue applied to Brazil, investigating what has caused inflation and output volatility to fall in the country. In so doing, we estimate a structural New Keynesian DSGE model using Bayesian techniques, across different sub-samples for the entire 1975-2012 period. Our main findings are that the Brazilian Great Moderation began in 1995, when the volatility of inflation, and output gap, dropped sharply. We have detected instabilities in the parameters describing the private sector, the monetary policy, and the variance of the shocks. Regarding the causes of the great moderation, changes in monetary policy and shocks explain the reduction in the instability of inflation (about 50% each, in some specifications). However, some assumptions also indicate that changes in the Phillips curve slope were also important for its stabilization. On the GDP side, we found that the sole reason behind its volatility fall was the reduction of the shocks hitting the economy. Therefore, the Brazilian Great Moderation was mainly originated by a mix of the "good

policy” (implied by the Real Plan) and “good luck” hypotheses additionally to changes in the price setters’ behavior.

INTRODUÇÃO GERAL

A economia brasileira vem passando por mudanças profundas ao longo dos últimos anos. O produto interno bruto (PIB) real, por exemplo, segundo dados de Bonelli e Rodrigues (2012), cresce à taxa média de 5% ao ano desde 1947. Além disso, a inflação foi controlada e drasticamente reduzida, passando de valores muito próximos aos hiperinflacionários entre 1984 e 1994, para uma média de 9% ao ano após 1995 (segundo o Índice Geral de Preços, disponibilidade interna, IGP-DI, calculado pela Função Getúlio Vargas)[1].

A dinâmica dessas alterações, contudo, é sinuosa. Ela é permeada de períodos de altos e baixos, de momentos de expansões e recessões, de booms de otimismo e crises e de descontinuidades. Assim, a distinção das forças motrizes subjacentes a esses fenômenos é essencial para a formulação de políticas econômicas adequadas ao atual cenário macroeconômico do país. Ainda mais quando se leva em consideração o

[1] A taxa de inflação medida pelo IGP-DI é disponibilizada pelo IPEA em: http://www.ipeadata.gov.br/. O PIB real pode ser consultado em Bonelli, R., e Rodrigues, C. (2012). PIB Trimestral: Proposta Metodológica e Resultados para o Perído 1947-79. *[mimeo]*, 24 pp.

elevado custo de suas oscilações[2]. É nesse contexto em que a presente pesquisa se insere, pretendendo, sobretudo, estudar as principais características e determinantes dos ciclos de negócios brasileiros entre os anos de 1947 e 2012.

Especificamente, objetivou-se, no primeiro capítulo:

i) Propor um método inovador de extração da tendência e ciclo da atividade econômica brasileira;

ii) Delimitar e caracterizar os ciclos de negócios no Brasil, extraindo medidas como persistência, duração e amplitude médias, e perdas e ganhos das recessões e expansões;

iii) Analisar a possibilidade de quebras estruturais, possivelmente múltiplas, na tendência de longo-prazo e na volatilidade das séries do PIB real.

E, no segundo capítulo:

i) Estudar as mudanças ocorridas na economia brasileira, com base em resultados obtidos com testes de quebras estruturais envolvendo o PIB real, a inflação e a taxa de juros; e,

ii) Avaliar os principais determinantes das mudanças observadas na economia ao longo dos anos, com intermédio de um modelo macroeconômico Novo-Keynesiano e técnicas bayesianas de estimação.

[2] Veja, por exemplo, Cunha e Ferreira (2004).

Para tanto, a tese contém, além desta Introdução Geral e da Conclusão Geral, outros dois capítulos inter-relacionados, porém independentes. Cada um deles está redigido em formato de artigo científico completo, constituído de introdução, metodologia, resultados e conclusão próprios.

Na primeira pesquisa, capítulo 1 da tese e intitulada "Trend-Cycle Decomposition of the Brazilian GDP: New Facts for the period between 1947 and 2012", uma série de tempo trimestral do PIB real é analisada durante todo o período de 1947 a 2012. A abordagem foca-se em mapear as principais características da atividade econômica no Brasil, levantando características como o grau de persistência temporal do PIB, a duração média, a amplitude de variação e as perdas e ganhos acumulados das recessões, das expansões e dos ciclos completos, além de avaliar a possibilidade de existência de quebras estruturais na tendência de crescimento de longo-prazo e na volatilidade da série de tempo em questão.

O método de decomposição utilizado, que se constitui em uma inovação proposta pelo presente autor, baseia-se na média aritmética dos resultados de diversas filtragens do tipo Hodrick-Prescott[3]. Resultados adicionais são discutidos a seguir, cabendo aqui destacar que uma das principais conclusões deste capítulo refere-se à constatação de que a economia do país se tornou sensivelmente mais estável após os anos de 1996/1997, prováveis datas de ocorrência de uma quebra estrutural na variância do componente cíclico do PIB.

Nesse sentido, o capítulo 2, intitulado "The Brazilian Great Moderation: Features and Explanations", investiga quais fatores geraram a redução observada nas variâncias da inflação e do PIB no país. Estima-se, para isso, um modelo dinâmico de

[3] Filtro de Hodrick e Prescott, discutido em detalhes a seguir. O leitor pode consultar, também, o artigo original: Hodrick e Prescott (1997).

equilíbrio geral estocástico (DSGE, da sigla em inglês) Novo-Keynesiano, através de técnicas bayesianas, ao longo de diferentes amostras para o período de 1975 a 2012. As variáveis consideradas neste caso são o PIB, a inflação, medida pelo IGP-DI, e a taxa de juros básica da economia, Selic.

Em concordância com o capítulo anterior, mostra-se que a Grande Moderação Brasileira[4] começou no ano de 1995, quando a volatilidade da inflação e do PIB caiu significativamente. As principais explicações para tal fenômeno são, para o caso da inflação, mudanças na política monetária advindas do Plano Real e a redução dos choques exógenos afetando a economia (50% cada, de acordo com a maioria das especificações). Entretanto, nas estimações em primeira diferença, percebeu-se que alterações na inclinação da curva de Phillips também foram importantes para a estabilização da inflação. Em relação ao PIB, a redução da variância dos choques foi o único fator por trás de sua maior estabilidade. O período atual de estabilidade atravessado pela economia brasileira é, portanto, fruto de um misto de política monetária efetiva, de mudanças no setor privado e de um ambiente macroeconômico favorável.

Nesse formato, a estrutura lógica da tese torna-se bastante intuitiva, com o primeiro capítulo descrevendo as características básicas dos ciclos de negócios da economia brasileira durante os últimos anos, e o segundo artigo relacionando tais características a parâmetros relacionados ao setor privado, à condução da política monetária e à magnitude dos choques que afetaram o país. Por fim, vale ressaltar que os capítulos foram redigidos em língua inglesa, objetivando maior visibilidade e divulgação da presente pesquisa.

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[4] Refere-se, assim, ao período de menor volatilidade na economia. É um termo padrão na literatura da área.

CAPÍTULO 1: Trend-Cycle Decomposition of the Brazilian GDP: New Facts for the period between 1947 and 2012

1.1. Introduction

Economics has traditionally studied business cycle, but the contributions of Burns and Mitchell (1946) were a watershed, prompting a wave of interest in regularities and features of economic activity and its fluctuations in many countries. Such investigation assumes great relevance whenever it comes to provide grounds for policy-making (both public and private), forecasting, model calibration, and theories testing, to name a few. However, as it is stated in the recent literature, in order to obtain consistent business cycle information, one of the main issues is how to separate the input series into trend and cycle components. The answer for that is not trivial, and it is the object of this research work.

We will focus on depicting facts about the Brazilian business cycles, by decomposing a quarterly and seasonally adjusted GDP time series for the 1947-2012 period. Amongst all the currently available trend-cycle decomposition methods, the Hodrick-Prescott filter (HP-filter, Hodrick and Prescott, 1997) stands out most. The HP-filter has been largely employed. Examples include Kydland and Prescott (1982; 1990), Backus Kehoe (1992), Ravn and Uhlig (2002) and, more recently, Perron and Wada (2009) and Kodama (2013), who applied it to U.S. and international data. For the Brazilian case, this filter was utilized, inter alia, by Ellery-Jr., et al. (2002), Ellery-Jr. and Gomes (2005) and Araújo, et al. (2008).

Other popular methods to extract the cyclical component of time series include the BN-decomposition (Beveridge and Nelson, 1981), based on unconstrained ARIMA models and estimated by Campbell and Mankiw (1987), Cochrane (1988) and Morley, et al. (2003) for the U.S., and by Cribari-Neto, (1990; 1993) for the Brazilian economy; the band-pass filter (Baxter and King, 1999), used by Basu and Taylor (1999) and Ellery-Jr., et al. (2002); and the unobserved components model, UC, due to Clark (1987) and considered by Morley, et al. (2003) and Perron and Wada (2009). As far as we know, the UC model has not been applied yet to the Brazilian GDP decomposition. Nevertheless, Kannebley and Gremaud (2003) employ such type of methodology in an interesting study concerning the secular trend of the Brazilian terms of trade.

Although the trend-cycle decomposition has become computationally simpler due to all abovementioned methods, practitioners still face some key problems. For instance, one can show that the HP-filter outcome is extremely dependent on the smooth parameter (λ) and, most of the time, the rule of thumb for setting up its value, provided by Hodrick and Prescott (1997) and broadly employed, is not adequate (Perron and Wada, 2009).

Another notorious problem is that distinct decomposition procedures may lead to rather different trend–cycle components and stylized facts about economic activity. Canova (1994, 1998), for example, studies this question for the U.S. economy, showing that some evidence is not robust to changes in the filter. Besides, the dissimilarities between the cyclic component of the BN and UC methods are examined by Morley et al. (2003) and Perron and Wada (2009). The BN-cycle tends to be quite noisy and leaves more of the fluctuation for the trend component, while the UC models lead to larger and more persistent cyclic oscillations. Therefore, the choice of a specific method for filtering the data is by no means inconsequential, and probably affects the main results and brings policy implications.

The Brazilian GDP trend and cycle decomposition may be also facing these problems. In this respect, some recent results contradict the common view that, since the Real Plan implementation in 1994, the Brazilian economy has become more stable. Araújo, et al. (2008) and Ellery-Jr. and Gomes (2005), for example, after using a HP-filter (λ=100), found that the Brazilian GDP volatility did not decrease in the post-war period. Additionally, Cribari-Neto (1990, 1993), while studying the annual Brazilian GNP and GDP data, respectively, from 1900 to 1990, and using the BN-filter, argued that the cyclic component of the Brazilian economic activity is small; that is, most of its oscillations are driven by "real-long-term" shocks to the trend. This conclusion does not match with Cunha and Ferreira (2004), who found that the welfare losses due to output fluctuations are significant in Brazil and reached up to 10%, a value higher than those estimated for the U.S. economy (e.g., Barlevy, 2004). Consequently, there is still room for improvements in the understanding of the Brazilian business cycle, which is a deep concern of the present work.

Two main contributions are provided. First, our estimation uses a new quarterly time series measured by Bonelli and Rodrigues (2012) for the period between 1947 and 1979, and by the Brazilian National Accounts System from then on (*Instituto Brasileiro de Geografia e Estatística*, IBGE, 2012). The first set of observations was calculated so as to be readily comparable to the second one, which avoids approximation errors. However, it should be clear that, when analyzing a quarterly time series, we are able to cover oscillations shorter than one year and to compare our business cycle dates to those established by the Brazilian Business Cycle Dating Committee, CODACE, for the years between 1980 and 2009[5]. Thus, as in the U.S. case, the Brazilian economy also has a natural benchmark for the trend-cycle decomposition evaluation when studying higher frequency data.

Second and more importantly, based on the theory of forecast combination, and by exploring the flexibility of the HP-filter, we provide a new scheme to compute average trend and cycle components in which the problems of filter selection are minimized. The basic idea is that, by varying the filter's smoothness parameter properly, one can potentially reproduce the results of almost, if not all, the other methods (from the BN-filter oscillating trend, to the smooth deterministic trends). In this sense, we calculate a large variety of HP-filters with different values for λ, and then we take an average from the decomposition outcomes. As pointed out by Timmermann (2006), this combination of different trend and cycle series is appealing at least for two reasons: i) it is more adaptable, outperforming individual models in the presence of structural breaks (Pesaran and Timmermann, 2005); and ii) it can be understood as a way to make the filtering procedure more robust against such misspecification biases and measurement errors, when compared to individual methods (Timmermann, 2006). Hence, the evidence reported here is more reliable than that which is grounded on "once and for all" decompositions.

Our main findings are the following: i) the model has almost matched the CODACE business cycle dates, with a correspondence of 88% and 86% during recessions and expansions, respectively; ii) the estimated trend component is noticeably flatter after the 1980s, depicting a major structural break that happened in that period, also known as the "lost decade"; iii) there is strong evidence that volatility decreased in

[5] CODACE's committee provides the Brazilian business cycle chronology between 1980 and 2009. Its researches will expand the dating process for the 1947-2012 years using the same data set employed in this work.

the country (for example, we found significant structural breaks which occurred around 1996/97); iv) the persistence of the cyclic series tends to oscillate between the 0.7-0.8 bands; v) the business cycle phases have a different duration in the full sample, with expansions and recessions lasting for, respectively, 8 and 6 quarters on average, which implies a full cycle of 3.5 years; however, during the Military Regime, Brazilian economy presented mean expansions about 80% longer than recessions; and, vi) the mean growth rates of the phases are quite different, reaching a value of 1.7% per quarter (or 6.8% per year) during expansions, and 0.45% per quarter (or 1.8% per year) during slowdowns; however, between 1985 and 1993, the mean growth rate during recessions was around -0.2% per quarter, i.e., -0.8% per year.

The results described above are wide-ranging. For example, we found that the Brazilian business cycles are asymmetric, with expansions exhibiting longer duration and accumulated movements than recessions. These asymmetries across business cycle phases are also observed in the OECD countries, as documented in Chang and Hwang (2011), Chauvet and Yu (2006) and Artis and Zhang (1999). Moreover, we found that the Brazilian long-term trend is reasonably similar to that described by Perron and Wada (2009) for the U.S. economy, except that, for the latter, the major break occurred in 1973. Our expansion and recession growth rates are also parallel to those obtained by Chauvet (2002).

The remainder of this paper is organized as follows. Section 2 presents and discusses the trend-cycle decomposition procedure. Section 3 presents some preliminary results, unit root tests and comparisons between our method and the CODACE business cycle dates. Section 4 brings the filtered Brazilian GDP’s facts and information, using a quarterly data set ranging from 1947 to 2012, while subsection 4.1 implements a number of robustness and structural change tests. Finally, section 5 shows the main conclusions and policy implications of the research work.

1.2. The Hodrick-Prescott filter and the average cycle

This section presents the trend-cycle decomposition method applied in the paper, covering briefly the mathematics of the HP-filter, then discussing its main caveats, and finally showing how we can overcome them.

The Hodrick-Prescott filter is a method developed for extracting a smoothed version, τ_t, from some given original series, say y_t. The τ_t component is considered as being the long-term trend, while the residuals, y_t - τ_t, contain the cyclic components. Strictly speaking, the HP-filter computes τ_t of y_t by solving:

$$\min_{\tau_t} \sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2, \qquad (1.1)$$

that is, the HP-filter minimizes the variance of y_t around the trend, subjects to a penalty that constrains the growth rate of τ_t, the second summation term (Hodrick and Prescott, 1997). The parameter λ controls the smoothness of the trend series. As it tends to infinity, τ_t approaches the linear trend case.

The value to be chosen for λ is still an open question in the economic literature, and it can have profound practical consequences. A wrong λ, for instance, may impute the greater part of the y_t's variation to the trend, leaving the cyclic component economically irrelevant. Nevertheless, most of the researchers, for the sake of simplicity, just follow the recommendations of Hodrick and Prescott (1997), setting it as

1600 for quarterly data[6] (e.g. Kydland and Prescott, 1990; Backus and Kehoe, 1992; Ellery-Jr., et al., 2002; Ellery-Jr. and Gomes, 2005; Araújo, et al., 2008; and Michaelides, et al., 2013; amongst several others).

On the other hand, Perron and Wada (2009) show that a λ=800,000 is good choice for detrending the U.S. quarterly real GDP during the period between 1947:01 and 1998:02. While Pedersen (2001), making an effort to find the best value for λ based on the theory of optimal filtering and on five different autoregressive processes[7], suggests a value around 1,000 and 1,050 for this parameter on quarterly data.

Possibly, the only consensus economists have reached regarding λ is that its value must represent the underlying structure of some data generating process (DGP). However, since a DGP may vary across countries and across the time, it turns out to be extremely difficult to elect a particular smoothness parameter as the true one. Indeed, a good procedure shall consider a set of conceivable values and find out a way to use this information in order to highlight features of the data set. This is exactly how we proceed in the present paper.

The method proposed here comprises two steps. First, it decomposes the original series, in our case the Brazilian quarterly GDP, into trend and cycle components by using the HP-filter with a variety of smoothness parameters. Second, it takes the arithmetic mean over the outcome of these filtering processes, which provides series with remarkable features, as discussed later. It is a simple method, nevertheless, strongly based on results obtained by the theory of forecast combination. Now, let us turn to details of each step, beginning with the second one.

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[6]They found this value by squaring the ratio of the cyclical component's variance, set as 5% per quarter, and the variance of second differenced term, set as 1/8% per quarter.

[7]A stationary $AR(1)$-process: $y_t = \varphi y_{t-1}+\varepsilon_t$, with φ=0.9 and φ=0.95; two near-unit root processes with φ=0.99 and φ=0.9999, and a near unit root $AR(2)$-process $y_t = \varphi_1 y_{t-1}+\varphi_2 y_{t-2}+\varepsilon_t$ with φ_1=1.3297 and φ_2=−0.3318.

The true trend and cycle components of an economic time series are unknown. Practitioners try to forecast them, employing a specific method and choosing some parameters of control, such as λ in the HP-filter case. Now, suppose that we are interested in forecast the variable y_c, say, the GDP cyclic component of any country, and that two predictions, y_{c1} and y_{c2}, are available, namely, the outcome of two different HP-filters provided by distinct analysts. Let the first guess be based on some N_1-vector of information x, i.e., $y_{c1}=g_1(x)$ while the second is based on some N_2-vector of information z, i.e., $y_{c2}=g_2(z)$[8]. If $\{x, z\}$, the full information set, were observable, it would be natural to construct a forecasting model based on all variables contained in x and z, i.e., $y_{c3}=g_3(x, z)$. On the other hand, if only the forecasts y_{c1} and y_{c2} are observed by the forecast user (while the underlying variables are not), then the theory of forecast combination states that the better strategy is to combine these predictions, using a model of the type $y_{cf}=g_c(y_{c1}, y_{c2}; w)$, where w refers to the combination weights (cf., Clemen, 1987; and Timmermann, 2006).

In this paper, we assign equal weights for w, since this assumption has been providing better results even when comparing to others more elegant combinations of weights. Clemen (1989, p.559), for example, after reviewing a large number of papers dealing with the forecast combination issues, states: "(…) *in many cases one can make dramatic performance improvements by simply averaging the forecasts.*" By their turn, Palm and Zellner (1992) find that adopting a simple average method is interesting because in many situations it will achieve a substantial reduction in the variance and bias. In addition, Timmermann (2006), analyzed a quarterly data set comprising up to 43 time series for the G7 economies between 1959 and 1999, and found that the out-of-

[8] Here, these two analysts use their information when choosing the smoothness parameter.

sample mean square forecast error (MSFE) for the arithmetic mean forecast is about 10% lower than the MSFE obtained by the best single model.

Another positive effect may arise from the combination of filter outcomes, namely, the higher degree of flexibility when facing structural breaks. Structural breaks are an important question when decomposing a time series and their incidence is almost certain during long time spans. Breaks can affect the stationarity of the series, introduce spurious correlations among its points, and make the trend-cycle decomposition troublesome, thus affecting analyses that do not account for this question. Perron (1989), for example, shows that the U.S. GDP trend may have no unit root if one takes into account a structural break occurred in 1973, due to the first oil price shock. In this sense, one should estimate the U.S. GDP trend as a linear one with a break in the mentioned year (these findings are confirmed by Perron and Wada, 2009, using a model of unobservable components with endogenous structural breaks).

Typically, it is difficult to timely detect structural breaks, but it is plausible that, on average, combinations of filter outcomes with different degrees of adaptability to breaks will outperform decompositions emerging from individual models. Some decomposition procedures have a more oscillating trend that will be only temporally affected by the break, while others have a smoother trend that will slowly adjust. As long as more data points are available after the break occurrence, slow-adapting models will perform better than fast-adapting ones, since the parameters of the former are more precisely estimated. On the other hand, if the data window from the most recent break is short, fast-adapting models can be expected to produce the best trend-cycle representations (see Pesaran and Timmermann, 2005). This intuition is easily expanded to the case where parameter and model uncertainty are present. As long as the DGP is a mutable process, the best decomposition model for a given economy will possibly change over time, in a sense that combining different filter outcomes can make the decomposition components more robust against such misspecification errors.

In short, the combination of filters is a way around the uncertainties arising from a complex data generating process. As stated by Winkler (1989, p.606): "(…) *in many situations there is no such thing as a 'true' model for forecasting purposes. The world around us is continually changing, with new uncertainties replacing old ones*." This insight implicitly assumes that one could not identify the underlying process, but that different filtering procedures are able to capture various aspects of the information contained in the time series, and produce more consistent business cycle facts by using an averaging scheme. Moreover, as indicated by Zarnowitz (1992, p.407), the idea we make use here is a "(…) *method for a decision maker to reduce the large-error risk associated with relying on one particular model or one individual's judgment*." Now, let us explain why we average over a variety of HP-filters.

As said before, the λ parameter of the HP-filter controls the smoothness of the trend. In this sense, we can benefit from its flexibility in order to mimic the trend and cycle components of other filtering methods. An illustration may explain this statement. First, we simulate a time series model as an autoregressive process taking the form $y_t = 0.2+0.99y_{t-1}+\varepsilon_t$, where ε_t is a Gaussian white noise. Then, we decompose the latter time series by utilizing two extreme case procedures: the noisy BN-ARIMA(2,1,0) filter, depicted in part "a" of Figure 1.1, below; and, the smooth third order polynomial trend, illustrated in part "c" of the same graph. Next, we use the HP-filter trying to replicate these two previous results. Part "b" shows the trend of a HP(λ=1)-filter, and part "d" a HP(λ=960,000)-filter. As we can see, the HP-filter is a good approximation for both methods, and by varying λ properly, one can reproduce an even larger range of filtering outcomes.

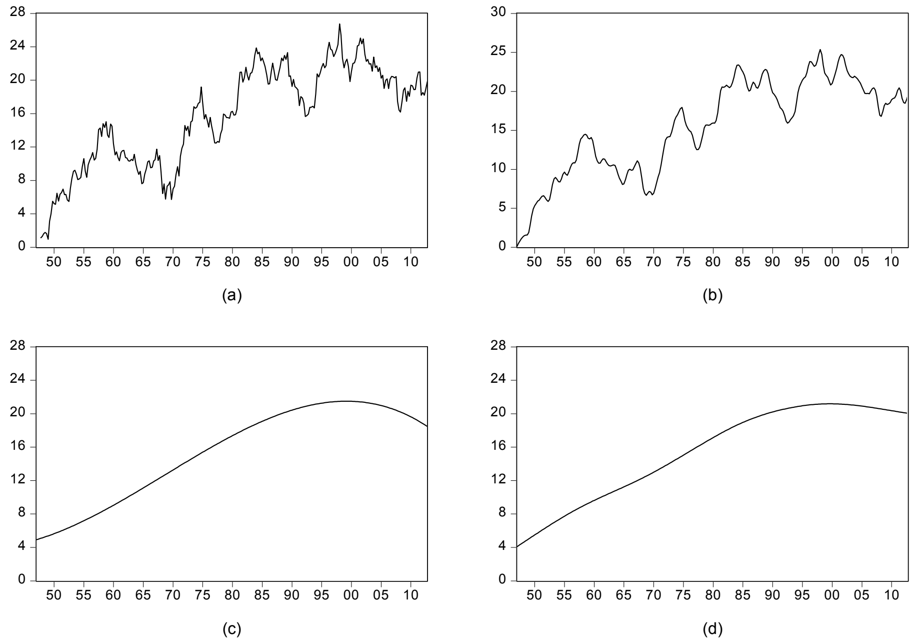

Fig.1.1: Trend component of the autoregressive process $y_t = 0.2+0.99y_{t-1}+\varepsilon_t$ according to the following models: (a) BN-ARIMA(2,1,0) filter; (b) HP(λ=1)-filter; (c) deterministic cubic trend; and, (d) HP(λ=960,000)-filter.

