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Monetary policy velocity and stock market effects: An empirical analysis for an emerging economy

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Abstract:

We contribute to the literature of monetary policy evaluation by proposing a concept and a measurement process of monetary policy velocity. Furthermore, we develop a theoretical model explaining how changes in such a velocity index are accompanied by effects in stock prices. Based on the case of Brazil's economy from February 2003 to December 2016, our empirical findings indicate that the Brazilian Central Bank robustly affected the domestic stock market level by adjusting monetary policy velocity over time, although such effects were performed in asymmetric ways.

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There is a theoretical and empirical literature that assesses the occurrence of a relatively high inertia (persistence) in the adjustments of the central bank's basic interest rate: the interest rate smoothing. For the US economy, for instance, the estimated coefficient that measures such an inertia ranges around 0.8 (Clarida et al., 1999). For the Brazilian economy, on which we focus here, some recent studies have reported an apparent increase of the monetary policy inertia, including estimates achieving 0.9 for the inertia degree over the last years (Silva et al., 2015; Moreira, 2015).

The assumed motivation for this gradualist strategy of the monetary policy can be: i) concerns with financial stability (Sack and Wieland, 1999); ii) the aim of managing the public's expectations (Rotemberg and Woodford, 1999; Woodford, 2003); and iii) a cautionary motivation against the structural uncertainty that surrounds the central bank's decisions (Bernanke, 2004). However, there also exists a controversy regarding the true determinants of the estimated monetary policy inertia built on conventional Taylor rules. According to some authors, such as Rudebusch (2006), the estimated high monetary policy inertia could be a spurious result of monetary policy responses to serially correlated shocks and/or of omitted variables in estimated reaction rules.

Our work proposes a monetary policy velocity index as an alternative to the common notion and estimates of monetary policy inertia. The advantage of such a new index is that it would avoid those empirical controversies – given that it can be measured directly by the observed interest rate target changes – and