Moreover, we save time when making use of this approach since it avoids subsequent, and necessary, adjustments on the time series when averaging components from distinct trend-cycle decomposition methods (see, e.g., Lamo, et al., 2013, who employ this alternative procedure).

An extra detail should be noted with respect to the algorithm that averages the HP-filter components. In order to extract the best results from such method, the degree of overlap information between the series must be low. That is, the more new features are presented by the different filtering outcomes, the more useful and general are the combined series (see the intuition in Winkler, 1989; and Clemen, 1987). Nevertheless, the differences between two specific HP-filter outcomes decrease as the smoothness parameter increases. The series implied by a λ=10,000, for example, is quite similar to another obtained by setting a λ=11,000. Therefore, if the algorithm's step increases together with λ, the method will provide averaged trend and cycle components that will hold richer information about business cycle.

In this regards, we divide the HP-filter into five groups related to the degree of the trend smoothness, as is shown below, in Table 1.1. In each group, the algorithm's step was chosen as a simple function of the λ originally proposed by Hodrick and Prescott (1997). In this table we highlight some interesting values for λ, fetched by the calculations. First we emphasize λ=1, number that leads to an extremely noisy trend component; next we have λ=960 and 1,120, which are closely related to the values suggested by Pedersen (2001); finally we utilize a variety of other λ, including λ=1,600 and 14,440 as recommended by Hodrick and Prescott (1997) for quarterly and monthly data, respectively, and λ=800,000, considered by Perron and Wada (2009) for the quarterly U.S. real GDP data. In all, we implement 43 different types of HP-decompositions that, on average, shall bear a good resemblance with the true Brazilian GDP's trend and cycle components.

Table 1.1: Number of HP-filters utilized for building the average trend and cycle series

Group	Values of λ	Algorithm step(1)	Number of filters
1	**1**; 17; 33; 49; 65; 81; 97; 113; 129; 145	$1{,}6x10$	10
2	160; 320; 480; 640; 800; **960**; **1,120**; 1,280; 1,440	$1{,}6x10^2$	9
3	**1,600;** 3,200; 4,800; 6,400; 8,000; 9,600; 11,200; 12,800; **14,400**	$1{,}6x10^3$	9
4	16,000; 32,000; 48,000; 64,000; 80,000; 96,000; 112,000; 128000; 144000	$1{,}6x10^4$	9
5	160,000; 320,000; 480,000; 640,000; **800,000**; 960,000	$1{,}6x10^5$	6
Total			43

Notes: (1) Algorithm step stands for the interval between two sequential λ's.

1.3. Preliminary results: unit roots and decomposition evaluation

Perron (1989), in a seminal paper, brought light on the effects of structural breaks while analyzing unit roots in economic time series. In this paper, he showed how a single break in a stationary variable can mislead the classical unit root tests towards the non-rejection of the null hypothesis (see, additionally, Enders, 2008). One major problem with Perron's (1989) methodology, however, is that he considers the breakdate as exogenous, i.e., known beforehand. Thus, one could choose the breakpoint dates based on its prior observation of the time series and, hence, problems associated with data-mining are applicable to Perron's approach (Zivot and Andrews, 1992; Christiano, 1992). Zivot and Andrews (1992), instead, propose a test that circumvents this problem, by estimating, rather than fixing, the breakpoint date. In this paper, we estimate Zivot and Andrews' (1992) statistics, as well as the Kwiatkowski, et al. (KPSS, 1992) tests, in order to asses on unit root question, and verify whether the deterministic or stochastic trend is a better assumption for the Brazilian quarterly GDP time series. Table 1.2 shows the test results.

Table 1.2: Unit root tests, Brazilian quarterly GDP, 1947:01 – 2012:04

Panel (a): Zivot and Andrews (1992) tests on level GDP					
Break Hypothesis	*Lags SIC (Max.: 8)*	*Critical values*			*Calculated t-statistic*
		1%	*5%*	*10%*	
Intercept	5	-5.34	-4.93	-4.58	-3.38
Trend	5	-4.80	-4.42	-4.11	-3.95
Both	5	-5.57	-5.08	-4.82	-4.78
Panel (b): KPSS tests on level GDP					
Test assumption	*Bandwidth*	*Critical values*			*Calculated t-statistic*
		1%	*5%*	*10%*	
Intercept	12	0.74	0.46	0.35	2.05
Trend and intercept	12	0.21	0.15	0.12	0.51

As we can see above, Panel (*a*) in Table 1.2 shows calculated t-statistics less than the 10% critical value for each one of the assumptions, that is, failing to reject the null of a unit root with a structural break. By its turn, Panel (*b*) displays KPSS tests rejecting the null of stationarity in both assumptions. Consequently, all tests are confirming the existence of a unit root in the log-levels of the Brazilian GDP data, even when one takes account to the possibility of one structural change.

As the log-level of the Brazilian quarterly GDP is non-stationary around a stochastic trend, we can turn our attentions to the decomposition components, since the HP-filter is able to remove up to four unit roots of a given series (see, e.g., Baxter and King, 1999; and Pedersen, 2001).

Figure 1.2, below, brings four series. First, part "a" shows the log-GDP time series with CODACE recession dates illustrated in the shaded areas. Part "b" depicts our first average time series, namely, our results for the Brazilian GDP long-term trend (solid line) and its two standard error bands (dashed lines). By visually inspecting Figure 1.2, one can clearly see a very smooth trend with a flatter slope after the 1980s. In fact, this reduction was remarkable: Brazilian long-term trend is now about 50% times less steep than it used to be before the mentioned year.

According to Perron (1989), this type of smooth stochastic trend is well-described as a unit root process with strong mean-reversion and fat-tailed distribution for the error sequences. As a result, most of shocks have a small, if any, long-term effect; only a few numbers of events can modify the trend permanently, as in the case of the highly unstable period of 1980s, in which Brazil has underwent a political regime switching (military to democratic), and several years of hyperinflation.

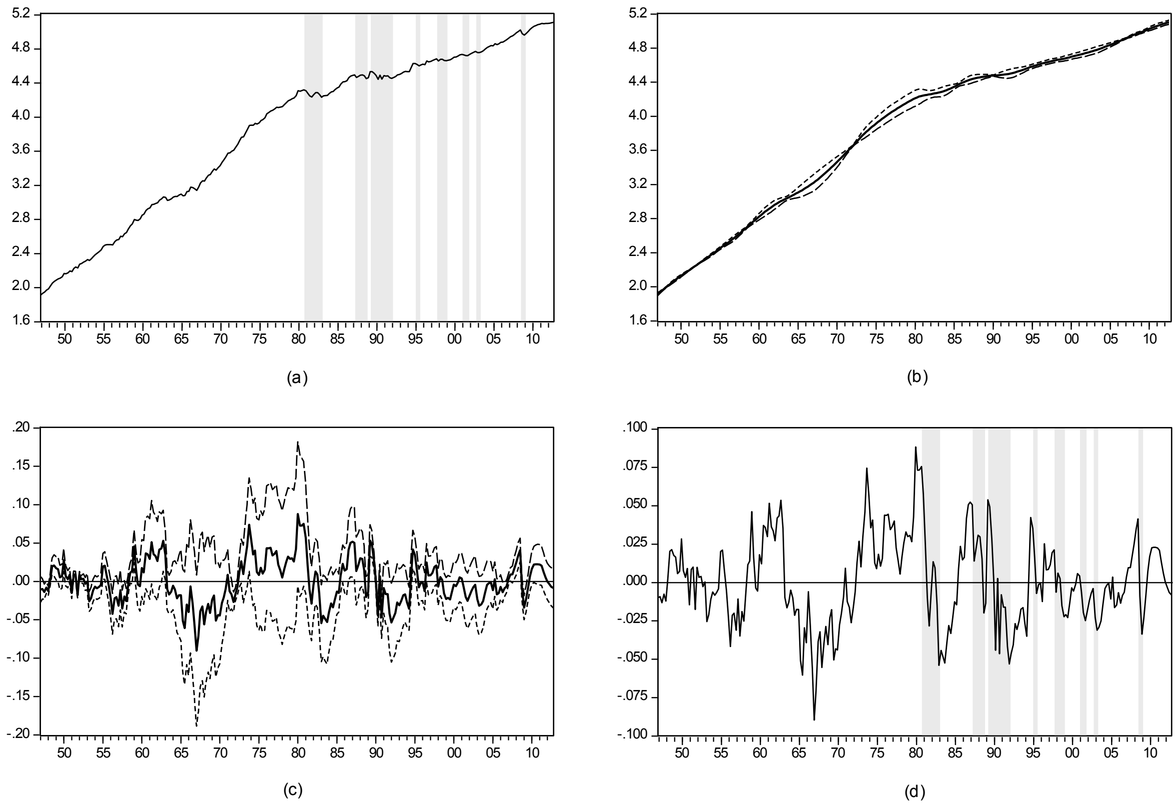

Fig.1.2: Brazilian time series. (a) Log of Brazilian quarterly real GDP; (b) average trend series (solid line) and two standard error bands (dashed lines); (c) average cycle series (solid line) and two standard errors bands (dashed lines); and, (d) average cycle series. Shaded areas are the CODACE recession dates.

Parts “b” and “c” also show that the trend and cycle components are less accurately calculated during the periods of 1965-1970, and 1974-1980. These periods may be associated with many political and economic instabilities, such as the beginning of the Military Regime; a high and increasing inflation (in 1964 Brazilian General Price Index - Internal Availability -reached a peak of 92% per year, for the whole 1947-1979 period); the extended slowdown in the GDP growth rate that Brazilian economy has passed through during 1963-1967, due to a large package of restrictive fiscal and monetary policies, aiming to control the soaring prices; an even longer period of high growth, over the 1968-1973 period, also referred as the Economic Miracle, in which the real GDP grew at a rate of 11% per year (Abreu, 1989); and, the break started around 1980.

Such sources of uncertainties would have affected the usual trend-cycle decomposition methods whenever it is assumed a particular specification for the filtering procedure. However, as we argued before, the average component series should be more robust to them, since different decomposition outcomes can adapt faster to the vast complexity of the real world economic time series.

In Figure 1.2, part “d”, we focus on the average cyclic series as well as on the CODACE recession dates (the Brazilian committee provides us the business cycle chronology for the 1980-2009 period). Besides, one can notice a high degree of matching between both series. Still, in order to access an exact measure of their correspondence, we need to transform our cyclic series in a binary indicator of the business cycle phases. For such, first, we find the turning point dates (peaks and troughs), and, second, we create our own dummy series, defining expansions as the period from a previous trough to the most recent peak, and recessions as the period from a previous peak to the most recent trough.

In order to find the turning points, we employ a simple rule created by Wecker (1979), and also employed by Canova (1994) and Pagan (1997), among others, where a peak is equal 1 when $\{\Delta y_{c,t} > 0; \Delta y_{c,t+1} < 0; \Delta y_{c,t+2} < 0\}$, where $y_{c,t}$ refers to the average cyclic component. Conversely, a trough series is equal to 1 when $\{\Delta y_{c,t} < 0; \Delta y_{c,t+1} > 0; \Delta y_{c,t+2} > 0\}$. We also require that peaks and troughs alternate, so if two or more peaks (troughs) are subsequent we select the one with a higher (smaller) value for y_c. Thus, the algorithm replicates a common view among media members and politicians that expansions (recessions) involve at least two quarters of positive (negative) growth.

Table 1.3 presents comparisons between our cyclic series and CODACE's business cycle dates. This table also refers to the binary indicators for expansions and recessions, S_t^E and S_t^R, respectively, derived from our decomposition after applying Wecker's (1979) rule. In a total of 120 quarters, our dummy indicator has a correspondence rate of 86% ((79+24)/120) during expansions, and 88% ((44+61)/120) in recessions.

Table 1.3: Decomposition-CODACE comparisons, 1980:01 – 2009:04

Expansions				*Recessions*			
	CODACE				*CODACE*		
S_t^E	1	0	Total	S_t^R	1	0	Total
1	79	8	87	1	44	11	55
0	9	24	33	0	4	61	65
Total	88	32	120	Total	48	72	120
Correspondence	86%			Correspondence	88%		

Moreover, while the errors in the course of expansions are quite similar, i.e., 8 cases in which our cycle series indicates a false upswing, and 9 cases in which it misses a real one; during recessions the average cyclic series misses only 4 in a total of 48 CODACE dates, i.e., a matching of 92%. Finally, it shall be noted that both series, S_t^R and CODACE, are perfectly coordinated during the 1989:02-1992:01, 2002:01-2003:02 and 2008:03-2009:01 recessions.

In order to compare the performance of our method, we depict below, in Table 1.4, correspondence rates of other four different methods, using the same Wecker's (1979) rule. The alternative decomposition methods considered are: a) the classical HP(λ=1600)-filter; b) an ARIMA(1,1,1)-BN filter; c) the Baxter and King (1999) band pass filter, assuming that business cycles lasts from 1.5 to 8 years; and, d) the unobservable components decomposition, considering that the cyclic component behaves as an AR(2), process (that is, UC(2) model).

As can be seen in Table 1.4, our averaged decomposition outperforms all the other methods, especially when it comes to expansions. Including, we have gotten qualitative gains even when comparing with the classical HP-filter, the second best option. It is important to note that if one had means to check methods' performance between 1965 and 1980, a period with large filtering instability, as Figure 1.2 shows, is possible to think that our method could have obtained even better results.

Table 1.4: Comparative performance of decomposition methods

Filtering method	Coincidence with CODACE in:	
	Expansions (%)	Recessions (%)
Mean cycle	86	88
HP(λ=1600)	82	85
ARIMA(1,1,1)-BN	31	20
Baxter-King	75	76
UC(2)	73	73

1.4. Features of Brazilian cyclic component from 1947 to 2012

In order to examine features of the Brazilian business cycle, we divide the sample into four distinct subsamples, namely, the years before the Military Regime, 1947-1963; the Military Regime itself, 1964-1984; the Democratic period before the Real Plan, 1985-1993; and the Real Plan period itself, 1994-2012.

In Table 1.5, which brings patterns of the business cycle phases, the average duration, a measure of the phase length, is calculated using the formula $\hat{D}^i = 1/(1-\hat{\alpha}^i - \hat{\beta}^i)$, where i = *E*, *R*, meaning expansions and recessions, respectively.

In this case, parameters are obtained by the OLS regression $S_t^i = \alpha^i + \beta^i S_{t-1}^i$, where i = E, R, and S_t^E and S_t^R represent the same binary variables analyzed in Section 1.3.

By its turn, the average range during the business cycle phases, $\hat{A}^i$, is estimated as the slope of the linear regressions between ΔGDP_t and S_t^i, and indicates the height of expansions or the depth of recessions, in a given period of time. Having the mean duration and range, total gains and losses of the business cycle phases follow directly by using the triangle approximation, C_{Ti}=0.5($\hat{D}^i$ *$\hat{A}^i$), where C_{Ti} refers to the cumulative movements inside a cycle's phase (aforementioned calculations follow Harding and Pagan, 2002).

Expansions in Brazil last for approximately eight quarters, or two years, and recessions have a mean duration of six quarters, or 1.5 years. The three longest expansions occurred from 1956:02 to 1961:02, related to the "*Plano de Metas*", a consistent and comprehensive plan of public investments; from 1967:01 to 1971:01 and 1971:04 to 1973:04, related to the Brazilian Economic Miracle period; and from 2003:02 to 2008:03, which was interrupted by the Great Recession.

On the other hand, the three longest recessions occurred from 1950:01 to 1953:02, related with unbalanced public accounts and a cambial crisis started around 1952; and the periods of 1981:01-1983:04, and 1989:02-1992:01, where political and economic instabilities led to hyperinflation, and negative growth (Brazilian GDP reduced -4.25 in 1981, -2.93 in 1983, -0.06% in 1988, -4.35% in 1990, and -0.47% in 1992, according data from the Brazilian System of National Accounts, IBGE). After that, 2009 was the only year in which Brazilian economy presented a negative growth, with -0.33% of variation in its GDP.

Table 1.5: Phase patterns, Brazilian business cycle

Statistics/Period	Pre-1964	Military	1985-1993	Real Plan	Full sample
Panel (a): Expansions					
Duration (quarters)	8.40	9.00	7.67	8.00	8.36
Range (%)	1.14	2.27	1.84	1.36	1.62
Total gain (%)	4.79	10.23	7.04	5.45	6.75
Mean growth (%)	2.09	2.09	1.26	1.13	1.70
Panel (b): Recessions					
Duration (quarters)	6.00	5.00	6.33	5.50	5.59
Range (%)	-1.23	-1.76	-1.80	-1.17	-1.44
Total loss (%)	-3.69	-4.41	-5.72	-3.21	-4.05
Mean growth (%)	1.10	0.49	-0.21	0.10	0.46

By closely inspecting Table 1.5, one can note that, while the business cycle phases change across the subsamples, the duration of a full cycle is quite constant, around 3.5 years, i.e., 14 quarters. Another interesting fact is that the duration of expansions are longer than that of recessions, even during the 1980s. Additionally, total gains are always higher than total losses, depicting a manifested asymmetry between the business cycle phases in the country. Besides, after the Real Plan, Brazilian economy has had milder expansions and recessions (see total gain and loss, in Table 1.5), which shows some evidence of increased stability in the country since the mid-1990s.

Persistence[9], by its turn, has been quite stable in Brazil, usually oscillating around the 0.7-0.8 bands, as can be seen in Table 1.6. However, during some recessions, such as those occurred in 1989:02-1992:01, 1997:04-1999:01 and 2008:03-2009:01, the cyclic series correlation has a tendency to reduce, probably due to a higher degree of uncertainty (as depicted by Figure 1.3, part "c", below).

Taking a closer look into the stability question, Table 1.6 shows that Brazilian volatility, measured as the standard deviation of the cyclic series, has surely decreased

[9] Persistence is defined as the first autoregressive coefficient of the cyclic component as in Pivetta and Reis (2007).

after 1994. In fact, the quarterly volatility after this year is less than half of that observed during the 1964-1984 period, and about 40% lower than its full sample value. In order to make international comparisons, we can reproduce statistics calculated by Aguiar and Gopinath (2007) for a set of developed countries, who found standard deviations in the order of 1.39% for Australia, 1.64% for Canada, 2.18% for Finland, 1.52% for Sweden, and 1.34% overall, between 1980 and 2003. Thus, after 1994, our results indicate that Brazilian instability may have been converging to a number comparable to those estimated in some developed countries.

Table 1.6: Volatility and Persistence of the Brazilian Business Cycle

Statistic/Period	Pre-1964	Military	1985-1993	Real Plan	Full sample
Stand. Deviation (%)	2.22	3.85	3.23	1.79	2.88
Persistence	0.74	0.89	0.73	0.71	0.82
N. Obs.	68	84	36	76	264

Figure 1.3, below, provides additional information about Brazilian business cycles. In that figure, we estimate moving standard deviation, variance, and persistence of our cyclic series using a 14-quarter window, which is the same average duration of a full cycle, besides the GDP 14-quarter mean growth-rate. These time series are depicted in parts “a”, “b”, “c”, and “d”, respectively.

As one can see, parts “a” and “b” of Figure 1.3 confirm that Brazilian instability has decreased since mid-1990s. Moreover, during periods of recessions, standard deviation and variance tend to increase, but after the mentioned period, peaks of volatility are consistently lower than the previous one (the only exception is the last international crises peak). In this sense, all the evidence reported so far seems to support the incidence of a delayed great moderation in Brazil, in lines with that found by several authors for the U.S. economy (see, e.g., Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; and Stock and Watson, 2002).

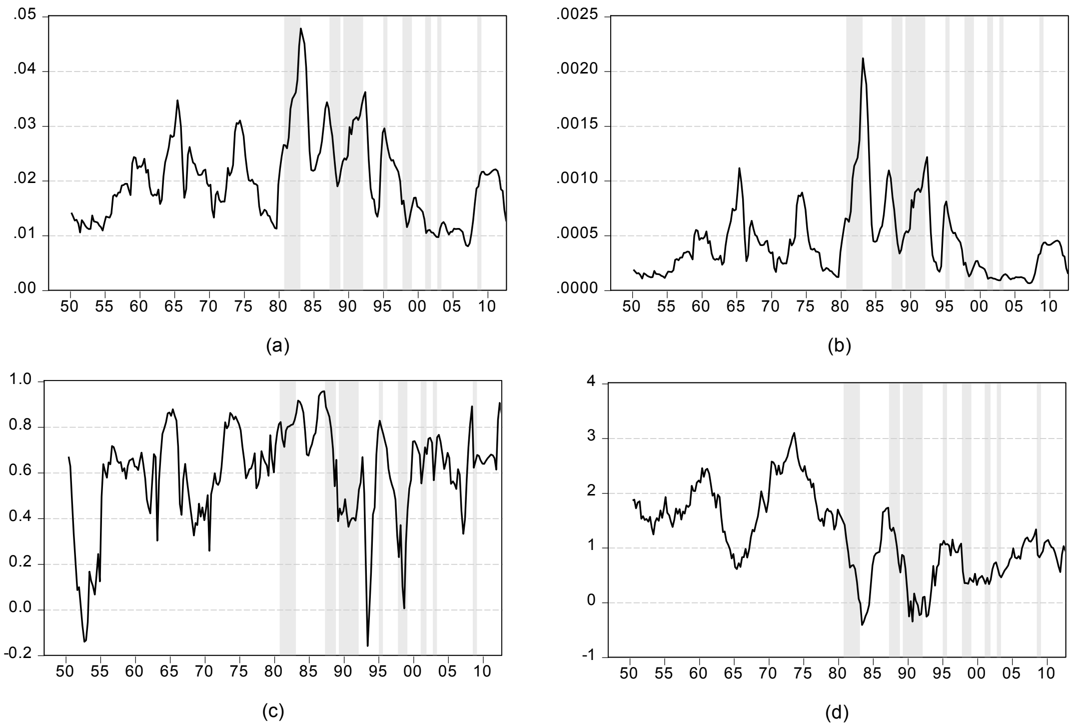

Fig.1.3: Brazilian moving statistics: (a) standard deviation; (b) variance; (c) persistence; and, (d) GDP growth rates. Note: moving window of 14 quarters, one full cycle period. Shaded areas represent CODACE recession dates.

According to Stock and Watson (2002), there are generally three main reasons for this phenomenon. The first one is related with structural changes that might have affected the economy; for example, the shift in output from goods to services (Moore and Zarnowitz, 1986), improvements in the inventory management made possible by the advancements in information-technology (McConnell and Perez-Quiros, 2000), and financial innovations that facilitates intertemporal smoothing of consumption and investment (Blanchard and Simon, 2001). The second reason would be improved monetary policy (e.g., Cogley and Sargent, 2005; Canova, 2009). And the third category is good luck, that is, a number of exogenous shocks that reduced U.S. volatility (Bernanke and Mihov 1998; Leeper and Zha 2003; Sims and Zha 2006).

Since the Real Plan implementation, Brazilian government has committed to foster a sustainable budget policy and the Central Bank's monetary rules have concentrated on price stability, especially after the adoption of the inflation targeting regime. Together, the more predictable monetary and fiscal policies and the low-inflation scenario might be the reason why the current Brazilian macroeconomic environment is less volatile. However, a consistent answer for this question is beyond the objectives of the present paper. Our focus is related to mapping process and raising questions and characteristics which shall be explained by future investigations.

Additional information is found in Figure 1.3, part "d". In the full sample, Brazilian economy has had 14 quarters of negative growth. The historical growth-rate peak was found in 1973:04, which equals to 3.09% per quarter, while the lowest value occurred in 1983:03, equaling to –0.42% per quarter. Before the 1980s, the 14-quarter growth rate of the GDP was swinging around 2% per quarter, a value closer to that believed as being the Brazilian natural growth-rate up to this year, which equals to 7% per year, as pointed out in many sections of Abreu's book (1989, p.222, for instance). Since then, the Brazilian's GDP long-term growth-rate seems to have converged to half of this value, about 1% per quarter.

1.4.1. Robustness tests on the decreased volatility and structural change tests

In this subsection, we seek to investigate further questions regarding the reduction of the Brazilian instability, since this is an interesting feature, also found in other countries that had not yet been detected by previous papers. Specifically, we intend to examine if this finding is robust to changes in the volatility measure, and when it has really happened.

Table 1.7 brings a variety of proxies for the volatility in the country. The first three series ("*Δgdp* variance (*i*)", i = 4, 8, 14) refer to the variance of the GDP log growth-rate considering 4, 8 and 14 quarters moving windows, respectively. Next, two classical measures of instability are presented, i.e., the absolute and the squared returns. Table 1.7 also shows the one step ahead forecasts of the conditional variance emerging from an ARIMA(7,1,0)-Garch(1,1) model for the log-GDP time series, and an ARIMA(5,1,0)-Garch(1,1) model for the mean HP-cycle. Both specifications were chosen according to the Akaike (1987) information criteria, where, for the sake of simplicity, we assume normally distributed disturbances. Finally, we present, within parenthesis, the classical Student's t and Welch's (1951) statistics for the null that the estimated volatility in a certain period is equal to that found after 1994. Welch (1951) test considers the possibility of different variances across subsamples[10].

The first pattern seen in Table 1.7 is that volatility increased from 1947 to 1993 and then, after 1994, it fell to lower levels. On average, the instability of the 1994-2012 years is 28% lower than that observed during 1947-1963; 41% lower than that under the Military regime; and, 63% lower than the volatility of the 1985-1993 years. The major difference across periods was measured by the variance of the growth rate within one year moving window, an approximation for the short-run volatility (*Δgdp* variance, 4 quarters). According to this proxy, instability has decreased about 40, 70 and 230% in the Real Plan, comparatively to the pre-1964, Military and 1985-1993 periods, in that

[10] We do not include the log-squared returns because of their several problems, such as negative, large, and/or undetermined values for volatility.

order. Conversely, the minor differences were estimated by the Garch(1,1)-GDP proxy, wherein the instability after 1994 has decreased 7, 21, and 64%, relatively to the periods in the same order as before. A second feature is that the period from 1985 to 1993, in which inflation levels were extremely high, was the most unstable in the Brazilian history, for nearly all volatility measures[11].

Table 1.7: More volatility statistics and mean equality tests

Statistic/Sample	Pre 1964	Military	1985-1993	Real Plan
Δgdp variance (4)	2.07 (1.95**; 4.03**)	2.51 (3.26*; 10.56*)	4.81 (4.49*; 11.33*)	1.47
Δgdp variance (8)	2.40 (2.25**; 5.61**)	3.15 (4.84*; 23.45*)	5.35 (5.55*; 17.22*)	1.82
Δgdp variance (14)	2.61 (3.08*; 11.08*)	3.32 (6.11*; 37.80*)	5.76 (8.16*; 37.28*)	2.01
Absolute returns	1.97 (3.77*; 13.75*)	2.08 (4.25*; 18.70*)	1.96 (2.88*; 6.07*)	1.24
Squared returns	0.055 (3.26*; 10.19*)	0.063 (3.87*; 15.67*)	0.063 (2.75*; 4.68*)	0.026
Garch(1,1) GDP	0.030 (1.35; 1,87)	0.034 (3.76*; 14.14*)	0.046 (4.68*; 12.40*)	0.028
Garch(1,1) HP-cycle	0.025 (2.96*; 9.48*)	0.028 (4.68*; 22.33*)	0.038 (5.53*; 16.98*)	0.022
Number of obs.	68	84	36	76

Notes: *, **, *** denotes statistical significance at 1, 5 and 10% levels, respectively. Inside parentheses are *t* and Welch (1951) mean equality test statistics. All figures refer to the Brazilian quarterly data, 1947-2012, and are in percentages.

Throughout this paper, we have assumed a fairly logical division in the data set, beginning with pre-Military period, then the Military regime itself, passing through the 1980s and, finally, the Real Plan's years. It seems to be a natural assumption, given the recent political history of the country. Nonetheless, statistically, this type of a priori division of the sample makes the breakdate endogenous (correlated with the data), and tests as those presented in Table 6 are likely to falsely indicate a break, when none in fact exists (Hansen, 2001).

[11] Exception for the absolute returns.

In order to circumvent this difficulty, we apply three different classes of methods, which are the Nyblom's L test of structural changes with unknown breakdate (Hansen, 1992), the Quandt (1960)-Andrews (1993) procedure, and the Hansen (2001) tests. The first one evaluates a structural change in all the parameters of a model, without assuming a specific date, but it does not provide an estimated date of change. The Quandt (1960)-Andrews (1993) and Hansen (2001) methodologies, however, do estimate a breakpoint date, besides providing complementary pieces of information.

When computing Nyblom's L test, we follow Hansen (1992) and McConnell and Perez-Quiros (2000), assuming that the Brazilian GDP log-growth rates behave according an AR(1) process with a drift. It is a simple yet powerful model, as showed by Hess and Iwata (1997). Proceeding in this way, we are able to test for breaks in the mean, in the autoregressive coefficient and in the variance of the time series, which are associated, respectively, to structural changes in the trend, persistence and volatility of the GDP.

In order to calculate Nyblom's L statistics for the null hypothesis of constancy in the model's parameters (μ, ϕ, σ^2), first we need to run OLS estimation, and then define:

$$f_{it} = \begin{cases} x_{it}\hat{e}_t, i = 1, \ldots, m, \\ \hat{e}_t^2 - \hat{\sigma}^2, i = m+1. \end{cases} \tag{1.2}$$

Where, x_{it} is equal to one, for the μ's case, and equal to Δgdp_{t-1} for the ϕ parameter's case; $\hat{e}_t$ represents the OLS residuals; $\hat{\sigma}^2$ the OLS model's variance; and m + 1 the total of parameters estimated, in our case, m = 3. By OLS definition, equation (1.2) is equivalent to $\sum_{t=1}^{n} f_{it} = 0$, i = 1, …, m + 1, n is the data set length. The variables f_{it} are the OLS first order conditions (Hansen, 1992). Now, we define $S_{it} = \sum_{j=1}^{t} f_{ij}$, the cumulative first order condition up to a given time *t*. Thus, by the first order condition, S_{in} = 0. Hansen (1992) provides two types of statistics, one for testing the stability of each parameter individually, and other for testing the stability of all parameters jointly. For the single parameter case, test statistics are given by,

$$L_i = \frac{1}{nV_i} \sum_{t=1}^{n} S_{it}^2, \tag{1.3}$$

where,

$$V_i = \sum_{t=1}^{n} f_{it}^2. \tag{1.4}$$

For the joint stability test, it is convenient to use matrix notation, that is,

$$L_c = \frac{1}{n} \sum_{t=1}^{n} \mathbf{S}_t^{'} \mathbf{V}^{-1} \mathbf{S}_t, \tag{1.5}$$

where,

$$V = \sum_{t=1}^{n} \mathbf{f}_t \mathbf{f}_t^{'}. \tag{1.6}$$

In Equations (1.5) and (1.6), the bold letters represent vectors which collect the (m + 1)- f_{it} and S_{it} elements. Expression (1.5) is an average of the squared cumulative sums of first-order conditions. Under the null hypothesis, these cumulative sums will tend to wander around zero, but under the alternative, they will not, thus developing a nonzero mean in parts of the sample, and leading to larger test statistics (Hansen, 1992).

Table 1.8 brings the output of Nyblom's L test. In this table, we present five Panels; from "*a*" to "*e*", in which Nyblom's tests are applied to different samples. First, Panel (*a*) shows the method for the whole data set. In this case, the estimation shows a clear break in the trend, with a calculated statistics of 1.27 that can be compared to the critical values of 0.47 (5%), or 0.35 (10%). Besides, we cannot find a significant break in the autoregressive parameter, and the variance presents a break only considering a critical value of 10%.

However, we have seen before that the variance results during the pre-Military and the post-Real Plan periods are somehow similar, and this might be distorting the tests. As presented in the table, if the sample is given in decades, the break in the variance becomes clearer, with the L statistic reaching a peak of 0.97 during the 1980s, and 0.94 after the 1990s. Besides, as long as we move the sample as before, the structural change in the mean, μ, disappears after 1980, which indicates that the break may have occurred around this year.

Results from Table 1.8 for the autoregressive parameter are mixed, and they may not have suffered a major change during the period of the analysis of the sample, as shown in Table 1.8 Panel (*a*), Table 1.6 and Figure 1.3.

Hansen (1992) tests are informative and have a solid statistical basis, but they lack information regarding the timing of the breaks. In this sense, we apply two other tests, the first one due to Quandt (1960) and Andrews (1993, henceforth Quandt-

Andrews), and the second one to Hansen (2001). Here we present the Quandt-Andrews test first, since Hansen (2001) utilizes some of its concepts.

Table 1.8: Nyblom's L test for stability of Brazilian real GDP growth – 1947:01 to 2012:04

Specification: $\Delta gdp_t = \mu + \phi\ \Delta gdp_{t-1} + \varepsilon_t$			
Panel (a): 1947:01 to 2012:04			
Parameter	Estimate	L_c	CV (5%; 10%)
μ	0.0103 (0.00)	1.268	0.47; 0.35
ϕ	0.1525 (0.01)	0.274	0.47; 0.35
σ^2	0.0003	0.363	0.47; 0.35
Joint L_c	1.7345		1.01; 0.85
Panel (b): 1960:01 to 2012:04			
Parameter	Estimate	L_c	CV (5%; 10%)
μ	0.0087 (0.00)	0.7643	0.47; 0.35
ϕ	0.1837 (0.09)	0.3911	0.47; 0.35
σ^2	0.0004	0.5634	0.47; 0.35
Joint L_c	1.5347		1.01; 0.85
Panel (c): 1970:01 to 2012:04			
Parameter	Estimate	L_c	CV (5%; 10%)
μ	0.0078 (0.00)	0.6332	0.47; 0.35
ϕ	0.2073 (0.01)	0.5784	0.47; 0.35
σ^2	0.0003	0.6917	0.47; 0.35
Joint L_c	1.7345		1.01; 0.85
Panel (d): 1980:01 to 2012:04			
Parameter	Estimate	L_c	CV (5%; 10%)
μ	0.0056 (0.00)	0.1426	0.47; 0.35
ϕ	0.0764 (0.25)	0.1363	0.47; 0.35
σ^2	0.0003	0.9688	0.47; 0.35
Joint L_c	1.1734		1.01; 0.85
Panel (e): 1990:01 to 2012:04			
Parameter	Estimate	L_c	CV (5%; 10%)
μ	0.0073 (0.00)	0.1273	0.47; 0.35
ϕ	-0.0651 (0.75)	0.3805	0.47; 0.35
σ^2	0.0003	0.9422	0.47; 0.35
Joint L_c	1.2292		1.01; 0.85

Notes: P-values are within parenthesis. L_c is the statistic for a break point in each of the parameters listed in the first column. CV is the critical value for both 5 and 10% of significance, according Hansen (1992).

The Quandt-Andrews method tests one or more unknown structural breakpoints in the sample for a specified equation. Quandt (1960) proposed a method that calculates

Chow's statistics for every point of the sample between two dates, say, t_1 and t_2[12]. Through this search procedure, the breakdate can be found either using the maximum of the Chow's statistics (the original Quandt's test), or the exponential and average statistics, for all Andrews (1993) and Andrews and Ploberger (1994) calculated tables of critical values, while Hansen (1997) provided approximate asymptotic *p*-values. In this research work, we apply the maximum and the exponential statistics, standard in the literature, and presented below, in equations (1.7) and (1.8), respectively:

$$MaxF = \max_{t_1 \leq t \leq t_2} (F(t)). \tag{1.7}$$

$$ExpF = \ln\left(\frac{1}{k}\sum_{t=t_1}^{t_2}\exp\left(\frac{1}{2}F(t)\right)\right). \tag{1.8}$$

When applying Quandt-Andrews tests, we assume two specifications, one for breaks in the AR(1) model, $\Delta gdp_t = \mu + \phi\ \Delta gdp_{t-1} + \varepsilon_t$, which tests for breaks in μ and ϕ, and other for breaks in volatility, where the dependent variable is a variety of proxies for the Brazilian instability, most of them listed before, in Table 1.7; κ is a parameter that refers to the average volatility, and υ_t is an error term. The positive point about this approach it that it allows testing for breaks in a vast number of instability indicators.

Finally, Hasen's (2001) test integrates both Hansen (1992) and Quandt-Andrews methodologies in a single framework. Assuming, again, an AR(1) process for the Brazilian GDP log-growth rates, Hansen (2001) procedure estimates and tests the time of a break occurrence for the full set of parameters (i.e., the OLS estimates for μ, ϕ and

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[12] Andrews' (1993) statistics diverge to infinity in probability if one uses them to the full sample. Thus, following his suggestions, we exclude from the analysis the first and the last 7.5% of the observations.

σ^2) by means of the maximum and exponential statistics. The results of Quandt-Andrews and Hansen (2001) tests are presented in Table 1.9.

Beginning with the break on the mean growth-rate of the process, μ, Table 1.9 shows that Quandt-Andrews method estimates it in the second quarter of 1980, while Hansen (2001) estimates a break in the first quarter of the same year. Besides, MaxF and ExpF Wald statistics for both methods are highly significant. In this sense, based on the findings of the trend-cycle decomposition, and on these results, one can be quite sure about the timing of the break on the trend: the first semester of 1980. The GDP's log-growth rate was estimated at 1.8% per quarter, before 1980, and 0.7% after that year, which is similar to the results found in Section 1.3. The evidence reported here agrees, therefore, with the Lost Decade view, which has imposed to the Brazilian economy a permanent slowdown in its rate of growth.

With respect to the autoregressive coefficient, Table 1.9 Panel (b) confirms our previous expectations, showing that at 10% of significance we cannot reject the null hypothesis of constancy in the ϕ parameter. Specifically, MaxF statistic was calculated as 7.24, with a p-value of 14%, while ExpF was calculated as 1.37, with a p-value of 12%. By reviewing Tables 1.6 and 1.8 Panel (*a*), we are able to reach the same conclusion.

Now, we shall turn attention to the volatility question. Additionally to the proxies presented before, Panel (a) from Table 1.9 brings three moving variances of the cyclic series (HP-mean cycle series), for windows of four, eight and 14 quarters, respectively, the "Moving var. cycle (*i*)", with i = 4, 8, and 14. Almost all short-term volatility measures, namely, Moving var. cycle (4), Δgdp variance (4), Garch(1,1)-GDP, and Garch(1,1)-HP cycle estimate one break around the years 1996 or 1997. This result is confirmed by the Hansen (2001) test in Panel (b), which estimates a break in 1996:04. All statistics are highly significant. The long-term instability measures, Moving var. cycle (8), Moving var. cycle (14), *Δgdp* variance (8), and *Δgdp* variance (14), by construction, postpone the timing of the break by few quarters.

Table 1.9: Breakdate tests

Panel (a): Quandt-Andrews methodology Specifications: i) $\Delta gdp_t = \mu + \phi\, \Delta gdp_{t-1} + \varepsilon_t$; and, ii) $\sigma^2_{t,proxy} = \kappa + \upsilon_t$ for variances			
Variable	Breakdate	MaxF (p-value)	ExpF (p-value)
Δgdp	1980:02	26.04 (0.00)	9.39 (0.00)
Moving var. cycle (4)	1996:01	13.42 (0.01)	3.98 (0.00)
Moving var. cycle (8)	1996:04	23.64 (0.00)	8.45 (0.00)
Moving var. cycle (14)	1997:04	40.98 (0.00)	17.09 (0.00)
Δgdp variance (4)	1997:03	20.81 (0.00)	7.37 (0.00)
Δgdp variance (8)	1998:03	30.83 (0.00)	12.15 (0.00)
Δgdp variance (14)	1999:01	49.60 (0.00)	21.71 (0.00)
Absolute returns	1991:02	25.25 (0.00)	8.98 (0.00)
Squared returns	1991:02	19.30 (0.00)	6.88 (0.00)
Garch(1,1) GDP	1997:03	18.53 (0.00)	6.71 (0.00)
Garch(1,1) HP-cycle	1997:03	28.40 (0.00)	11.49 (0.00)
Panel (b): Hansen (2001) methodology Specification: $\Delta gdp_t = \mu + \phi\, \Delta gdp_{t-1} + \varepsilon_t$			
Parameter	Breakdate	MaxF (p-value)	ExpF (p-value)
μ	1980:01	24.18 (0.00)	8.04 (0.00)
ϕ	1990:02	7.24 (0.14)	1.37 (0.12)
σ^2	1996:04	66.92 (0.00)	28.24 (0.00)

Note: In Panel (a), Hansen (1997) p-values.

Two series disagree with this timing, estimating 1991:02 as the breakpoint; they are the squared returns, and the absolute returns. Nevertheless, these series seem to be an exception to the other findings, in a sense that we can be quite sure about a break around 1996 and 1997.

Table 1.10 also supports the break occurrence in 1996 or 1997. In this table, we calculate the percentage change before and after the break for our short-term volatility measures. In general, the break in 1996/97 is more relevant, since the estimated reduction in volatility is larger, comparatively to the pre-break date. Thus, our results show a significant reduction in the Brazilian instability, which is, nowadays, about 50% lower than it was before the break (1996/97).

Table 1.10: Volatility proxies' percentage change, pre and post-break

Variable/Break	1991 (*Δ%*)	1996 (*Δ%*)	1997 (*Δ%*)
Moving var. cycle (4)	-38.91	-54.87	-55.31
Δgdp variance (4)	-38.35	-58.33	-61.57
Absolute returns	-40.99	-40.95	-42.38
Squared returns	-61.49	-65.14	-68.46
Garch(1,1) GDP	-14.10	-24.42	-25.94
Garch(1,1) HP-cycle	-15.34	-29.77	-31.02
Mean	-39.44	-51.03	-53.44

Note: Figures for Brazilian quarterly data, 1947-2012.

Next, we analyze the possibility of multiple structural changes in Brazilian output volatility. When doing so, Bai and Perron (1998) procedure is employed. This method searches for breaks successively, aiming to reduce the regression's sum of squared residuals. Whenever a breakdate is identified, data is split and another break is assessed inside the smaller samples. The algorithm stops at a number of, say, l breaks, which minimizes some information measure (here, the Bayesian Information Criterion, BIC, is utilized). Trimming parameter is set at 15%, as usual. Results are shown in Table 1.11.

According to Table 1.11, most of the considered volatility proxies present two structural breaks. The only exceptions are absolute and squared returns, in which, in both cases, only one breakpoint was detected (1991:01). The remaining variables indicate that Brazilian instability has an interesting inverted U-shape pattern, peaking in the period from 1980, or 1985, to the first half of the 1990's. Moreover, regarding dates of the last break, results in Table 1.11 are consistent with the evidence previously presented, in which we estimate a regime of lower volatility beginning around 1996 or 1997.

Table 1.11: Multiple breaks test in volatility

Volatility proxy	l^*	Breakdates	Volatility in sample: 1	2	3
Moving S.D. cycle (4)	2	1979:04; 1995:04	1.3	1.8	0.9
Moving var. cycle (4)	2	1979:04; 1995:04	1.5	3.2	1.0
Δgdp variance (4)	2	1987:03; 1997:02	2.3	5.3	1.0
Absolute returns	1	1991:01	2.3	1.3	-
Squared returns	1	1991:01	0.063	0.026	-
Garch(1,1) GDP	2	1987:03; 1997:01	0.032	0.049	0.026
Garch(1,1) HP-cycle	2	1988:03; 1997:04	0.027	0.040	0.019

Note: (*) l stands for the number of estimated breaks.

Finally, Figure 1.4, below, displays the moving standard deviations of the HP-cyclic time series, when using only the 1990-2012 sample, part "a", and the 1994-2012 sample, part "b". In this figure, we compute the moving standard deviation, using, again, moving windows of four, eight, and 14-quarter-long, respectively.

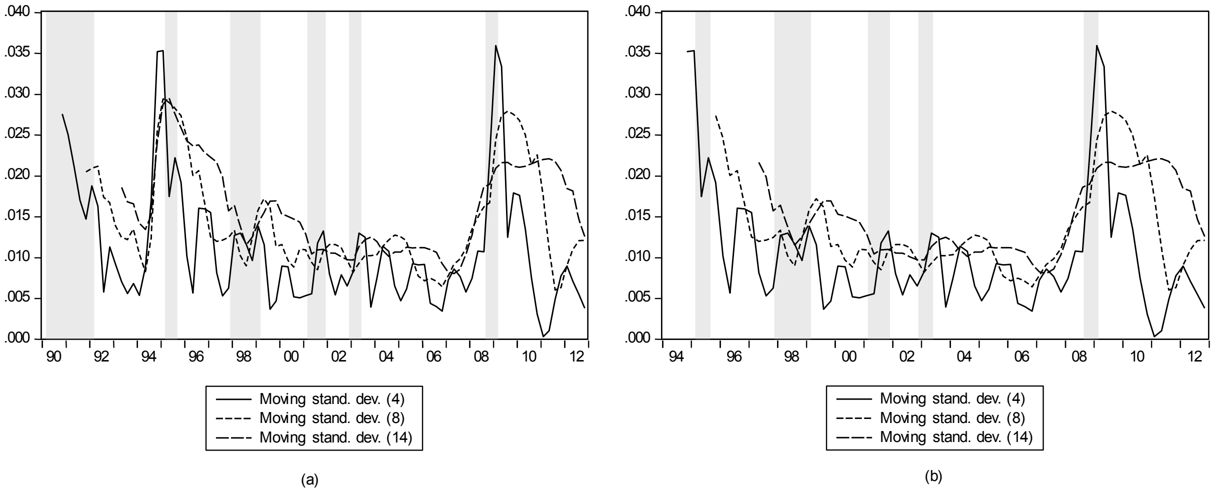

Fig.1.4: (a) Moving standard deviations after 1990:01; and, (b) moving standard deviations after 1994:01. Note: shaded areas refer to CODACE recession dates.

The data show that, after the last break, Brazilian instability has become cyclic and has presented phases of higher volatility in recessions, which is the case of the first three quarters of 1995, when the economy was adjusting to the new monetary and fiscal scenario, and during the Great Recession; and phases of lower volatility. Besides, although the Great Recessions did not have the same impact on Brazil instability as the crises of the 1980s, their effects were quite relevant in the post 1994 conjuncture.

1.5. Conclusions

The present work aimed to provide new facts about the Brazilian business cycle during the period of 1947 and 2012. Therefore, we have decomposed the quarterly and seasonally adjusted real GDP into its mean trend and cycle components, by estimating and averaging on a variety of HP-filter outcomes. In this sense, we provide many pieces of information which can be utilized in other models and studies.

Our three main findings are the following: Brazilian business cycle is asymmetric, with expansions lasting longer than recessions; the country's long-term trend has a break at 1980, thus becoming noticeable flatter after that (real long-term growth rate was reduced by 50%, from a value of 8% per year, during 1947-1980, to 4% per year, from then on); and, volatility has a structural break around 1996/97, when a "Brazilian Great Moderation" may have started. We also found that after the 1990s, Brazilian volatility has become cyclic, tending to grow larger in face of a major crisis.

Specifically to the volatility reduction, it shall be clear that the present paper concluded that it happened *after* the Real Plan implementation. We are not stating, however, that the Real Plan *was* the only or the most important source of such phenomenon. As we discussed before, the strand of literature investigating on this issue usually finds that changes in the private sector, in the monetary policy conduction, and in the size of the shocks hitting the economies can, each one of them, be responsible for the structural break in the variance. Thus, we leave this topic for future research.

All these regularities, namely, phase asymmetries and a decreased volatility over the time, are also observed in the OECD countries, in a sense that Brazilian business cycle, although delayed (and contrary to the evidence reported by previous papers), does share central qualitative features with other decentralized market economies.

Finally, the Brazilian business cycle facts reported here suggest that policies to promote growth can be productive, since during expansions the cumulative increases in GDP from the beginning to the end of the phase are larger than the cumulative losses of recessions. However, it is extremely important that the governmental actions do not put at risk all the achievements obtained since the stabilization of the economy.

CAPÍTULO 2: The Brazilian Great Moderation: Features and Explanations

"It's a kind of magic…"
Roger Taylor and the Queen (1986)

2.1. Introduction

Economic studies have recently documented an amount of evidence supporting a common business cycle feature among industrialized countries, including the U.S. and many OECD members, which is a substantial decline in volatility of macroeconomics aggregates, for example, inflation and real GDP (see, e.g., Kim and Nelson, 1999; McConnel and Perez-Quiros, 2000; Stock and Watson, 2002; Cecchetti et al., 2006; and Summers, 2005). The beginning of the period of increased stability, also known as the Great Moderation, is usually detected in the middle of the 1980s, with 1984 being a good point estimate.

Since then, the literature has tried to investigate the most important causes of such phenomenon. In this regard, three candidates have drawn researchers' attention. The first one argues that private sector changes, for instance, information-technology-led improvements in inventory managements (McConnel and Perez-Quiros, 2000; and Barnett and Chauvet, 2008), and innovations in financial markets that makes intertemporal smoothing of consumption and investment easier (Blanchard and Simon, 2001), are responsible for the volatility fall of the GDP in the U.S. The second category is related to the Central Banks' actions, in which credible, and committed policies may have stabilized inflation and GDP fluctuations (the good policy hypothesis; see, e.g., Taylor, 1999; Cogley and Sargent, 2005; and, Gianonne et al., 2008). The third source of explanation is reductions in the variance of the exogenous shocks hitting the economies, or the good luck hypothesis, where the drop in the volatility of inflation and output is mostly associated with a favorable macroeconomic environment (Stock and Watson, 2002; Moreno, 2004; Primiceri, 2005; Smets and Wouters, 2007; and, Canova, 2009).

As far as we know, similar studies for Brazil are relatively scarce. The history of high inflation in the country imposes serious barriers for empirical testing in the monetary policy field, whenever longer periods are considered. Nevertheless, there are important results in the literature. Pastore (1997), for example, showed that monetary policy was essentially passive from 1975 to 1983, with real exchange rate being kept fairly constant over the time, due to import substitution programs. Minella (2003), by his turn, investigated monetary policy and basic macroeconomic relationships involving output, inflation rate, interest rate, and money. Based on vector autoregressive (VAR) models, the author compares three different periods, i.e., moderately-increasing inflation (1975–1985), high inflation (1985–1994), and low inflation (1994–2000). His main results are that monetary policy shocks have significant effects on output; monetary policy shocks do not induce reductions in the inflation rate in the first two periods, but there are indications that they have gained power to affect prices after the Real Plan was launched.

Regarding exclusively the Real Plan period, Barbosa-Filho (2008) showed that inflation targeting managed to reduce inflation in Brazil in the 1999 and 2002 currency crises, and that the economic growth was slower e less volatile under this regime than during exchange rate targeting (operated from 1994 to 1998). While Mello and Moccero (2011), estimating a conventional New Keynesian model in a VAR context for Brazil, Chile, Colombia and Mexico, showed that the post 1999 regime has been associated with greater responsiveness by the monetary authority to changes in expected inflation in Brazil and Chile; that the lower interest-rate volatility in the post 1999 period owes more to a benign economic environment than to a change in the policy setting; and, that the change in the monetary regime has not yet resulted in a reduction in output volatility in these countries.

There is therefore a lack of research on the Great Moderation issue applied to the Brazilian case, the point which we shall concentrate in the present paper. Basically we aim to provide answers to the following questions: Has this phenomenon happened in the country, that is, has the volatility of inflation and GDP dropped? When? And, finally, what are its main determinants?

We believe, however, that experience would lead most of professionals to a good guess for these questions, which is the Real Plan launch. It is natural to think in that way, since output gap[13] standard deviation fell from 3.3% per quarter during 1975-1994, to 1.6% per quarter during 1995-2012; a 50% reduction. Moreover, changes in inflation were even more remarkable, with average quarterly inflation rate falling from about 39% to 2%, and its volatility diminishing from 38% to 2.2% in the same period[14]. Thus, our paper also addresses to additional research topics, which are: Was the Real Plan and its monetary policy important for these reductions? In case of a positive answer, how much?

Specifically, our paper analyzes the entire 1975-2012 period, using quarterly data on inflation, output gap, and interest rate, in a standard New Keynesian DSGE model. The methodological approach followed in this paper is based upon three fundamental blocks. First, we divide the data into sub-samples according to a test of (possibly multiple) breaks at unknown dates, applied on a VAR system (Qu and Perron,

[13] Measured by the cyclical component of HP-filter decomposition (λ=1600; Hodrick and Prescott, 1997). GDP data is provided by Bonelli and Rodrigues (2012).
[14] General Price Index – Internal Availability (IGP–DI), published by Getúlio Vargas Foundation.

2007). We then characterize the most significant variations in the macroeconomic aggregates across the samples, identifying periods of higher or lower volatility. Second, we estimate the theoretical model in each subsample using Bayesian techniques, and observing the systematic changes occurred in parameters related to the private sector, the monetary policy, and the exogenous shocks over the time. Finally, we divide our sample into periods pre and post Real Plan, taking into account our structural breaks test results, and analyze which set of parameters matter the most for the volatility fall in the country, using a counterfactual method based on Canova (2009).

The importance of the paper lies on the evidence showing that the welfare losses due to output fluctuations are significant in Brazil, reaching up to 10% of the aggregate consumption (Cunha and Ferreira, 2004). Besides, Fischer (1981), Ball and Cecchetti (1990), Feldstein (1997), and Lucas (2000) found that high and volatile inflation is socially costly. A 10% rate, for example, can produce losses of around 3% of the real GDP, via savings and investments misallocation, or losses of value of real balances (Moreno, 2004). In countries where inflation has a past of values far higher than such benchmark, as it is the Brazilian case[15], the distortionary costs of inflation are even higher. In this sense, as pointed out by Moreno (2004), the current era of low inflation and volatility constitutes a major macroeconomic development, where the understanding of the driving forces behind this phenomenon can greatly improve the monetary policy effectiveness. Furthermore, we provide here new and interesting business cycle facts for the economy, which can be used for future research[16].

Our main findings are that, according the structural breaks test, the Brazilian Great Moderation initiated comparatively late, in 1995, year when the volatility of

[15] Yearly inflation reached triple-digit figures between 1988 and 1994.
[16] Our research has an additional benefit, i.e., its results and/or methodological procedures could be applied to others developing countries with a similar historic of inflation.

inflation, output gap, and interest rate dropped sharply. We also detected that the inclination of the Phillips curve has reduced, and agents have become more forward-looking over the time. Similar results were found for the U.S. economy by Moreno (2004), and Canova (2009). Besides, monetary authority has become more averse to inflation; the coefficient of this variable in the Taylor rule is about three times higher than the weight of GDP deviations after 1995. Lastly, exogenous shocks hitting the economy have become milder, as it has been documented for several other countries.

Concerning the causes of the great moderation, the reduction of Phillips curve inclination was the only private sector parameter with statistically significant effect on the fall of inflation volatility. Moreover, the larger part of such feature of the data is due to changes in monetary policy, and reductions in the size of the exogenous shocks hitting the economy. On the GDP side, we found that the sole reason behind its volatility fall was the reduction of the shocks (similar results were found by Mello and Moccero, 2011, when analyzing data from 1996 to 2006). Therefore, the Brazilian Great Moderation is mainly a mix of the "good policy" and "good luck" hypotheses. Improved monetary policy was important to reduce both levels and volatility of inflation, but its success was also owed to a favorable economic environment.

The remainder of this paper is organized as follows. Section 2 discusses briefly the monetary policy in the country between 1975 and 2012. Section 3 describes the theoretical model. Section 4 brings the econometric methodology, based on Bayesian techniques, the description of the data, and the structural break results. Section 5 presents our main results, and Section 6 concludes.

2.2. A brief review of the macroeconomics and the monetary policy in Brazil (1975-2012)

In this section we present review of the Brazilian macroeconomic panorama between 1975 and 2012, giving special attention to the monetary policy conduction in the period. Such information provides important grounds for the econometric findings of the following sections.

Between 1967 and 1973, the Brazilian economy grew at unusually high rates; GDP, for example, increased 10% per year on average; employment, 4%; fixed capital investments were steady at a rate of 21% of the GDP per year; and, industrial production increased 10 and 14% per year, between 1967-1970 and 1971-1973, respectively. Besides, by 1973 the Brazilian economy was flooded with external loan capitals. As one can expect, inflation rate (IGP-DI), which was moderate in almost the entire period at a rate of 20% per year, after 1973 was clearly accelerating, reaching 35% in 1974, 29% in 1975, and 51% per year on average during 1976-1979, as a result of the internal and external demand pressures (Carneiro, 1989).

In the first years of Geisel's term, his economic team was not completely aware of the severity of the international crisis, which started in 1973 due to the oil shocks, and the President was not willing to accept the political costs of a contractionary monetary policy that could reduce the distortions of an overheated economy. Thus, although the nominal rate has increased in the period, real Selic rates were negative in 1974, 1975, and 1976. Moreover, the fall in the M1 monetary aggregate (real terms) in 1976 and 1977 was compensated by loans of the Central Bank and *Banco do Brasil*[17] to

[17] The first bank to operate in the country, founded in 1809.

commercial banks, in order to keep the liquidity, and by the II National Development Plan[18] (II PND), a governmental plan launched late in 1974, and based on the stimulus of sectors such as capital goods, basic inputs, heavy electronics, and energy (Carneiro, 1989).

The II PND policy was successful regarding growth rates of the economic activity; real GDP grew 7% on average per year between 1974 and 1979, and the investment rate was stable at 25% of the GDP. This policy, however, was mainly financed by external debt, which grew by US$ 10 billion per year between 1974 and 1979. Additionally, the external debt services were eight times higher in 1979 (US$ 4 billion) than in 1973 (US$ 0.5 billion). Thus, by 1980, in the first years of President Figueiredo's term, the Brazilian economy was suffering with an upward trending inflation, high level of external debt, and unbalanced public finances, three key ingredients of the Lost Decade.

During the period of 1980 and 1984, Brazilian macroeconomic policy was extremely dependent on the availability of external funding. Foreign-exchange reserves were reducing in face of a duplication of the oil prices in 1980 and investors were not willing to rollover the Brazilian external debt. It became clear by the time that contractionary policies were needed (Carneiro and Modiano, 1989).

Indeed, in 1981 the Brazilian government started a set of policies trying to restrain salaries, public spending, and real liquidity. For example, real M1 growth rate was negative from 1981 to 1984, and real interest rate was positive and above the international level in 1982, 1984, and 1985. In this sense, real GDP growth rate was -4.25% in 1981, 0.83% in 1982, -2.93% in 1983. Industrial production fell 5% in 1983,

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[18] In Portuguese, Plano Nacional de Desenvolvimento.

and capital goods sector retracted 55% between 1981 and 1983. Inflation, however, kept its trend, being 95, 100, 211, and 223% per year from 1981 to 1984 (Carneiro and Modiano, 1989).

In the second half of the 1980's with the ending of the military regime, there was a feeling in the new democratic government that orthodox instruments, including changes in the interest rates and monetary aggregates, were ineffective and socially costly (Marques, 1988). Meanwhile, inertial inflation models have gained force amongst economists and politicians in the country (see, e.g., Modiano, 1983; Lopes, 1984; and, Resende, 1985). In such class of models, in chronic inflation environments, economic agents are assumed to adopt a defensive stance on pricing, always trying to restore the peak of real income in periods of price increase. When all agents do that, inflation is perpetuated. In other words, in the absence of any shock, inflation is equivalent to that of the previous period (a random walk). In this context, in February 1986 was launched the first attempt to stabilize the economy based on the inertial inflation concepts, the so-called Cruzado Plan.

With the new monetary plan advent, the so far Brazilian currency, Cruzeiro, was replaced by another one, Cruzado, and three digits were eliminated. Prices and exchange rates were indeterminately frozen at their February 1986 level. The minimum wage was readjusted with 16% of real gains, and could be corrected if accumulated inflation were above 20%. Additionally, indexation was regulated in long term contracts and not allowed in short term ones (lasting less than one year). This plan, however, had no clear position about the monetary and fiscal policy (in fact, in most of the time, interest rate was below the international level and negative in real terms (see, Moraes, 1990).

The Cruzado Plan was initially successful; real GDP growth rate was about 7.5%, and monthly inflation was stable at 1% from March to October 1986. However, a consumption bubble originated from appreciated salaries and negative interest rate had quickly pressed on prices (Marques 1988). Commodities disappeared from stores, and goods such as gas and gasoline were under rationing (Cati et al., 1999). An extra premium over the price of many goods (nondurables and durables) was frequently asked to consumers. In April 1987 monthly inflation rate had returned to 20%, staying at this level until June of the same year, when the economic team gave up on the plan.

By June, with the substitution of the Minister of Finance, another monetary plan was attempted, the Bresser Plan. Mixing orthodox and heterodox elements, such as public deficit reductions, positive real interest rate, rules for wage adjustments, and frozen prices, this plan was relatively successful at the short term, shrinking internal demand and reducing inflation rates to 9 and 4.5% in July and August, respectively. However, in October prices were allowed to be readjusted forcing inflation to rise again. Additionally, in 1988 the new Brazilian Constitution was enacted, expanding significantly social benefits and, thereby, the government spending (Modiano, 1989). By the end of 1988, monthly inflation rate was above 25% most of the time, and the economy was in recession again (real GDP growth rate was -0.1% in 1988).

In January 1989, Cruzado's accumulated inflation (IGP-DI) was about 7,000%, the highest ever seen in the Brazilian history. The currency was discredited and the economy's uncertainty was immeasurable. In this context, a third monetary plan was launched, the Summer Plan. The latter introduced a new official currency, called Cruzado Novo, and another three digits were cut out. Indexation mechanisms were not allowed in contracts, prices were frozen, and contractionary fiscal and monetary policies were intended. Besides, a one-to-one parity with the U.S. dollar was announced, expecting to produce positive psychological results on the economics agents.

The Summer Plan, however, was unsuccessful when cutting government spending, since the fiscal reform had no political support (Bresser-Pereira, 1989). In addition, the population was not confident about the plan's effectiveness; consumption bubbles would always appear anticipating new rounds of price adjustments. The monetary anchor with the dollar was ineffective; the premium asked in the black market was about 200% already in May of the same year. By the end of President Sarney term, in the beginning of 1990, monthly IGP-DI inflation rate was about 70%. The country was on the verge of hyperinflation and economic chaos.

In March 1990, with the beginning of President Collor term, another monetary plan was tried. Commonly known as Collor Plan, it re-introduced Cruzeiro as the currency, but this time using a one-to-one parity with Novo Cruzado, the previous one. Prices and wages were frozen and under official control, exchange rate was appreciated, and the economic team had announced a series of fiscal adjustments, such as spending cuts, privatizations, creation of a new tax on financial operations (IOF), and so on. As pointed by Pastore (1991) and Carvalho (2006), however, the most distinguished feature of the plan was the confiscation of 80% of all M4 financial resources, which were converted into long-run deposits under the responsibility of the Brazilian Central Bank.

The motivations behind this policy, according to Carvalho (2003), was to reduce the tendency to an accelerated monetization in the economy, which increases the aggregate demand after abrupt deflationary processes, and the liquidity of the financial assets, known at that time as indexed money[19].

The confiscation of assets had a severe dampening effect on money supply, thus reducing inflation during the first months of the plan; from March to June, it was below 10% per month. Economic activity fell sharply as well; industrial production reduced 40%, and industrial employment 6 and 4% in the first and second semester of 1990, respectively. Overall, real GDP growth rate was -4.5% in this year.

Due to confiscation policy characteristics, however, banking sector faced a liquidity and confidence crisis. These institutions did not exactly know their cash stances, forcing the Central Bank to finance them in order to avoid serious bank runs. Therefore, this policy failed in its main objective, which was to give the money supply control back to the Central Bank. Besides, as long as the total debt problem was not solved in the fiscal area, it was only a matter of time until inflation return (Carvalho, 2003). In fact, from November 1990 to February 1991 general price level changes were about 18% per month on average. Accumulated inflation in 1990 was 1477%.

In February 1991, another economic plan was attempted under President Collor term, the so-called Collor II Plan. Mixing again heterodox with orthodox instruments, such as prices and wages control, and public tariffs adjustments, this plan could not stop inflation rate for more than four months, which stabilized at about 25% per month, and ended 1991 in 480%. The government team and their economic policies were

[19] The indexed money was comprised by financial assets with instantaneous liquidity, monetary correction, and a positive interest rate, including, among others, savings account, the major part of the investment funds, and monthly government bonds that were bought at the overnight rate (Carvalho, 2006). Developed over the years, the indexed money worked as mechanism of protection against the effects of hyperinflation. But, it also worked as a source of endogenous money supply, i.e., whenever agents see that inflation rate would be above interest rates, they could assume a protective stance by withdrawing their deposits and raising consumption of durables above their income, adding extra money in the economy, since liquidity was guaranteed by the Central Bank (Pastore, 1991).

completely discredited by the Brazilian population, due to the incapacity of stopping prices explosion and to numerous corruption accusations. The economic and political crisis ended up with the impeachment of President Collor in December 1992, year when inflation was about 1160% and GDP growth rate was -0.5%. The former president was replaced by Itamar Franco, who inherited a monthly inflation rate of 30 to 40% between January 1993 and July 1994, month when the Real Plan was launched.

The Real Plan was being prepared since 1993[20]. In December of this year the government announced it as having three phases. The first one attempted to balance the operational budget; the second one introduced a new account unit, in order to adjust relative prices; and, the third one established the conversion between this account unit and the new currency, the Real (Bacha, 1997).

As explained by Bacha (1997), before Real Plan, the government budget had traditionally been approved with a large deficit. But, with nominally predetermined spending and indexed taxes, inflation was an important element of fiscal balance. Thus, the first policy, by predicting budgetary cuts of about 20% for the 1994 and 1995 fiscal years, signalized to economic agents that the government would be able to finance its expenditures without inflationary taxes (corroborating the view that the ex-ante equilibrium of the public finances was an essential step towards inflation control).

The second and third stages of the plan were extremely innovative, breaking, effectively, the inertial trend of inflation in the country (Bresser-Pereira, 1994). The idea was first to promote the total indexation of the economy's prices and contracts to a single and trustable unit of account to, only then, replace the old currency, Cruzeiro Real (CR$), by the new one, Real (R$). In this sense, in March 1994 the government

[20] Its main ideas date back to the middle of the 1980's. See Bresser-Pereira (1994) for a discussion.

introduced a mechanism known as “Real-Value Unit”, or URV, a daily-adjusted index, which had a maximum parity of one-to-one with the US Dollar (the exchange rate anchor), that would serve as benchmark for the economy, indexing its prices, wages, and contracts. After establishing the URV, it was replaced by the new currency in July 1994, using a conversion rate of CR$2750 = R$1[21].

In practical terms, the parity with the Dollar was guaranteed by the Central Bank, which kept the exchange rate oscillating within R$0.85/US$1 and R$1/US$1, on a system of asymmetric bands. This policy was made possible by a high level of international reserves, which had accumulated US$40 billion in June 1994[22].

Since then, in fiscal area the Brazilian government has intensified the privatization process, and has been working with budget surpluses, instituting, in the end of 1998, targets for the primary result (Oliveira e Turolla, 2003; Bresser-Pereira, 2003). Notwithstanding, in 2007 and 2010 it was launched a set of fiscal policies intended to accelerate GDP growth rate in the country, in the form of tax exemptions and direct public investments (these programs are known as Growth Acceleration Program[23] I and II, or simply PAC I, and PAC II). Thus, real GDP growth, which had been modest between 1998 and 2003, at about 1.6% per year, reached 6, 5, and 7.5% in 2007, 2008, and 2010, respectively[24].

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[21] The URV promoted a gradual realignment of the most important relative prices in the economy, giving time to contracts to be adjusted, and avoiding that after a sudden stop of the inflationary process the delayed indexation could generate additional pressures on the prices, as happened before with the earlier policies of prices control (Bresser-Pereira, 1994; Sicsú, 1996; and, Bacha, 1997).

[22] Batista-Jr. (1993), and data from the Balance of Payments show the commercial surplus since 1984 as the main determinant of international reserves accumulation.

[23] Programa de Aceleração do Crescimento, in Portuguese.

[24] In 2009, due to the Great Recession effects, real growth rate was -0.33%.

The exchange rate policy[25] was an important instrument during the earlier years of the Real Plan, keeping agents' expectations stabilized. However, its overvaluation generated persistent trade and current account deficits (the latter via interest payments) in the country, which, by 1998, became critical (Goldfajn and Minella, 2005). Additionally, in 1997 the economy was hit by an external financial crisis that also affected Mexico, the Asian Tigers, and Russia. Thus, the macroeconomic panorama requested a change in the exchange rate policy, which occurred in January 1999 with the implementation of a system of dirty fluctuations (the up-to-date regime).

Regarding monetary policy, as tested by Pastore (1997), it was essentially passive in the period before the Real Plan. From 1975 to 1983, for instance, real exchange rate was kept relatively constant, due to import substitution programs, with the Central Bank mainly working accommodating the international capitals inflow. With the outbreak of the external debt crisis in 1984 and 1985, which closed the country's access to financial markets, Central Bank operated actively for a short period, setting real interest rate above the international levels in order to reduce aggregate demand, and to minimize bond prices' fluctuations. After that, from 1986 to 1994, the acceleration of the inflationary process subdued, in a severe way, the Central Bank options and operations. During this period, money was completely endogenous, and the monetary policy was primarily focused on avoiding massive runs to real and, or, international assets (Paula, 1996). According to Garcia (1995), the objective was not to reduce inflation, but only to circumvent hyperinflation in this period.

The monetary policy has progressively become more active from 1995 on. In the first phase of the Real Plan, there was a legal commitment for keeping exchange rate

[25] Started as a crawling band regime, it increasingly turned to a crawling peg system between 1995 and 1998 (see, e.g., Goldffajn and Minella, 2005).

relatively constant, and interest rate was an important instrument in this regard. Nonetheless, by exogenously monitoring the inflow of international resources, the Central Bank had room for pursuing a somewhat independent monetary policy. Deposit requirements (compulsory) were also employed for adjusting aggregate demand, especially during the beginning of the plan implementation (Bacha, 1997).

Since 1999, alongside with the changes in the exchange rate policy, monetary authorities have introduced a system of inflation targeting for anchoring agents' expectations in the country. Inflation targets are defined by the National Monetary Council (Conselho Monetário Nacional, CMN[26]) for a calendar year, and pursued by the Central Bank via interest rate changes.

There is a strand of literature suggesting that inflation targeting has resulted in less-volatile monetary environments in industrial countries, since it would enhance policy-making transparency and effectiveness, by sanctioning a more aggressive response of the Central Bank to deviations of inflation from its target (see, e.g., Kuttner and Posen, 1999; and, Woodford, 1999, 2004).

In this regard, recent Brazilian literature has present mixed and interesting results. On one hand, a variety of papers have found that monetary policy, measured as interest rate shocks, has had significant contractionary effects on the economic activity in the Real Plan period (Minella, 2003; Fernandes and Toro, 2005; Céspedes et al., 2008; and, Mendonça et al., 2010), especially after inflation targeting regime has been implemented (Minella et al., 2003; Barbosa-Filho, 2008; and, Mello and Moccero, 2011). On the other hand, studies have also found pieces of evidence supporting

[26] The CMN has three members, the Minister of Finance (chairman), the Minister of Planning and Budget and the President of the Central Bank.

monetary policy passivity after the Real Plan, in the form of price-puzzle[27] (see, for example, Moreira et al., 1998; Rabanal and Schwartz, 2001; Arquete and Jayme-Jr., 2003; and, Sales and Tannuri-Pianto, 2005).

In this sense, the effect of the monetary policy on the economic stability of the country is still a fruitful line of research, whether considering the period before or after the Real Plan. The present paper aims to provide additional information regarding this issue, being a useful guide for the monetary policy conduction.

2.3. Theory: A three-equation New Keynesian model for monetary policy evaluation

In this section we present a small-scale New Keynesian (NK) framework that contains three equations, i.e., an aggregate demand, or *IS*-curve; an aggregate supply, or Phillips curve; and, a Taylor-type policy rule. All these equations are behavioral, derived from optimizing and forward looking agents, addressing, therefore, to the Lucas critique. Related versions of it have been largely employed, see, for example, in Svensson (2000), Stock and Watson (2002), Moreno (2004), Canova (2009), and Creel et al. (2013), among others, for the international case; and, Minella et al. (2003) and Mello and Moccero (2011) for the Brazilian case. But, before we proceed developing the full block of the model's equations, it is interesting to provide a brief review of its main elements and features.

[27] Price-puzzle refers to a positive causation from positive interest rate shocks to increases in the price level. This phenomenon would emerge when Central Banks react with a lag to increases in the inflation expectations. However, Sims (1992), Romer and Romer (2004), and Rabanal (2007), among others, argue that the price-puzzle may simply arise as measurement errors in the VAR methodology, since it cannot identify the unexpected component of monetary policy shocks.

According to Galí (2009), the New Keynesian system has inherited important characteristics from Real Business Cycle models (RBC)[28], such as: i) infinitely-lived households, who maximize the utility from consumption and leisure, subject to a budge constraint; ii) a large number of firms with identical technology and subject to random fluctuations[29]; and, iii) the equilibrium is stochastic process for all the economy's endogenous variables, consistent with all the constraints and with the optimizing behavior of the agents (it is a market clearing equilibrium, in a dynamical, stochastic fashion, often known as Dynamic Stochastic General Equilibrium models, or simply DSGE).

There are, however, significant differences between the RBC and the New Keynesian approaches, from which emerge their main divergences regarding policy making. They are (see, Romer, 2012; Galí, 2009; and Mankiw, 1990): i) NK models assume monopolistic competition, where the price of goods and inputs are set by private agents, according to their objective functions; ii) NK models deal with nominal rigidities, i.e., firms may face constraints on the frequency or on the magnitude of the price adjustments, and workers face some kind of friction on their nominal wages; iii) NK models present short-run non neutrality of money, as a consequence of the nominal rigidities. In this sense, changes in the nominal interest rates due to monetary policies are not fully compensated by changes in the expected price levels, thus affecting the real interest rates, and then the consumption and investments levels, finally resulting in changes on production and unemployment. In the long run, with the flexibility of the prices and wages, the economy reverts back to its natural equilibrium, determined only by real factors.

[28] See, for instance, Kydland and Prescott (1982), Prescott (1986).
[29] Medium-scale New Keynesian models can incorporate endogenous technology or capital accumulation (Smets and Wouters, 2003). For our objectives a small-scale framework is sufficient.

Taking account to the points highlighted in the last paragraph, the most important corollary is that in the NK models, the economy's response to shocks is inefficient, since prices and wages stickiness avoid it to attain the full-employment equilibrium. Therefore, as the money is not neutral in the short run, there may be room for beneficial interventions by the monetary authority (central banks)[30].

The international literature has found strong evidence supporting nominal rigidities assumptions. Taylor (1999), for example, estimates that prices are fixed for one year in average, and that prices re-adjustments are not synchronized, which could validate the hypothesis of staggered prices in the US economy. Similar results are found by Nakamura and Steinsson (2008) that estimates the median duration of a price at about eight to 11 months in the U.S., and by Dhyne et al. (2006), the latter for the Euro area. By their turn, Kanczuk and Botelho (2003) find that, after the Real Plan, a model with one fourth of prices fixed at the short run describes the Brazilian economy better than one with fully flexible prices.

However, as we are analyzing the Brazilian economy during the entire 1975-2012 period, it is necessary to compute for a wider range of price-stickiness' degrees over the years. Between 1985 and 1993, for example, the economy experienced years of extremely high inflation, situation when the prices are normally adjusted on a higher frequency (see, e.g., Marques, 2013; and, Lopes, 1984). Nevertheless, our estimation procedure is flexible enough to capture changes in price rigidities, as well as in other parameters.

After providing a brief background of the empirical results supporting the NK assumptions, we are able to proceed describing the building blocks of our dynamical

[30] The RBC literature, on the other hand, states that every fluctuation of the economy is an optimal response of the agents, households and firms, to exogenous shocks. In this context, fiscal and monetary policies are counterproductive and should be avoided (Kydland and Prescott, 1982; and, Plosser, 1989).

model. In this sense, subsections 2.1, 2.2 and 2.3 present, respectively, the IS (demand) curve, the Phillips (supply) curve, and the monetary policy rule (Taylor rule).

2.3.1. IS-curve

This section is mainly based on Galí (2009) and Moreno (2004). In this model, there is a representative household who seeks to maximize its lifetime utility coming from consumption and leisure, that is,

$$\mathrm{E}_0\left\{\sum_{t=0}^{\infty}\psi^t U(C_t, N_t)\right\} \tag{2.1}$$

Where C is an index of aggregate consumption; N represents hours of work; ψ is time preference, or impatience parameter, $0 < \psi < 1$; and, t is the time index. Utility function is assumed to be continuous and twice differentiable, with $U_{c,t} \equiv \dfrac{\partial U(C_t, N_t)}{\partial C_t} > 0$,

$U_{cc,t} \equiv \dfrac{\partial^2 U(C_t, N_t)}{\partial C_t^2} \leq 0$, $U_{n,t} \equiv \dfrac{\partial U(C_t, N_t)}{\partial N_t} \leq 0$, $U_{nn,t} \equiv \dfrac{\partial^2 U(C_t, N_t)}{\partial C_t^2} \leq 0$, meaning that the marginal utility is positive and non-increasing in consumption, while the marginal disutility of labor, $-U_{n,t}$, is positive and non-decreasing.

Our aggregate consumption index is a continuous of i differentiated goods (produced by i firms in a monopolistic competitive environment), with $i \in [0,1]$, thus,

$$C_t \equiv \left(\int_0^1 C_t(i)^{1-1/\varepsilon} di \right)^{\varepsilon/(\varepsilon-1)}, \tag{2.2}$$

where, ε is the elasticity of consumption. Using (2.2) and a conform aggregate price index, P, the following relationship represents the flow of budget constraints:

$$P_t C_t + Q_t B_t \leq B_{t-1} + W_t N_t - T_t. \tag{2.3}$$

Following Galí (2009), in (2.3), $P_t C_t$ represents the consumption expenditures in time t; B_t denotes the quantity of one-period, nominally riskless bonds purchased in t (with maturity in t + 1); each bond pays one unity of money at maturity, and has a price of Q_t; W_t is the nominal wage; and T_t is the lump-sum additions or subtractions to period income (e.g., taxes, subsidies, or dividends). In order to constraint the household behavior, we still need to a transversality condition, that is, $\lim_{t \to \infty} \mathrm{E}_0 \{Q_t B_t\} = 0$.

One can find the household's optimality conditions by plugging (2.3) into (2.1) and solving the unconstrained maximization problem for the path of consumption. However, here we take a shortcut, simply employing a variational argument in order to find its equilibrium. Consider, first, that agent wants to raise its consumption level while offering more work and keeping all the other variables unchanged. If he or she is maximizing, it must be the case where: $U_{c,t} dC_t + U_{n,t} dN_t = 0$, for all dC_t, dN_t. In words, if the agent is on its optimal path, he or she cannot increase its utility by working and consuming more in t. Additionally, if he or she is satisfying the budget constraint, then: $P_t dC_t = W_t dN_t$. The previous argument provides us the first optimality condition, which is:

$$-\frac{U_{n,t}}{U_{c,t}} = \frac{W_t}{P_t}. \tag{2.4}$$

We now analyze the impact on the expected utility of a consumption reallocation between dates t and $t + 1$, while holding consumption, and hours worked in other periods unchanged. Again, if the agent is maximizing, it must be the case that: $U_{c,t} dC_t + \psi \mathrm{E}_t \{U_{c,t+1} dC_{t+1}\} = 0$, for all dC_t, dC_{t+1}. That is, if the household is on its optimal path, decreased consumption today must be equally compensated by increased (discounted) consumption in $t + 1$. As the agent is not offering additional hours of work, its increase in future consumption is made possible by additional savings, $-P_t dC_t$, allocated in one-period bonds, thus: $P_{t+1} dC_{t+1} = -\frac{P_t}{Q_t} dC_t$. Combining these two latter equations, we find the second optimality condition for the household, i.e.:

$$Q_t = \psi \mathrm{E}_t \left\{ \frac{U_{c,t+1}}{U_{c,t}} \frac{P_t}{P_{t+1}} \right\}. \tag{2.5}$$

Above, (2.5) is the well-known Euler equation. In order to clarify the conditions needed for the equilibrium, we specialize to the isoelastic class of utility functions,

$$U(Ct, Nt) = \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi}, \tag{2.6}$$

where σ and φ measure the elasticity of utility with respect to consumption and hours of work. In that case, (2.6) makes (2.4) and (2.5) become, respectively,

$$\frac{W_t}{P_t} = C_t^{\sigma} N_t^{\varphi}, \tag{2.7}$$

$$Q_t = \psi E_t \left\{ \left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \frac{P_t}{P_{t+1}} \right\}. \tag{2.8}$$

In order to find our IS-curve with micro-foundations, we need to log-linearize (2.8) around its steady-state. In this sense, we divide both sides of (2.8) by Q_t, and then we take the exponential of the logarithms on the right side of the resulting equation, that is,

$$1 = E_t \{ \exp[-\ln Q_t - \sigma(\ln C_{t+1} - \ln C_t) - (\ln P_{t+1} - \ln P_t) + \ln \psi] \}. \tag{2.9}$$

Given that i_t = -logQ_t is the log of the gross yield on the one-period bond[31], and defining -b = log ψ, and π_{t+1} = logP_{t+1} – logP_t, (2.9) becomes,

$$1 = E_t \{ \exp(i_t - \sigma \Delta c_{t+1} - \pi_{t+1} - b) \}. \tag{2.10}$$

[31] The yield on the one period bond is defined by $Q_t = (1 + yield)^{-1}$. Thus, $i_t = -\log Q_t = \log(1 + yield) \approx yield$.

In equations (2.9) and (2.10) the lowercase letters denote the natural logs of the original variables. In the steady state, with certainty, consumption and prices grow at a constant rate, say, γ and π, then, by (2.10), the real interest rate is:

$$i - \pi = \sigma\gamma + b. \qquad (2.11)$$

A first-order Taylor approximation of $\exp(i_t - \sigma\Delta c_{t+1} - \pi_{t+1} - b)$ around the steady state (2.11) yields a result that we plug into the second line of (2.10) in order to obtain the log-linearized Euler equation:

$$c_t = \mathrm{E}_t\{c_{t+1}\} - \delta(i_t - \mathrm{E}_t\{\pi_{t+1}\}), \qquad (2.12)$$

where $\delta = 1/\sigma$. In equation (2.12), variables now are measured as log-deviations from their steady state values. As in our model consumption is the only source of aggregate demand, we may substitute c_t in (2.12) by $y_t \equiv (\log Y_t - \gamma)$, where Y_t is the economy's output and y_t is the output gap,

$$y_t = \mathrm{E}_t\{y_{t+1}\} - \delta(i_t - \mathrm{E}_t\{\pi_{t+1}\}). \qquad (2.13)$$

Equation (2.13) is the IS-curve. Its most important feature is that it implies an inverse relationship between the expected *ex ante* real interest rate and the output gap (Romer, 2012). Moreover, according Clarida, et al. (1999), and as we assume here, with the nominal interest rate as policy instrument, it is not necessary to specify an equilibrium equation for the monetary market (a LM curve). Therefore, (2.13) is also the aggregate demand equation of the economy.

In this model, the dynamics of output gap is entirely due to exogenous shocks. The business cycle literature, however, has been consistently finding evidence of endogenous persistence in the economy's output (see, for instance, Kydland and Prescott, 1990; Backus and Kehoe, 1992; and Basu and Taylor, 1999). In this regard, following Fuhrer (2000) and Moreno (2004), we may assume a utility function with habit formation, where households alters their consumption paths slowly. In this case, (2.13) is generalized to

$$y_t = -\delta(i_t - \mathrm{E}_t\{\pi_{t+1}\}) + \theta_g y_{t-1} + (1-\theta_g)\mathrm{E}_t\{y_{t+1}\} + v_{1,t}, \tag{2.14}$$

where, in equation (2.14), $0 \leq \theta_g \leq 1$ index the influence of lagged versus future output gap on its current value (persistence), and we added an *i.i.d.* disturbance related to measurement errors and/or exogenous shocks on the aggregate demand, $v_{1,t}$. We now proceed presenting the New Keynesian Phillips curve (NKPC).

2.3.2. The Phillips curve

The Phillips curve represents the supply side of the economy, relating inflation and output gap. We focus on the work of Calvo (1983), but similar qualitative implications are obtained by Taylor's (1979) model of fixed prices.

Calvo (1983) assumes that prices change stochastically. More specifically, firm's opportunities to change its price follow a Poisson process. Thus, the probability that firms are able to change their prices is the same in each period; regardless of when it was the last time they did it[32]. Besides, as in Taylor (1979), prices are fixed between the times they are adjusted (Romer, 2012).

Following Calvo (1983), each period a fraction α ($0 < \alpha \leq 1$) of firms chosen at random set new prices, say, x_t. The remaining fraction of firms ($1 - \alpha$) receive an average price that is equal the price charged by all firms in the previous period, p_{t-1}. Thus, we may write,

$$p_t = \alpha x_t + (1-\alpha) p_{t-1}, \tag{2.15}$$

as the economy's average price in t. Subtracting p_{t-1} from both sides, (2.15) becomes an expression showing that inflation is determined by the firms changing their price (equation 2.16),

$$\pi_t = \alpha(x_t - p_{t-1}). \tag{2.16}$$

Firms set their new prices, x_t, as a weighted average of the expected profit-maximizing prices for the next periods, p^* (Romer, 2012). In this sense,

$$x_t = \sum_{j=0}^{\infty} \frac{\beta^j q_j}{\sum_{k=0}^{\infty} \beta^k q_k} \mathrm{E}_t\{p^*_{t+j}\}, \tag{2.17}$$

[32] Consequently, the waiting time for a price change is without memory or, in other words, *i.i.d.*

where β is a discount factor; and, q_j is the probability the price set in period t will still be in effect in period $t + j$. Given Calvo's (1983) Poisson assumption, $q_j = (1 - \alpha)^j$. Thus, (2.17) is simplified to[33],

$$x_t = [1-\beta(1-\alpha)]\sum_{j=0}^{\infty}\beta^j(1-\alpha)^j \mathrm{E}_t\{p_{t+j}^*\}. \tag{2.18}$$

We now rewrite (18) expressing x_t in terms of p_t* and $E_t\{x_{t+1}\}$, that is,

$$\begin{aligned} x_t &= [1-\beta(1-\alpha)]\mathrm{E}_t\{p_t^*\} + \beta(1-\alpha)[1-\beta(1-\alpha)]\left[\sum_{j=0}^{\infty}\beta^j(1-\alpha)^j \mathrm{E}_t\{p_{t+1+j}^*\}\right], \text{or} \\ &= [1-\beta(1-\alpha)]p_t^* + \beta(1-\alpha)\mathrm{E}_t\{x_{t+1}\}, \end{aligned} \tag{2.19}$$

where, the second line uses the fact that p_t* is known at time t, and shifts (2.18) one period ahead.

The concluding steps in order to obtain our Phillips curve involve subtracting p_t from both sides of (2.19) and rewriting $x_t - p_t$ as $(x_t - p_{t-1}) - (p_t - p_{t-1})$, to get,

$$(x_t - p_{t-1}) - (p_t - p_{t-1}) = [1-\beta(1-\alpha)](p_t^* - p_t) + \beta(1-\alpha)(\mathrm{E}_t\{x_{t+1}\} - p_t). \tag{2.20}$$

Now, using (2.16) to write $(x_t - p_{t-1}) = \pi_t/\alpha$, $(E_t\{x_{t+1}\} - p_t) = E_t\{\pi_{t+1}\}/\alpha$, and substituting in (2.20), give us the following expressions,

[33] Note: the sum (S) of an infinite geometric progression with ratio r, $0 < r < 1$, is $S = a_1/(1 - r)$.

$$\pi_t = \frac{\alpha}{1-\alpha}[1-\beta(1-\alpha)](p_t^* - p_t) + \beta \mathrm{E}_t\{\pi_{t+1}\}, \tag{2.21}$$

and, finally, replacing $p_t^* - p_t$ by ϕy_t in (2.21) where ϕ is a parameter measuring real rigidities (a low value for ϕ means a high degree of real rigidity)[34], we are able to find that,

$$\pi_t = \lambda y_t + \beta \mathrm{E}_t\{\pi_{t+1}\}, \tag{2.22}$$

where $\lambda \equiv \frac{\alpha[1-(1-\alpha)\beta]\phi}{1-\alpha}$. Equation (2.22) is a formulation for the New Keynesian Phillips curve. It says that inflation depends on an expected (or core) inflation term and the output. Equation (2.22), however, does not imply an inflation inertia. Following Ball (1994), we define inflation inertia as a continuous high inflation caused by a large cost (measured in output loss) of reducing it. In order to introduce this feature in equation (2.22), we use an approach developed by Christiano et al. (2005). These authors, rather than fixing prices between each round of price adjustments, assume that prices are indexed to the previous period's inflation rate. Economically, this is a reflection of firms that do not continually obtain and use all available information. In this case, (2.15) becomes,

$$p_t = (1-\alpha)(p_{t-1} + \pi_{t-1}) + \alpha x_t. \tag{2.23}$$

[34] $p_t^* - p_t = \phi y_t$ comes from a standard profit-maximization problem by monopolistic firms. It states that the price-setter's optimal relative price is increasing in aggregate output. This may arise from several reasons, for instance, increases in the costs of production inputs, diminishing returns to the factors, and/or costs of adjusting output (Romer, 2012).

Using (2.23) and solving the model in the same way we have done before, it can be shown that (2.22) is generalized to:

$$\pi_t = \kappa y_t + \theta_i \pi_{t-1} + (1-\theta_i)\beta \mathrm{E}_t\{\pi_{t+1}\} + v_{2,t}, \tag{2.24}$$

where, in equation (2.24), $0 \leq \theta_i \leq 1$ index the influence of lagged versus future inflation on its current value (inflation inertia); κ is a function of α, β, and ϕ; and, we added an *i.i.d.* disturbance related to measurement errors and/or exogenous shocks on the aggregate supply, $v_{2,t}$. Equations (2.14) and (2.24) are the building blocks of the New Keynesian model. They have a recursive structure: the Phillips curve (eq. 2.24) determines inflation given the path of output gap; while (2.14) determines output gap as a function of the real expected interest rates. In order to close the model it is only necessary to describe our monetary policy rule (i.e., the determination of nominal interest rates).

2.3.3. The monetary policy rule

Here we follow the influent paper of Clarida et al. (1999), where the monetary policy has two components,

$$i_t = \rho i_{t-1} + (1-\rho) i_t^*, \tag{2.25}$$

$$i_t^* = \bar{i}^* + \gamma_i (\mathrm{E}_t \pi_{t+1} - \bar{\pi}) + \gamma_g y_t. \tag{2.26}$$

where $\bar{i}^*$ is the desired interest rate, and $\bar{\pi}$ is the long-term desired inflation. Equation (2.25) models the tendency of central banks towards smoothing interest rates, while (2.26) is the "Taylor rule", in which the monetary authority reacts to deviations of expected inflation from its target, and to deviations of output from its equilibrium level (output gap). By plugging (2.25) into (2.26) and adding a *i.i.d.* monetary shocks, $v_{3,t}$, we write the final equation of the theoretical model, the monetary policy rule:

$$i_t = \bar{c} + \rho i_{t-1} + (1-\rho)(\gamma_i \mathrm{E}_t\{\pi_{t+1}\} + \gamma_g y_t) + v_{3,t}, \tag{2.27}$$

where, $\bar{c} = (1-\rho)(\bar{i}^* - \gamma_i \bar{\pi})$.

The next section deals with the estimation method of equations (2.14), (2.24), and (2.27). But, before we proceed, it is noteworthy that we would rather use a model without exchange rates in this paper. This variable was used before as a policy instrument, stimulating investments, as with the imports substitution policies (between 1975 and 1984), and controlling inflation, as in the early years of the Real plan (1994 to 1998). Thus, its value had been fixed by the monetary authority for several periods for policy purposes, making difficult its utilization in regression methods. Besides, Mello and Moccero (2011) estimated a model similar to ours, but including exchange rate, for the period after 1999. They found that changes in the nominal exchange rate were not statistically significant in the Brazilian Central Bank's reaction function.

2.4. Methodology: estimation, series, and samples

In this section, we first describe the method of estimation, in which Bayesian techniques are employed. Second part presents the utilized time series. Third section deals with the division of the data into sub-samples of estimation, the structural breaks test, and with the approaches utilized to investigate the sources of the observed changes in the country.

2.4.1. Estimation method

The theoretical model employed in this paper, comprising equations (2.14), (2.24), and (2.27), has 12 parameters, including nine of which with a structural interpretation (δ, θ_g, κ, θ_i, β, $\bar{c}$, ρ, γ_i, γ_g), and three auxiliary ones ($\sigma_1^2, \sigma_2^2, \sigma_3^2$). The first set of coefficients is related to the private sector (δ, κ, β), to inertia (θ_g, θ_i), and to the monetary policy rule ($\bar{c}$, ρ, γ_i, γ_g); by its turn, the second set represents the variance of the disturbances in each equation. Estimation is carried out by Bayesian methods.

As Zellner (1971) shows, Bayesian estimation connects calibration exercises, through the specification of priors, to methods of estimation, via maximum likelihood function, confronting, in this way, the model with the data. Moreover, priors are seen as weights on the likelihood function, prioritizing certain areas of the parameters subspace[35].

Following Zellner (1971), An and Schorfheide (2007), and Fernández-Villaverde (2000), a density function describing a prior belief is defined as $p(\boldsymbol{\alpha})$ where

[35] A Bayesian approach for estimating DSGE models is appealing for several reasons. For example, as pointed out by Fernández-Villaverde (2010), the likelihood function of systems as we are working here is highly dimensional and complicated, probably having many local maxima, minima, and flat surfaces. Thus, even the most sophisticated maximization algorithms have tremendous difficulties finding the estimated parameters and their standard errors. Moreover, Bayesian techniques provide us a simple way to introduce prior knowledge of the data by restricting parameters to shapes and regions that match the economic theory.

$\boldsymbol{\alpha}$ is a vector containing all the model's parameters; and, $p(\cdot)$ stands for a probability density function (pdf), such as normal, gamma, uniform, among others.

In order to obtain the likelihood function, $f(z_T|\boldsymbol{\alpha})$, where z_T sums up all the observable variables of the model (inflation, output gap, and interest rates, described in details below), we first write our system of equations in a state space format so that the likelihood can be calculated by means of the Kalman filter and the prediction error decomposition (Canova, 2009). Thus, equations (2.14), (2.24), and (2.27) are organized as,

$$\begin{aligned} z_{1t+1} &= A_1(\boldsymbol{\alpha})z_{1t} + A_2(\boldsymbol{\alpha})v_{t+1}, \\ z_{2t} &= A_3(\boldsymbol{\alpha})z_{1t}. \end{aligned} \tag{2.28}$$

Where, in (2.28), $z_{2t} = [\pi_t, y_t, i_t]$; $z_{1t} = [\pi_{t-1}, y_{t-1}, i_{t-1}, v_{1t}, v_{2t}, v_{3t}]$; and, the matrices A_i, i = 1, 2, 3, are nonlinear functions of the structural parameters $\boldsymbol{\alpha}$.

Our goal is to use $p(\boldsymbol{\alpha})$ and (2.28) in order to estimate $p(\boldsymbol{\alpha}|z_T)$, the posterior density of the parameters. Using the Bayes theorem, the latter can be written as

$$p(\boldsymbol{\alpha}|z_T) = \frac{p(\boldsymbol{\alpha})f(z_T|\boldsymbol{\alpha})}{f(z_T)}, \tag{2.29}$$

where the numerator corresponds to the prior and the likelihood function, respectively; and, the denominator is the marginal density of the data, obtained by integrating $p(\boldsymbol{\alpha})f(z_T|\boldsymbol{\alpha})$ with respect to $\boldsymbol{\alpha}$, in our case, a 12-dimensional vector. Although an analytical computation of the posterior density (eq. 2.29) is practically impossible, we can make use of numerical routines in order to obtain the posterior distribution of $\boldsymbol{\alpha}$ (that is, their point estimates and confidence intervals).

In this sense, as suggested by Schorfheide (2000), we employ the Random-Walk Metropolis-Hastings (RWMH) algorithm, which comprises the following steps:

1. Use an optimization routine to maximize the log-posterior kernel[36] $(\ln f(z_T|\boldsymbol{\alpha}) + \ln p(\boldsymbol{\alpha}))$. Denote the posterior mode by $\tilde{\boldsymbol{\alpha}}$;
2. Let $\tilde{\boldsymbol{\Sigma}}$ be the inverse of the Hessian computed at the posterior mode $\tilde{\boldsymbol{\alpha}}$;
3. Draw $\tilde{\boldsymbol{\alpha}}^{(0)}$ from $\mathrm{N}(\tilde{\boldsymbol{\alpha}}, c_0^2\tilde{\boldsymbol{\Sigma}})$;
4. For s = 1, …, n_{sim}, draw a proposal $\boldsymbol{\alpha}^*$ from the jumping distribution $\mathrm{N}(\boldsymbol{\alpha}^{(s-1)}, c^2\tilde{\boldsymbol{\Sigma}})$. The jump from $\boldsymbol{\alpha}^{(s-1)}$ is accepted ($\boldsymbol{\alpha}^{(s)} = \boldsymbol{\alpha}^*$) with probability $\min\{1, r(\boldsymbol{\alpha}^{(s-1)}, \boldsymbol{\alpha}^*|z_T)\}$ and rejected ($\boldsymbol{\alpha}^{(s)} = \boldsymbol{\alpha}^{(s-1)}$) otherwise. Where $r(\boldsymbol{\alpha}^{(s-1)}, \boldsymbol{\alpha}^*|z_T) = \dfrac{\ln(\boldsymbol{\alpha}^*|z_T)p(\boldsymbol{\alpha}^*)}{\ln(\boldsymbol{\alpha}^{(s-1)}|z_T)p(\boldsymbol{\alpha}^{(s-1)})}$ defines the acceptance ratio. Update the jumping distribution if necessary;
5. After having repeated step four several times, build histograms of the posterior distribution of the parameters.

As explained by An and Schorfheide (2007), under general regularity conditions the posterior distribution of $\boldsymbol{\alpha}$ is asymptotically normal. Moreover, the RWMH algorithm generates a sequence of $\boldsymbol{\alpha}$ that will be averaged to approximate posterior moments and confidence intervals for the estimated parameters.

[36] We use a Monte Carlo based one, option 6 in Dynare 4.3.3, the software utilized. This method is useful when posterior mode is difficult to obtain with standard optimization routines (Newton type ones, e.g., Klein, 2000; Sims, 2002). It provides a suitable covariance matrix for the RWMH algorithm.

Specifically, when running the RWMH algorithm, we set the scale parameter (constant c in step 4, above) such as that the acceptance rate is about 20 and 50%. Thus, the algorithm is allowed to visit the tails of the parameters distribution, and would not get trapped around regions of local maxima in the parameters subspace. Moreover, for all the samples of estimation we draw five MH-chains of 40,000 iterations each, keeping 14,000 draws in order to construct the histograms. Convergence is addressed by the Brooks and Gelman's (1998) method.

Priors are assumed to be factored as $p(\boldsymbol{\alpha}) = \prod_{i=1}^{12} p(\alpha_i)$, that is, parameters have independent distributions. When selecting the shape of the priors' distributions, we proceed as suggested by Canova (2009), setting: inverse gamma distributions for parameters that must be positive (δ, κ, $\sigma_1, \sigma_2, \sigma_3$); gamma distributions for parameters that are truncated below a certain value ($\bar{c} \geq 0$, $\gamma_i \geq 1$); beta distributions for parameters lying in an interval (θ_g, θ_i, β, ρ); and, normal distributions for the remaining parameters (γ_g). The $\gamma_i \geq 1$ restriction follows from Galí at al. (1999) who solved the problem of a discretionary central bank that minimizes a social loss-function. It also assures a single solution for the theoretical system, given reasonable values of the other parameters (see, for example, Clarida, et al. 2000; Lubik and Schorfheide, 2004; and, Romer, 2012). This is a standard setup, employed by several authors in the DSGE literature (see, e.g., Smets and Wouters, 2003, 2007; Silveira, 2008; Canova, 2009; and, Levine et al., 2012).

Means of the priors are set around standard calibrated values, while standard deviations are set loosely, in order to minimize the effect of subjective beliefs, thus letting the algorithm to move away from the priors if data is informative. Table 2.1 shows the first two moments of each prior.

Table 2.1: Priors' shapes, means and standard deviations

Parameter	Shape	Prior mean	Prior standard deviation	Range
δ	Inverse Gamma	2.00	0.25	Strictly positive
κ	Inverse Gamma	2.00	1.00	Strictly positive
β	Beta	0.98	0.01	[0, 1]
θ_g	Beta	0.80	0.25	[0, 1]
θ_i	Beta	0.80	0.25	[0, 1]
$\bar{c}$	Gamma	2.00	0.25	$[0, \infty)$
ρ	Beta	0.80	0.25	[0, 1]
γ_i	Gamma	1.50	0.25	$[1, \infty)$
γ_g	Normal	0.50	0.25	$(-\infty, \infty)$
σ_1	Inverse Gamma	0.01	0.50	Strictly positive
σ_2	Inverse Gamma	0.01	0.50	Strictly positive
σ_3	Inverse Gamma	0.01	0.50	Strictly positive

2.4.2. Data and procedures

The time series we use in this paper are quarterly spaced and, when necessary, seasonally adjusted with the X-12 method. Sample ranges from the first quarter of 1975 to the last one of 2012.

Quarterly inflation rate, π_t, is approximated by the average of the monthly rate within each quarter[37]. The latter is measured as variations in the General Price Index – Internal Availability (IGP–DI), published by Getúlio Vargas Foundation, which imputes weights of 60, 30, and 10% to, respectively, wholesale, consumer, and construction price indexes.

Whereas the literature evaluating monetary policy in Brazil has mainly focused on consumer price indexes when measuring inflation (see, e.g., Silveira, 2008; and, Mello and Moccero, 2011), here we work with the general price index, provided that it

[37] This proxy allows for a better fit in the Bayesian estimation. Besides, as long as desired inflation goes to the intercept term in (2.27), we do not necessarily need to use annualized quarterly inflation rates in our estimations.

has a longer time series, including data between 1975 and 1980, essential for our comparative purposes. This, however, shall not alter our main conclusions[38]. In order to keep the database conformity, quarterly nominal interest rate, i_t, is the average of the monthly Selic rates within each quarter. Selic measures the Brazilian basic interest rates, and it is published by the Central Bank (BACEN) [39].

When it comes to the output gap, y_t, we follow Orphanides (2004) who suggests a flexible way to compute it, such as deviations from a Hodrick-Prescott filter (HP-filter, Hodrick and Prescott, 1997) or a quadratic deterministic trend, or even the growth rate of the log-GDP. According to this author, model based methods for computing the potential output and, therefore, the output gap, fails to quickly adjust to persistent adverse shifts in the trend, as it has occurred in Brazil in the beginning of the 1980's (period broadly known as the *Lost Decade*). As a result, estimates of potential output during this period may appear consistently overestimated, which leads to output gap misperceptions. In this sense we define our output gap proxy as the cyclic component coming out from a HP-decomposition over the log-GDP time series, when assuming the classical smoothing parameter of 1,600. Additionally, for robustness, we also run our estimation for the output growth rule. GDP data is provided by Bonelli and Rodrigues (2012).

Concerning whether inflation and interest rates are stationary, results presented in the literature so far are mixed. Regular ADF tests tend to conclude that inflation and interest rates are I(0), but this feature is probably due to the presence of structural breaks and, or, abrupt governmental interventions. Cati et al. (1999), for example, built a test

[38] As matter of fact, the correlation between the official consumer price (also known as IPCA, provided by Instituto Brasileiro de Estatística e Geografia, IBGE) and the general price (IGP-DI) series is 0.998, for the period from 1980 to 2012.
[39] Both are available at https://www.ipeadata.gov.br.

that accounts for such intervention, obtaining pieces of evidence that support the unit root hypothesis for the inflation rate and interest rates in Brazil, between 1974 and 1993. In the present paper, instead of going thoroughly over this controversial issue, we assume both specifications for the variables entering in our systems, that is, one with inflation, output gap, and interest rates in levels, and another where we take the first difference of inflation and interest rates. When doing so, our results are also enriched, since they offer important insights for the evaluation of the monetary policy whenever it is dealing with the level or the growth rate of inflation. Figure 2.1 below depicts the analyzed time series.

As one can easily see in Figure 2.1, Brazilian inflation and interest rates are highly unstable, showing periods of rapid growth and sudden stops. Besides, they are remarkably more stable after 1995. Such feature makes the estimation for the entire 1975-2012 period unmanageable, with inconsistently estimated parameters. Concerning this problem, we divide our full sample into specific sub-samples, according to a three equation test for multiples structural breaks that occur at unknown dates, as described below (the test is due to Qu and Perron, 2007). Once we have defined our sub-samples, we estimate the system of equations (2.14), (2.24), and (2.27) for each one of them, comparing the results subsequently.

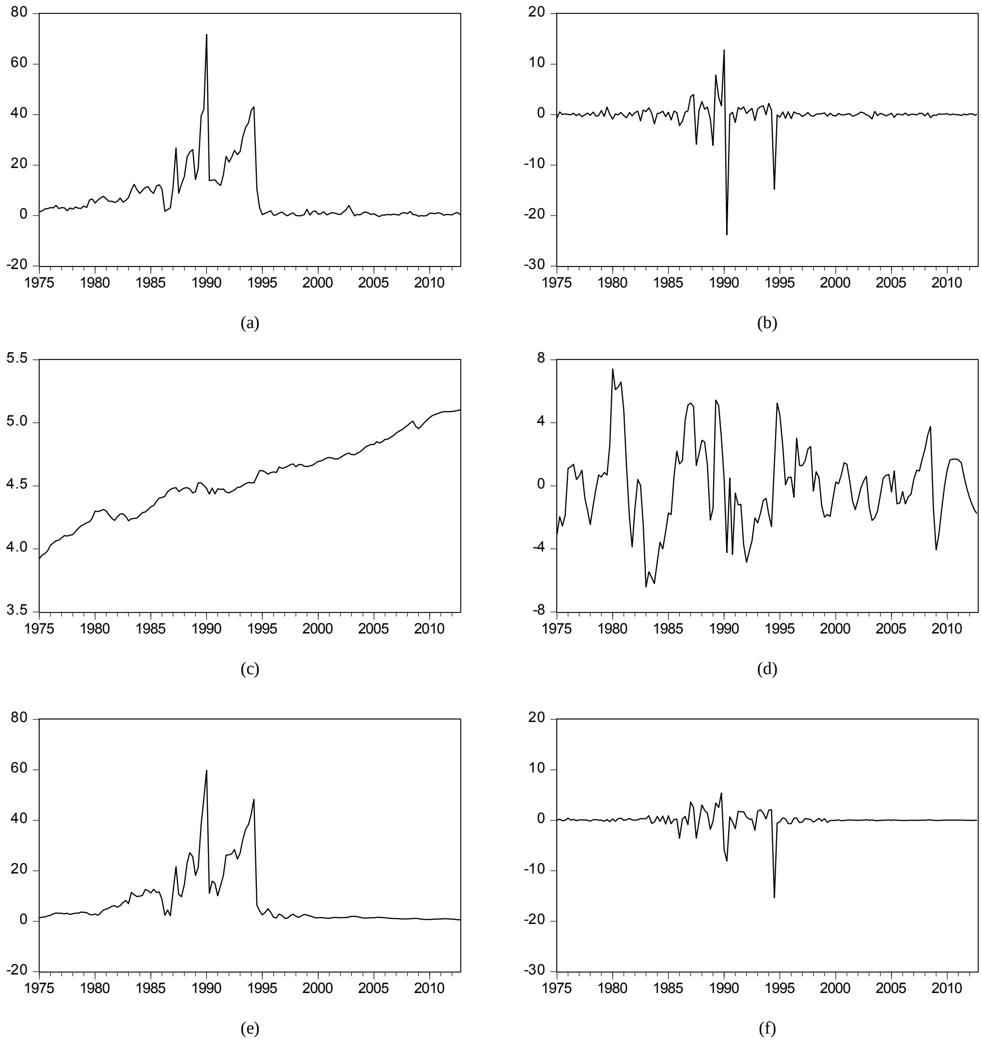

Fig.2.1: Time series. (a) IGP-DI inflation; (b) first difference of IGP-DI; (c) log real GDP in levels; (d) HP-filtered output gap; (e) interest rates, Selic; and, (f) first differences of Selic.

2.4.3. Structural breaks and sub-samples of estimation

In order to assess the possibility of structural change in the Brazilian economy, we apply a test of (possibly multiple) breaks at unknown dates, on a three equation VAR(p)[40] (Qu and Perron, 2007). The three variables entering the VAR are inflation, output gap[41] (HP-filter rule), and interest rates. The same we use in the estimation of our theoretical model.

[40] Vector of auto-regressions, *p* is the lag order.
[41] Results also apply for the output growth rule.

As stated by Perron (2006) the estimation of break dates by the means of a system of equations is appealing because it is more accurate than the single equation case, since variables may affect each other via likelihood function. This result is true even if some of the equations have invariant parameters across regimes. Besides, Bai et al. (1998) show that the precision of the asymptotic confidence interval for a particular break date increases proportionally to the number of time series which have a common structural break date.

Hess and Iwata (1997) have shown that an ARIMA(1, 1, 0) model describes well the duration and amplitude of the log real U.S. GDP. Following this result we estimate our autoregressive system as a VAR(1), assuming the variables in levels, or taking the first difference of inflation and interest rates. We allow for breaks in all parameters, including intercepts, autoregressive parameters, and in the covariance matrix of the errors. Moreover, given the length of data, we allow for three breaks at most, that is, four different regimes, and we rule out breaks that could appear at the first and final 15% of the data (setting the trimming parameter at 0.15). Estimation is carried out via an iterative feasible generalized least squares procedure (details in Qu and Perron, 2007). Test results are described in Table 2.2.

As Table 2.2 shows, for the assumption of one structural break, in both specifications, that is, levels or first differences, a breakpoint is estimated around 1994/1995. That latter is the most dominant structural change in our system, since it is the first one being highlighted by the data. It is also statistically significant, with fairly tight confidence intervals.

Table 2.2: Multivariate structural changes dates

Specification[1]	SupLR. Statistic[2]	Break number 1 [90% C.I.]	Break number 2 [90% C.I.]	Break number 3 [90% C.I.]
Levels (at most 1 break)	482*	-	-	**1994.I** [1993.III, 1994.II]
Levels (at most 2 breaks)	685*	-	**1985.I** [1984.IV, 1986.IV]	**1994.I** [1993.III, 1994.II]
Levels (at most 3 breaks)	880*	**1985.II** [1984.IV, 1986.IV]	**1994.I** [1993.III, 1994.II]	**2002.III** [2001.IV, 2003.IV]
Differences (at most 1 break)	560*	-	-	**1995.IV** [1989.II, 1996.I]
Differences (at most 2 breaks)	786*	-	**1985.II** [1985.I, 1992.IV]	**1995.IV** [1987.III, 1996.I]
Differences (at most 3 breaks)	897*	**1985.II** [1985.I, 1993.II]	**1994.III** [1992.II, 1994.IV]	**2003.III** [2002.II, 2003.IV]

Notes: (1) 18 parameters changing across regimes; (2) *, **, and *** denote statistical significance at 1, 5 and 10%, respectively.

Considering the possibility of two structural changes, the levels specification suggests the first quarters of 1985 and 1994 as breakpoints, while in the first difference, the second quarter of 1985 and the fourth quarter of 1995 are the estimated breakpoints. Again, the dates of changes are similar in both setups, but confidence intervals are narrower when variables are in levels. Besides, the sequential test developed by Qu and Perron (2007) indicates two breaks instead of one for both specifications (test statistic is 205 for variables in levels; and, 226 for the first difference case).

The last significant break is estimated around 2003, with the sequential likelihood test suggesting three as the number of structural changes in our estimated VAR. Statistics are now 195 and 102 for inflation and nominal rates in levels and differences, respectively. In both cases, significance is high, rejecting, therefore, the null of two breaks against the alternative of three breaks.

Based on the results of Table 2.2, we are able to define four sub-samples to be used in the Bayesian estimation. We set the first sample ranging from 1975.I to 1984.IV; the second one from 1985.I to 1994.IV; the third one from 1995.I to 2004.IV;

and, the last one from 2005 on. When doing so, we delimit our different samples according to the structural breaks test, while keeping each one of them, except to the last one, with the same length, 40 time series observations. This procedure is important for minimizing the differences in the parameter estimation that would emerge from changing the precision of the estimates (Canova, 2009).

In Table 2.3, we depict mean, standard deviation, and persistence of each variable, taking account to the different samples. Persistence is defined as the first autocorrelation coefficient, as it is common in the business cycle literature. By analyzing this table, some interesting facts appear. First, mean and standard deviation of the output gap have been falling over the years. For instance, the standard deviation after 1995 is half of its value in the previous years. Moreover, we cannot reject the null of equal means and variances between the samples of 1995-2004 and 2005-2012. Conversely, output gap persistence is quite stable across the samples.

Second, inflation rates in levels show a remarkable decrease in its mean and standard deviation after 1995. The period of 1985-1994 contains the peak of these statistics for the variable, when the seasonally adjusted inflation reached an average value of 840% per year, approximately.

If one compares the last two samples, that is, 1995-2004 and 2005-2012, regarding to inflation's mean and variance, equality tests t and F lead to the rejection of the null at 1% of statistical significance. Thus, the reduction in the mean inflation rate and in its instability after 2005 is significant, which agrees with our structural break tests. Nominal interests rates have a similar pattern to the one described for inflation.

Finally, mean values of the first difference of inflation and interest rates has also decreased over the years. The most interesting feature of these variables is related to the persistence. While in the post 1995 years inflation has become anti-persistent, that is, tending to alternate high and low (or negative) values, interest rates have become persistent, meaning that a higher Selic today will probably be followed by an even higher value tomorrow. These results may reflect tighter monetary policy conduction by the Brazilian Central Bank. We address to this question in the next sections.

Table 2.3: Subsamples descriptive statistics

Stat.[1]/Sample	1975-1984	1985-1994	1995-2004	2005-2012	Full sample
			Output gap (*HP filter*)		
Mean	-0.52	0.24	0.21	0.09	0.00
Std. Dev. (%)	3.46	3.06	1.53	1.74	2.62
Persistence	0.87	0.69	0.65	0.71	0.77
			Inflation		
Mean	5.45	20.56	0.91	0.46	7.18
Std. Dev. (%)	2.94	14.1	0.84	0.47	11.03
Persistence	0.96	0.55	0.21^{NS}	0.42	0.81
			Nominal rates - Selic		
Mean	5.02	21.14	1.86	0.97	7.58
Std. Dev. (%)	3.20	13.75	0.79	0.25	10.96
Persistence	1.00	0.63	0.60	0.96	0.85
			Δ(*Inflation*)		
Mean	0.06	-0.07	-0.01	0.01	-0.004
Std. Dev. (%)	0.63	5.45	0.37	0.21	2.81
Persistence	-0.24^{NS}	-0.26^{NS}	-0.45	-0.42	-0.26
			Δ(*Selic*)		
Mean	0.08	-0.06	-0.02	-0.01	-0.002
Std. Dev. (%)	0.33	3.51	0.27	0.03	1.80
Persistence	-0.45	0.04^{NS}	0.01^{NS}	0.38	0.04^{NS}
N. obs.	40	40	40	32	152

Notes: (1) NS stands for a not significant parameter at 10%.

In general lines, the structural change test and the divisions of the sample are in line with the previous literature as well. It is a common view that the period from 1975 to 1984 can be classified as "moderate to accelerating inflation", the one from 1985 to 1994 as "high or hyperinflation", and after 1995 as "low inflation" (see, Cati, et al. 1999; Minella, 2003, for example). Here we apply a methodology that confirms such partitions, by estimating and testing for multiple breaks in a VAR(1) with inflation, output gap, and interest rates as variables. However, the breakpoint test also suggests a change around 2003/2004. When inspecting Table 2.3, one is lead to conclude that this break is related to an even higher stability of inflation and interest rates in the economy.

The division of the sample according the breakpoint dates allows us to understand the monetary policy conduction throughout the time in Brazil, and to associate it to the facts in Table 2.3. However, another relevant question pops up from the last table: given the results presented so far, the Brazilian economy has clearly entered in a period of "Great Moderation" after 1995. Is this a reflection of the Real Plan? Or, in another words, what is the importance of this monetary plan for the increased stability in the country?

According to Stock and Watson (2002), the explanations for this phenomenon in the U.S. economy, which has begun around 1984, are divided in three main categories. The first one is related with changes in the private sector, such as improvements in the inventory management made possible by the advancements in the information-technology (McConnell and Perez-Quiros, 2000; and, Barnett and Chauvet, 2008), and financial innovations that facilitates intertemporal smoothing of consumption and investment (Blanchard and Simon, 2001). The second reason would be improved monetary policy (e.g., Cogley and Sargent, 2005; Canova, 2009). And, the third category is good luck, that is, comparatively milder exogenous shocks impinging the U.S. economy since then (Bernanke and Mihov, 1998; Leeper and Zha, 2003; Moreno, 2004; and, Sims and Zha, 2006).

By using the New Keynesian system we can address to all these factors in a simple way. First, we estimate the model before and after the Real Plan, taking notes to the simulated variances of the variables and the parameters' values. Then, we reestimate the model after the Real Plan while fixing a specific set of parameters at their pre Real Plan posterior mean values. Therefore, the question is: will the restricted model reproduce the observed fall in the volatility of output and inflation? The sets of parameters hold constant at each round of estimation are: (δ, θ_g, κ, θ_i) representing the private sector and inertia; (ρ, γ_i, γ_g) for the monetary policy; and, ($\sigma_1^2, \sigma_2^2, \sigma_3^2$) for good luck hypothesis.

When setting the pre and post the Real Plan samples, we discard the year of 1994 since it can be understood as a transition period. In this sense, pre Real Plan sample is defined from 1975q1 to 1993q4, and post Real Plan from 1995q1 to 2012q4. When doing so, we are able to examine the contribution of each particular factor to the Brazilian Great Moderation.

2.5. Results

Results are presented in two sections. First, we check the ability of the estimated models in reproducing the volatility drop of inflation, GDP, and Selic rate. Following that, changes in models' parameters over time are analyzed. Second, we investigate which group of parameters has a significant impact on the volatility reduction, that is, what would be the main determinants of the Brazilian Great Moderation.

2.5.1. Volatility drop and parameter changes

As shown previously, the Brazilian economy has passed by three structural breaks between 1975 and 2012; a major one in 1995, and two lesser ones in 1985 and 2003, approximately. This fact has encouraged us to divide our data into four periods, as follows: 1975-1984, 1985-1994, 1995-2004, and 2005-2012. The most remarkable change across these subsamples is the drop of the volatility in the country, in which, for example, real GDP's standard deviation fell 50% after 1995, while the instability of inflation and nominal rate had even sharper reductions (see Table 2.3 in this regard).

Accordingly, we first verify the adequacy of the models to this feature, which is done in Tables 2.4 and 2.5 below. Table 2.4 brings estimated posterior standard deviations when output gap is derived from a HP-filter (λ=1600), both considering the variables in levels, in Panel a, and first differences of inflation and Selic rate, in Panel b. 90% confidence intervals for the statistics are presented inside brackets. Table 2.5, by its turn, has the same structure, except that output gap is measured by the first difference of real log-GDP.

Table 2.4: Estimated posterior standard deviations of the endogenous variables for the HP-filter specification

Variable/Sample	1975-1984	1985-1994	1995-2004	2005-2012
	Panel a: levels			
Inflation	8.41	41.26	1.98	1.45
	[5.5, 10.5]	[27.6, 53.5]	[1.5, 2.4]	[1.2, 1.6]
Gap (HP-filter)	3.77	5.01	1.83	2.02
	[3.1, 4.3]	[4.2, 5.8]	[1.3, 2.1]	[1.6, 2.4]
Selic rate	8.02	39.87	2.69	1.76
	[5.2, 10.1]	[22.8, 51.4]	[2.2, 3.2]	[1.3, 2.2]
	Panel b: differences			
ΔInflation	1.95	18.36	1.87	1.03
	[1.7, 2.2]	[14.8, 21.8]	[1.5, 2.1]	[0.9, 1.2]
Gap (HP-filter)	2.80	5.11	1.63	1.59
	[2.3, 3.2]	[4.1, 6.6]	[1.3, 1.9]	[1.3, 1.8]
ΔSelic rate	1.67	12.81	1.33	0.82
	[1.3, 1.9]	[9.5, 16.6]	[1.0, 1.5]	[0.6, 0.9]

Notes: 90% confidence interval is between brackets.

As can be seen in Table 2.4, the drop in the volatility is present. In Panel a, for example, the upper 90% limit of the variables' standard deviation after 1995 is smaller than the lower limit in the previous samples, which denotes a significant structural break on the country's instability. In Panel b, although results show a reduction on the volatility, significant breaks occur only after 2005, since the 1995-2004 statistics are not statistically different from those obtained in the first sample, considering a 90% confidence interval.

Table 2.5: Estimated posterior standard deviations of the endogenous variables for the output growth specification

Variable/Sample	1975-1984	1985-1994	1995-2004	2005-2012
		Panel a: levels		
Inflation	5.39	39.51	1.49	0.95
	[3.5, 6.6]	[24.9, 49.9]	[1.2, 1.7]	[0.7, 1.1]
Gap (ΔGDP)	1.55	2.58	0.62	0.53
	[1.2, 1.8]	[2.1, 3.0]	[0.5, 0.7]	[0.4, 0.6]
Selic rate	5.70	38.50	2.11	1.27
	[3.6, 7.0]	[23.0, 48.7]	[1.7, 2.4]	[1.0, 1.4]
		Panel d: differences		
ΔInflation	1.74	16.95	1.14	0.59
	[1.5, 1.8]	[14.7, 18.5]	[1.0, 1.2]	[0.57, 0.64]
Gap (ΔGDP)	0.70	2.63	0.37	0.28
	[0.6, 0.8]	[2.2, 3.0]	[0.3, 0.4]	[0.2, 0.3]
ΔSelic rate	1.30	13.18	0.73	0.22
	[1.1, 1.5]	[10.7, 14.6]	[0.6, 0.8]	[0.17, 0.22]

Notes: 90% confidence interval is between brackets.

In Table 2.5, where output gap is measured as the first differences of real log-GDP, for both assumptions, that is, with inflation and nominal rate in levels and differences, respectively, the reduction on the variables' standard deviation is significant after 1995 at 90% of statistical confidence. Whichever the case depicted in Tables 2.4 and 2.5, however, a clear inverted U-shape pattern emerges from the estimated standard deviations of the variables across different samples, with peaks located in the 1985-1994 sample. Such result reinforces our conviction towards a Great Moderation period in Brazil after 1995.

We now analyze systematic changes in the estimated models parameters. Results are presented in a graphical form, such that the exposition of a large set of information is eased. The interested reader may turn his/her attention to Tables A.1, A.2, and A.3, in annex, which bring the complete output of the estimation processes. Hence, we begin analyzing the private sector and inertia coefficients, depicted in Figure 2.2, below. Estimated parameters in this figure are presented separately in four parts, *i* to *iv*. In each one of these, letters *a*, *b*, *c*, and *d* stand for the models considering, respectively, HP-filter output gap, and inflation and Selic in levels; HP-filter output gap, and inflation and Selic in differences; first difference output gap, and inflation and Selic in levels; and, lastly, output gap, inflation, and Selic in first differences.

The parameter controlling IS-curve inclination, δ (delta), which captures contemporaneous dependence of the output gap on changes in the ex-ante real interest rate, is fairly constant over time in all four models, being estimated at 1.5 or 2.0. Thus, one is lead to conclude that monetary policy impacts more than proportionally on real economic activity. There is also a little evidence that this effect has grown in the last years, as showed by models *b* and *d* (however, the 90% confidence intervals for δ are overlapped across subsamples in every tested case). Similar values for the IS inclination were found by Mello and Moccero (2011), when utilizing a VAR methodology for the periods 1996-1998, and 1999-feb/2006, with monthly data.

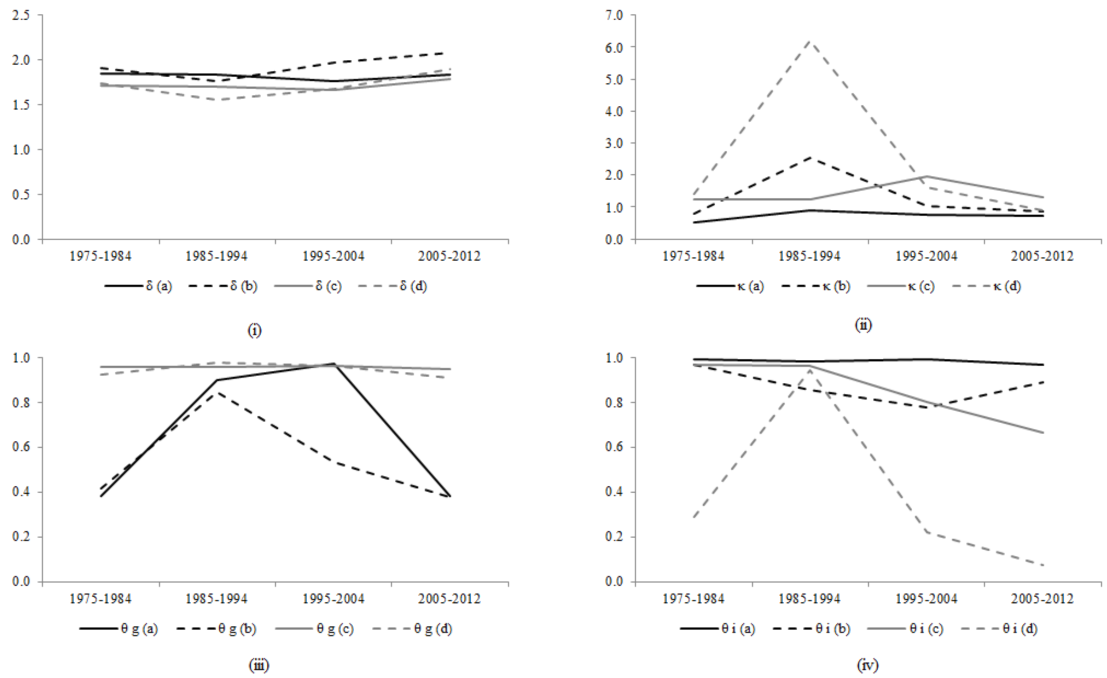

Fig.2.2: Changes in private sector and inertia parameters across subsamples in different models. Model (a) Inflation and Selic rate in levels, HP-filter measuring output gap; (b) inflation and Selic rate in differences, HP-filter measuring output gap; (c) inflation and Selic rate in levels, log-GDP in differences measuring output gap; and, (d) inflation and Selic rate in differences, log-GDP in differences measuring output gap.

The influence of output gap on inflation, measured by κ in the Phillips curve, has an interesting dynamic over time. In most of the cases, this parameter reaches a peak in the sample ranging from 1985 to 1994 (the only exception is depicted in Figure 2.2, part *ii*, model *c*). Besides, if it is considered models where inflation and interest rate are in differences, that is, in rates of growth, this effect is even more pronounced (see models *b* and *d* in Figure 2.2). Thus, agreeing with the macroeconomic review previously presented, such dynamic is reflecting the effects of consumption bubbles generated right after the price-freezing economic plans. Following the Real Plan implementation, output gap coefficient on inflation has been smaller than one, being located around 0.75 and 0.9.

Endogenous output persistence is captured by θ_g in our models. Whenever output gap is measured by the HP-filter, this parameter tends to be smaller in the last years of the sample. However, if one uses the first difference of GDP as a proxy for the output gap, θ_g is estimated as the unity in most of the time, approximating the NKPC to the backward-looking framework utilized by Svensson (1997), and Ball (1999). In this sense, based on our estimations, drawing general conclusions about the persistence in the aggregate demand is troublesome. Perhaps, Table 2.3 is more informative in this regard, where we show that the autoregressive coefficient of output gap oscillates around 0.75 over the years.

The next parameter to be analyzed in Figure 2.2 is θ_i, which captures inflationary inertia degree in the models (see part *iv* of this figure). It is, without any doubt, one of the most important sources of information of our estimations, given the importance of the inflationary process in recent Brazilian history. For the case illustrated in model *a*, where variables are in levels, and output gap is derived from a HP-filter, our results show that inflation inertia has slowly reduced over time, with a 90% confidence interval of [0.98, 1.00] for θ_i in the first sample, and [0.92, 1.00] between 2005 and 2012. In model *c* of Figure 2.2 part *iv*, where we measure the output gap as the first difference of real log-GDP, this result strengthens, with point estimates for θ_i starting at 0.97 ([0.91, 1.00]) between 1975 and 1984, and 0.97 ([0.89, 1.00]), 0.81 ([0.66, 1.00]), and 0.67 ([0.50, 0.81]), in the next three samples, respectively.

In models *c* and *d* of Figure 2.2 part *iv*, where inflation and Selic rate are in rates of growth, both estimations indicate a reduction of inflation inertia. In model *c*, the smallest value for θ_i is found in the 1994-2005 years, being estimated at 0.78. In model *d*, our results are rather interesting, with θ_i being estimated at 0.29 in the first sample, and 0.94, 0.21, and (only) 0.07 in the next three samples, respectively. Thus, according model *d*, inflation inertia has greatly weakened after 1995, reflecting on a Phillips curve that has become more forward-looking over time, with price setters putting a higher weight on expected future inflation. Besides, the peak of inertia was found between 1985 and 1994, matching with the information previously presented, during the review of the Brazilian macroeconomic panorama.

Overall, we can conclude that the inflationary inertia has reduced in Brazil over the years, but this reduction is extremely more apparent in the specifications with variables in rates of growth. Therefore, even in the years following 1995, the inflationary process still tends to be persistent, but it does not have an explosive dynamic, as it used to have before this year. Our results, in which concerns to the cases where inflation is in levels, are related with Figueiredo and Marques' (2009) findings who, using a monthly IGP-DI data ranging from 1994:8 to 2008:1, and a ARFIMA-GARCH methodology, showed that inflation is a stochastic process with long memory.

We now analyze changes on the policy set of parameters. Figure 2.3 brings information about the coefficients governing interest rate smoothness, ρ, and the weights of inflation and output gap in the Taylor rule, γ_i and γ_g. Beginning with ρ, it tends to be small and alike in all of our estimation setups. Its values are around 0.05, varying from 0.01 in 1985-1994, when all variables are in differences (Figure 2.3, model d), to 0.12 in 2005-2012, when inflation and interest rate are in differences, and output gap is measured by the HP-filter (Figure 2.3, model b). Besides, 90% confidence interval includes 0.00 most of the times. In this sense, our results support that the Brazilian Central Bank have not been pursuing gradual monetary policy conduction over time; interest rate adjusts quickly towards the Bank's intended value[42]. This is an

[42]This may be a reflection of our interest rate data, which is a quarterly average of the monthly data. The Brazilian Monetary Policy Committee (Copom) meets at least eight times in each calendar year since 1996. Therefore, monthly (raw) data may better detect the smoothing behavior if it exists. Minella et al.

interesting feature of the Brazilian economy, since authors as Moreno (2004), and Canova (2009) found higher values for ρ (usually above 0.8), reflecting the smoothing behavior of the FED.

Regarding the weights of the monetary policy rule, when inflation and interest rates are in levels, specifications *a* and *c* of Figure 2.3, one can see that the models fit well some of the features highlighted before, such as: i) in the years before the Real Plan, monetary authority imputed a higher weight on the output stabilization; and, ii) after 1995, Central Bank has increasingly become more adverse and responsive to elevations in the inflation expectations. As we have seen before, there was a feeling in the Brazilian economic team that conventional instruments for controlling inflation were ineffective. Thus, price-freezing stabilization plans, especially the ones implemented between 1985 and 1990, always attempted to stop the inflation inertia without generating large output losses, avoiding the political and social costs of a restrictive policy. After 1990, however, when the economy was suffering from a deflagrated hyperinflationary process, inflation itself became the worst social problem in the country, gaining a much higher weight in the Central Bank reaction rule over time. Considering specifications in differences, represented in models *b* and *d* of Figure 2.3, coefficients' patterns through the years are pretty much the same as before.

(2003), and Mello and Moccero (2011), for example, using data with this frequency for the periods 1999:7-2002:12, and 1999:1-2006:2, respectively, found estimates of about 0.7 for ρ in Brazil.

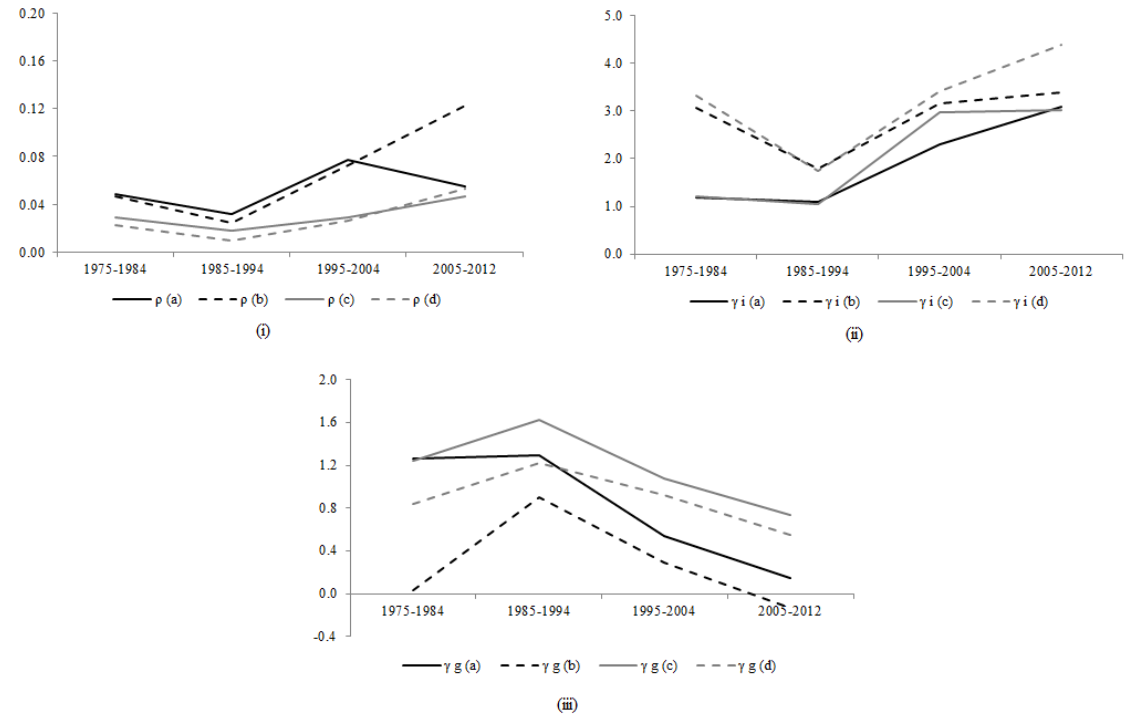

Fig.2.3: Changes in policy parameters across subsamples in different models. Model (a) Inflation and Selic rate in levels, HP-filter measuring output gap; (b) inflation and Selic rate in differences, HP-filter measuring output gap; (c) inflation and Selic rate in levels, log-GDP in differences measuring output gap; and, (d) inflation and Selic rate in differences, log-GDP in differences measuring output gap.

In Figure 2.4 we present the last set of estimated parameters, referring to the exogenous instabilities of the system, which are represented by the standard errors of the shocks on the IS and Phillips curves, σ_1 and σ_2, respectively, and on the Taylor rule, σ_3. Two facts emerge from this figure. First, the size of the shocks faced by the Brazilian economy in 1985-1994 was much larger than the observed in the U.S. Estimations for that country show that the standard deviation of disturbances reaches 3.0 at most in systems similar to the one employed here (see, e.g., Stock and Watson, 2002; Moreno 2004; and, Canova, 2009). Since the first half of the 1990s, however, shocks in Brazil have also become milder, being estimated at 3.0 (σ_1, both output gap specifications), 1.0 (σ_2, inflation in levels), and 1.4 (σ_3, interest rate in levels). Second, all three graphs in Figure 2.4 display an inverted U-shape pattern, closely related to that observed in the raw data (see Table 2.5, above). Nevertheless, this information should not conduct us to hastily conclude that the milder shocks are the main causes of the increased stability in Brazil. As Canova (2009) points out, in some cases, variations in parameters that are statistically large may produce only small economic consequences. Thus, in the next section we address to this question deeply, investigating which set of parameters can explain the Brazilian Great Moderation.

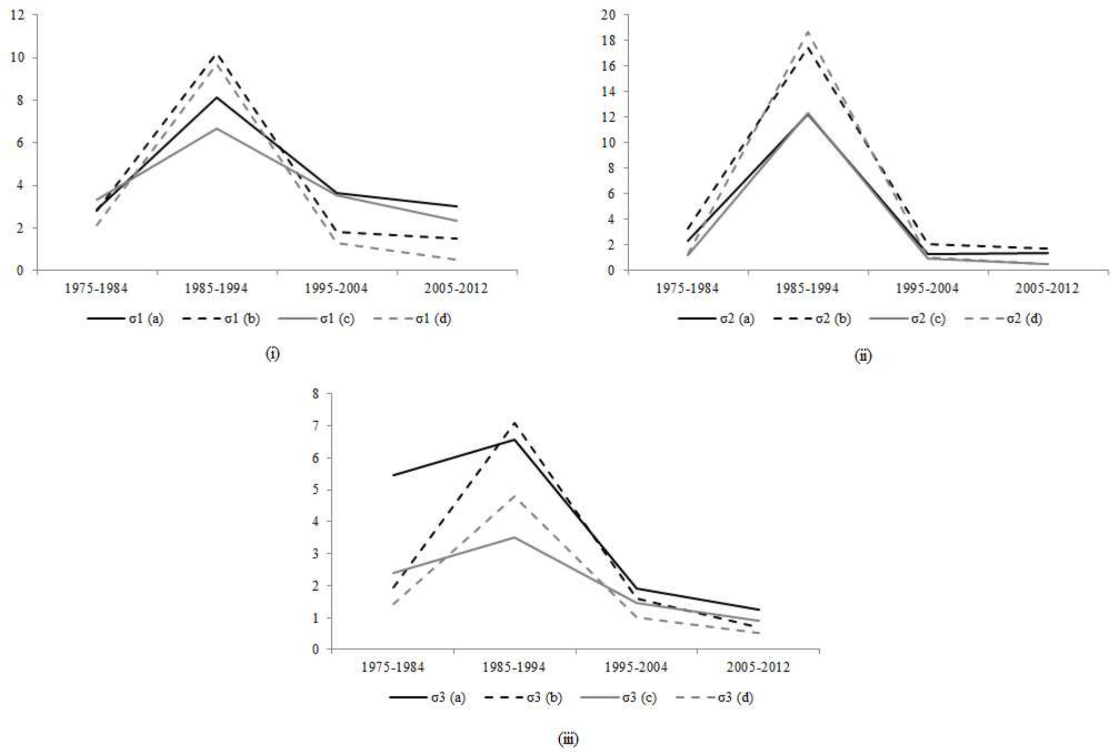

Fig.2.4: Changes in shock parameters across subsamples in different models. Model (a) Inflation and Selic rate in levels, HP-filter measuring output gap; (b) inflation and Selic rate in differences, HP-filter measuring output gap; (c) inflation and Selic rate in levels, log-GDP in differences measuring output gap; and, (d) inflation and Selic rate in differences, log-GDP in differences measuring output gap.

2.5.2. Explanations for the Brazilian Great Moderation

Now, we seek to explain the causes of the drop in the volatility of output and inflation in Brazil. Such feature of the data, also seen in many industrialized countries after 1984, is associated with changes in the private sector, monetary policy, or the shocks impacting the economic activity (see, for example, Bernanke and Mihov, 1998; McConnell and Perez-Quiros, 2000; Moreno, 2004; Cogley and Sargent, 2005; and Canova, 2009).

For the Brazilian case, the instability has decreased relatively late (by the middle of the 1990s, as we have already shown). There exists, therefore, a chronological coincidence between the Real plan launch and the period of lower volatility, which could lead us to conclude, perhaps erroneously, that changes in the monetary policy were the only cause behind this structural break. Thus, when evaluating the effects of several possible explanations for the volatility fall, the present paper provides a useful guide for policy making in the country.

As it was stated before, in order to analyze the volatility fall we estimate the theoretical model using two samples, the first one over 1975-1993, or pre Real Plan, and the second one over 1995-2012, or post Real Plan. Next, we repeat the estimation over the Real Plan period, while restricting some parameters at their 1975-1993 estimated values. According Canova (2009), this procedure allows us to investigate whether the restricted models are able to reproduce the volatility fall observed in the data. In each respective turn, one of the following set of parameters are fixed: δ, θ_g, κ, θ_i for the private sector and inertia; ρ, γ_i, γ_g for the monetary policy; and, $\sigma_1^2, \sigma_2^2, \sigma_3^2$ for the good luck hypothesis. Results are presented in Table 2.6, below.

The evidence in Table 2.6 is clear. First, whenever we consider inflation and interest rate in levels, that is, specifications *a* and *c*, if the policy parameters had remained at their pre Real Plan values, inflation instability would have been about 5 times higher (compare, for example, the values 1.6 and 8.2 in Panel *a*). Output gap volatility, however, is rather unresponsive to changes in the policy rule in all estimations. By their turn, exogenous shocks strongly affect the volatility of inflation and output gap. In some estimation, these variables would have been four or five times higher if the shocks had stayed at their 1975-1993 values. Thus, the improved stability of the economic environment has also been a key ingredient of the Brazilian Great Moderation.

Table 2.6: Posterior moments. Restricted and unrestricted specifications, 1995-2012 sample

Variable	Unrestricted stand. error, post Real [90% C.I.]	Stand. Errors restricting parameters (pre Real values)		
		Private and Inertia	Policy	Shocks
Panel a: inflation and Selic in levels, HP-filter gap				
Inflation	1.6 [1.4, 1.6]	1.4	8.2	5.6
Output gap	1.9 [1.7, 2.1]	1.8	1.6	3.1
Panel b: inflation and Selic in differences, HP-filter gap				
Inflation	1.2 [1.1, 1.3]	2.5	2.0	7.5
Output gap	1.3 [1.1, 1.5]	1.3	1.6	3.5
Panel c: inflation and Selic in levels, ΔGDP gap				
Inflation	1.3 [1.1, 1.4]	1.3	5.3	5.2
Output gap	0.6 [0.4, 0.6]	0.7	0.7	1.8
Panel d: inflation and Selic in differences, ΔGDP gap				
Inflation	1.0 [0.9, 1.0]	2.6	1.1	6.4
Output gap	0.4 [0.4, 0.8]	0.3	0.3	1.8

Private sector as a whole had no statistically significant effect on the volatility of inflation and output gap whenever one considers variables in levels (Panels *a* and *c*). However, in specifications *b* and *d*, where inflation and Selic are in differences, this situation changes, with private parameters affecting inflation significantly. In order to filter which parameter of this set matter the most, we have implemented our comparative exercise restricting, in each turn, the Phillips curve inclination and inflationary inertia in models *b* and *d* at their pre Real plan values[43]. Results are presented in Table 2.7, below.

Table 2.7: Posterior moments when some private parameters are restricted, models *b* and *d*, 1995-2012 sample

Variable	Unrestricted stand. error, post Real [90% C.I.]	Stand. Errors restricting (pre Real values): Inflationary inertia (θ_i)	Stand. Errors restricting (pre Real values): Phillips curve inclination (κ)
Panel b: inflation and Selic in differences, HP-filter gap			
Inflation	1.2 [1.1, 1.3]	1.3	2.3
Output gap	1.3 [1.1, 1.5]	1.5	1.4
Panel d: inflation and Selic in differences, ΔGDP gap			
Inflation	1.0 [0.9, 1.0]	1.3	2.6
Output gap	0.4 [0.4, 0.8]	0.5	0.4

If inflationary inertia is restricted, the effects on the volatility of inflation and output gap are almost irrelevant. For example, considering the specifications *b* and *d* of Table 2.7, when we restrict θ_i at their pre Real Plan values, inflation and output volatility would be, respectively, 1.3 and 1.5 (Panel *b*), and 1.3 and 0.5 (Panel *d*). Thus,

[43] Consumption elasticity and output persistence are quite stable along the estimation samples, being disregarded at this point of our analysis.

albeit there were reductions in inflation inertia, with price setters becoming more forward looking, this change does little to explain the volatility fall.

The inflation inertia issue deserves an in-depth look, given its importance for the formulation of the recent monetary plans. Our results show that the reduction of inflation inertia, i.e., of the importance of past inflation on the future values of this variable, is not a decisive element for improving macroeconomic stability in the country. In other words, even if the inertia had been totally eliminated, while monetary policy and exogenous shocks had remained at their pre Real Plan levels, inflation would continue to rise and, almost certainly, new indexing mechanisms would have been created. Moreover, GDP volatility is not affected by the inflationary inertia degree.

On the other hand, if Phillips curve inclination is restricted, inflation volatility would have been twice as higher after 1995. The explanation for this result is very interesting indeed. Such parameter, κ, is related with real rigidities in price setting, and it reached a peak in the sample from 1985 to 1994[44]. During these years, monetary policy often froze prices for short periods of time, thus leading price setters to readjust them in every possible situation, in order to restore relative prices and profits. Moreover, it is easy to think that menu costs were negligible in this hyperinflationary context. Our paper confirms, therefore, the common vision that an important feature of the Real plan was the URV mechanism, which allowed a gradual realignment of prices in the economy, stabilizing price setters' behavior after its implementation.

Table 2.8, below, brings additional results regarding the volatility fall in Brazil. In this table, we present our four specifications, that is, variables in levels and HP-filter output gap, inflation and Selic rate in differences and HP-filter output gap, variables in

[44] A greater κ denotes more flexible prices.

levels and output growth rule for the gap, and inflation and Selic rate in differences and output growth rule for the gap, respectively, in Panels *a*, *b*, *c*, and *d*. “Pre Real” plan column denotes the posterior standard error of the variables in the 1975-1993 period; by its turn, “Restricted” column shows the same statistics for the post Real plan period, while the exogenous shocks and the policy rule parameters are fixed at their first sample values. Therefore, the question we want to address is whether the volatility in the economy after 1995 would be similar to the one observed during 1975-1993, if shocks and monetary policy had remained unchanged over the time. As can be seen in Table 2.8, in most of the estimations, the restricted models reproduce a significant percentage of the first period instability. Especially in the levels assumptions (Panels *a,* and *c*), all ratios are very close to 100%, and, sometimes, they are even higher. In this sense, exercises in Table 2.8 show that both sources of explanations, that is, the good policy and good luck hypotheses, can account for the Great Moderation in the country.

Table 2.8: Comparisons between pre and restricted post Real Plan volatilities

Variable/Std. Deviation	Pre Real	Restricted (policy + shocks)	Percentage	Pre Real	Restricted (policy + shocks)	Percentage
		Panel a			*Panel b*	
Inflation	41.2	38.5	93.4	10.6	8.6	81.1
Output gap	3.8	3.9	102.6	4.1	4.5	109.8
Selic	40.4	37.8	93.6	8.1	5.1	63.0
		Panel c			*Panel d*	
Inflation	37.8	38.5	101.9	8.8	7	79.5
Output gap	1.8	1.8	100.0	1.1	1.4	127.3
Selic	36.8	37.8	102.7	6.7	4	59.7

In conclusion, our investigation shows that the main sources of the Brazilian Great Moderation are as the following. Regarding to the volatility of inflation, both good luck and improved monetary policy hypothesis are correct. The Real plan implementation and its monetary policies have truly been important to reduce inflation instability. But, smaller shocks played another key role in this respect. No source of explanation, by itself, can account for the entire volatility drop, but considered together, they almost completely reproduce the pre Real Plan volatility (with data in levels, for example, both hypotheses accounts for about 50% of the volatility fall). Regarding to output gap, the reduction of the volatility, instead, is only due to the reductions of the shocks. No parameter change in the Taylor rule accounts for the increased GDP stability since 1995.

As a final result we present, in Table 2.9 below, some piece of evidence showing that the Great Recession has not changed the current regime of low volatility in Brazil. Using dates provided by the Brazilian Business Cycle Dating Committee, which sets such recession from 2008.III to 2009.I in the country, we split two samples of 15 observations covering periods before and after this event. Specifically, we work with a data set from 2004.IV to 2008.II, and another one ranging from 2009.II to 2012.IV. Next, trying to circumvent the lack of a longer time series, we estimate posterior volatilities of inflation, output gap, and Selic rates setting the algorithm to implement 100.000 Metropolis-Hastings draws.

As showed by Table 2.9, volatility before and after the Great Recession in Brazil are pretty much the same. For example, in Panel *a*, with inflation and Selic in levels, and HP-filter gap, figures in the second sample are slightly larger than estimates for the first period. The same happens in Panel *b*. However, the estimated posterior standard errors of the variables are smaller in the last sample in Panels *c* and *d*. In this sense, based on this result, and on the fact that 90% confidence intervals of the estimated volatilities are overlapped in every case reported by Table 2.9, we can conclude that the Brazilian economy kept in its low volatility regime after the Great Recession.

Table 2.9: Posterior standard errors of the variables pre and post Great Recession

Variable	Volatility (Stand. errors) in Brazil	
	Before G. Recession	After G. Recession
	Panel a	
Inflation	1.58	1.82
Output gap	1.40	1.77
Selic	1.79	1.61
	Panel b	
Inflation	1.21	1.49
Output gap	1.10	1.57
Selic	0.87	1.01
	Panel c	
Inflation	1.44	1.19
Output gap	0.77	0.53
Selic	2.15	1.62
	Panel d	
Inflation	0.74	0.62
Output gap	0.33	0.28
Selic	0.61	0.55

Note: Panel *a*: inflation and Selic in levels, HP-filter gap; Panel *b*: inflation and Selic in differences, HP-filter gap; Panel *c*: inflation and Selic in levels, ΔGDP gap; Panel *d*: inflation and Selic in differences, ΔGDP gap.

2.6. Conclusions

In this paper we investigate the occurrence of a volatility fall in Brazil, in similar process of those occurred in many OECD countries. In this purpose, we estimate a small-scale New Keynesian DSGE model, using time series spanning from 1975 to 2012, and Bayesian techniques. The main conclusions and results are depicted below.

Using a test for unknown break points in a VAR system, we have detected the presence of three structural changes in the data; the first one in 1985, the second one in 1995, and a third one around 2003. Therefore, we show that the common procedure for dividing the data into periods of moderately high inflation (1975-1984), explosive inflation (1985-1994), and stability (1995 on) has statistical background in analysis of monetary policies in Brazil. The last break may be related to the consolidation of the inflation-targeting regime. After this year, observed inflation rate was always inside the limit bands. Moreover, our results also indicate an additional reduction in the mean and standard deviation of inflation and interest rate following the mentioned year.

We found that the inflation and output volatility has a clear inverted U-shape pattern, reaching a peak in the sample between 1985 and 1994. From 1995 on, instability has noticeably decreased in the country, with inflation and output becoming far more stable, a phenomenon that we labelled "Brazilian Great Moderation". Consequently, another result of the paper is that the volatility fall in Brazil was delayed by 10 years, when comparing with the major industrialized countries.

On the inflation side, the main explanations of such feature of the data are milder shocks, related to the good luck hypothesis, and changes in the monetary policy parameters. Over time, the weight of inflation in the Taylor rule has been increasing as opposed to the weight of the output gap, which tended to reduce. Thus, since 1995 the Brazilian Central Bank has been focusing on controlling inflation rather than exploring the tradeoff between inflation and output growth, a policy that has been important to keep inflation on track. On the output side, we found that the sole reason behind its volatility fall was the reduction of the shocks hitting the economy (similar results were found by Mello and Moccero, 2011, when analyzing data from 1996 to 2006). In this sense, our results are in line with some well-known papers in the literature, which focused on the U.S. case, for instance, Stock and Watson (2002), Moreno (2004), Primiceri (2005), Cogley and Sargent, (2005), Sims and Zha (2006), and Canova (2009).

Changes in private sector parameters, such as more forward looking price setters and declines in inflation inertia cannot explain the Brazilian Great Moderation. The most interesting result we have obtained regarding this set of parameters refers to the reduction of the Phillips curve inclination after 1995, denoting that price-setting became stickier after the Real plan, which reduced volatility of inflation growth rates.

Therefore, the main lesson of the paper is that the Real Plan and its subsequent monetary policy were remarkably successful regarding the reduction of inflationary instability in the country, but they are not the sole determinant of this structural change. Milder exogenous shocks hitting the economy have also been contributing in this sense. Thus, the Brazilian Central Bank shall assume that the continuity of the low inflation regime rests on monetary policies that keep their emphasis on inflation control. Depending on the force of the shocks, inflation will rise again, but without credible responses by the Central Bank, this movement will be even worse.

2.7. ANNEXES:

Table A1: Private and inertia parameters estimates in each subsample

Coefficient/sample	Priors	1975-1984			1985-1994			1995-2004			2005-2012		
		Posterior	CI10%	CI90%	Posterior	CI10%	CI90%	Posterior	CI10%	CI90%	Posterior	CI10%	CI90%
						Panel a							
Delta (δ)	2.00	1.851	1.503	2.190	1.831	1.435	2.174	1.759	1.439	2.002	1.834	1.496	2.174
Kappa (κ)	2.00	0.527	0.452	0.585	0.910	0.728	1.177	0.759	0.585	0.914	0.735	0.555	0.911
Beta (β)	0.98	0.980	0.965	0.995	0.979	0.964	0.993	0.983	0.974	0.994	0.980	0.964	0.996
Theta g (θ_g)	0.80	0.383	0.202	0.556	0.900	0.706	1.000	0.976	0.921	1.000	0.382	0.001	0.840
Theta i (θ_i)	0.80	0.994	0.984	1.000	0.984	0.948	1.000	0.992	0.977	1.000	0.970	0.915	1.000
						Panel b							
Delta (δ)	2.00	1.913	1.607	2.290	1.760	1.483	2.062	1.974	1.633	2.313	2.080	1.724	2.484
Kappa (κ)	2.00	0.797	0.624	0.956	2.526	1.426	3.795	1.040	0.726	1.330	0.845	0.658	1.047
Beta (β)	0.98	0.980	0.966	0.996	0.979	0.963	0.995	0.980	0.966	0.995	0.981	0.966	0.995
Theta g (θ_g)	0.80	0.416	0.268	0.599	0.849	0.580	1.000	0.534	0.293	0.782	0.379	0.166	0.583
Theta i (θ_i)	0.80	0.971	0.911	1.000	0.858	0.653	1.000	0.777	0.503	1.000	0.891	0.682	1.000
						Panel c							
Delta (δ)	2.00	1.712	1.425	1.995	1.707	1.416	2.005	1.668	1.374	1.946	1.785	1.454	2.114
Kappa (κ)	2.00	1.247	0.929	1.573	1.245	0.858	1.622	1.968	1.458	2.508	1.297	0.975	1.593
Beta (β)	0.98	0.982	0.970	0.996	0.980	0.966	0.996	0.980	0.964	0.995	0.979	0.960	0.992
Theta g (θ_g)	0.80	0.960	0.881	1.000	0.958	0.868	1.000	0.964	0.886	1.000	0.951	0.841	1.000
Theta i (θ_i)	0.80	0.968	0.906	1.000	0.966	0.893	1.000	0.805	0.658	1.000	0.667	0.504	0.810
						Panel d							
Delta (δ)	2.00	1.739	1.449	2.015	1.560	1.348	1.748	1.676	1.396	1.914	1.897	1.578	2.228
Kappa (κ)	2.00	1.420	1.025	1.788	6.194	4.393	7.775	1.624	1.162	2.025	0.899	0.681	1.100
Beta (β)	0.98	0.979	0.963	0.994	0.979	0.969	0.995	0.981	0.967	0.996	0.979	0.962	0.993
Theta g (θ_g)	0.80	0.925	0.783	1.000	0.980	0.934	1.000	0.962	0.885	1.000	0.911	0.738	1.000
Theta i (θ_i)	0.80	0.290	0.159	0.419	0.943	0.791	1.000	0.218	0.114	0.315	0.074	0.007	0.136

Note: CI10% and CI90% stand for the lower and upper limits of the 90% confidence interval, respectively.

Table A2: Policy parameters estimates in each subsample

Coefficient/sample	Priors	1975-1984			1985-1994			1995-2004			2005-2012		
		Posterior	CI10%	CI90%	Posterior	CI10%	CI90%	Posterior	CI10%	CI90%	Posterior	CI10%	CI90%
						Panel a							
Constant ($\bar{c}$)	2.0	1.506	1.208	1.849	1.831	1.498	2.181	1.790	1.531	2.069	1.591	1.239	1.946
Rho (ρ)	0.8	0.048	0.000	0.100	0.031	0.000	0.066	0.077	0.000	0.155	0.055	0.001	0.118
Gamma i (γ_i)	1.5	1.194	1.082	1.299	1.092	1.036	1.146	2.302	1.848	2.716	3.086	2.523	3.727
Gamma g (γ_g)	0.5	1.264	0.994	1.531	1.298	1.025	1.566	0.541	0.296	1.031	0.144	-0.146	0.438
						Panel b							
Constant ($\bar{c}$)	2.0	1.654	1.380	1.977	1.965	1.634	2.378	1.520	1.213	1.896	1.328	0.996	1.633
Rho (ρ)	0.8	0.047	0.001	0.104	0.025	0.000	0.050	0.073	0.001	0.151	0.123	0.012	0.218
Gamma i (γ_i)	1.5	3.059	2.442	3.593	1.798	1.398	2.116	3.157	2.519	3.894	3.390	2.720	4.040
Gamma g (γ_g)	0.5	0.029	-0.197	0.251	0.897	0.599	1.256	0.293	0.009	0.606	-0.136	-0.374	0.104
						Panel c							
Constant ($\bar{c}$)	2.0	1.461	1.145	1.722	1.700	1.321	2.052	1.717	1.365	2.043	1.584	1.231	1.868
Rho (ρ)	0.8	0.029	0.000	0.058	0.018	0.000	0.038	0.029	0.000	0.062	0.047	0.000	0.100
Gamma i (γ_i)	1.5	1.208	1.103	1.331	1.060	1.026	1.096	2.974	2.432	3.504	3.032	2.367	3.671
Gamma g (γ_g)	0.5	1.243	0.924	1.578	1.625	1.320	1.967	1.077	0.742	1.416	0.738	0.394	1.083
						Panel d							
Constant ($\bar{c}$)	2.0	1.627	1.306	1.960	1.950	1.538	2.372	1.435	1.105	1.703	1.010	0.800	1.192
Rho (ρ)	0.8	0.022	0.000	0.049	0.009	0.000	0.019	0.026	0.000	0.051	0.053	0.000	0.107
Gamma i (γ_i)	1.5	3.326	2.667	3.949	1.754	1.572	1.938	3.409	2.847	3.953	4.391	3.929	4.959
Gamma g (γ_g)	0.5	0.842	0.494	1.184	1.219	0.985	1.548	0.925	0.593	1.275	0.548	0.213	0.894

Note: CI10% and CI90% stand for the lower and upper limits of the 90% confidence interval, respectively.

Table A3: Exogenous shocks estimates in each subsample

Coefficient/sample	Priors	1975-1984			1985-1994			1995-2004			2005-2012		
		Posterior	CI10%	CI90%	Posterior	CI10%	CI90%	Posterior	CI10%	CI90%	Posterior	CI10%	CI90%
								Panel a					
Sigma 1 (σ_1)	0.01	2.839	2.110	3.678	8.124	5.996	10.390	3.643	2.789	4.767	3.028	2.047	3.935
Sigma 2 (σ_2)	0.01	2.366	1.910	2.895	12.233	10.366	14.499	1.343	1.078	1.606	1.405	0.973	1.853
Sigma 3 (σ_3)	0.01	5.450	3.977	6.600	6.578	5.299	7.907	1.914	1.458	2.574	1.255	0.665	1.941
								Panel b					
Sigma 1 (σ_1)	0.01	2.807	2.112	3.518	10.230	7.445	12.818	1.802	1.363	2.278	1.485	1.008	1.999
Sigma 2 (σ_2)	0.01	3.297	2.514	4.046	17.425	12.112	21.292	2.042	1.438	2.564	1.771	1.196	2.288
Sigma 3 (σ_3)	0.01	1.934	1.350	2.428	7.079	5.363	8.579	1.604	1.072	2.095	0.711	0.425	0.985
								Panel c					
Sigma 1 (σ_1)	0.01	3.334	2.298	4.330	6.665	4.353	8.512	3.534	2.689	4.407	2.344	1.704	3.067
Sigma 2 (σ_2)	0.01	1.248	1.012	1.450	12.365	10.029	14.549	0.952	0.725	1.171	0.511	0.386	0.629
Sigma 3 (σ_3)	0.01	2.386	1.907	2.962	3.524	2.866	4.382	1.475	1.195	1.746	0.907	0.712	1.134
								Panel d					
Sigma 1 (σ_1)	0.01	2.113	1.554	2.599	9.692	7.349	11.320	1.319	0.994	1.618	0.515	0.359	0.675
Sigma 2 (σ_2)	0.01	1.286	1.030	1.547	18.662	14.507	24.187	1.044	0.766	1.225	0.553	0.436	0.668
Sigma 3 (σ_3)	0.01	1.435	1.109	1.740	4.797	4.096	5.518	0.993	0.776	1.216	0.511	0.370	0.675

Note: CI10% and CI90% stand for the lower and upper limits of the 90% confidence interval, respectively.

CONCLUSÃO GERAL

Em termos gerais, as principais conclusões da presente tese são bastante instigantes. Primeiramente, o capítulo 1 mostra que os ciclos de negócios da economia brasileira possuem características similares aos de nações industrializadas, em estágio de desenvolvimento mais avançado. Por exemplo, foi mostrado que as fases dos ciclos são assimétricas, com expansões mais longas que recessões, e que houve uma quebra estrutural na variância em meados da década de 1990, características também observadas na maioria dos países membros da Organização para a Cooperação e Desenvolvimento Econômico (OCDE).

Adicionalmente, com o Capítulo 1, mostrou-se que a tendência de crescimento de longo-prazo brasileira sofreu uma quebra estrutural após os anos de 1980, como reflexo da "década perdida". Dessa forma, a taxa de crescimento da economia reduziu-se em 50%, de um valor médio de 8% ao ano no período de 1947 a 1980, a 4% ao ano após isso. A persistência da série cíclica, contudo, é bastante estável ao redor das bandas 0,7-0,8. Logo, a função impulso-resposta do PIB brasileiro apresenta um decaimento lento, indicando que choques exógenos tendem a ter um efeito duradouro sobre a atividade econômica.

Por sua vez, a principal conclusão do segundo capítulo é que a economia brasileira passou por várias mudanças estruturais. A mais importante delas ocorrida em 1995, ano em que um período de Grande Moderação se iniciou no país (perceba-se que o resultado deste capítulo é bastante similar ao anterior). Foi também verificada uma alteração sistemática nos parâmetros da regra de Taylor da política monetária. O peso imputado às variações de preços cresceu consideravelmente entre 1975 e 2012, enquanto que o peso dado às variações do hiato do produto se reduziu no mesmo período, inclusive, aproximando-se de zero após o ano de 2005.

As alterações na política monetária foram importantes para a redução da inflação e de sua volatilidade, mas parte do efeito total também é devido à alterações no sistema de precificação do setor privado e à redução dos choques exógenos que afetaram a economia (ou seja, um misto das hipóteses *good policy* e *good luck* com contribuições do setor privado).

Com respeito à redução da volatilidade do PIB, não é possível afirmar que tal fenômeno tenha sido gerado pela mudança da política monetária, até porque, como foi mostrado, o Banco Central Brasileiro pondera muito pouco às variações do PIB atualmente. Assim, é seguro afirmar que o Plano Real foi bastante efetivo para a redução da inflação, mas a queda na volatilidade do PIB é inteiramente devida a um ambiente macroeconômico mais favorável.

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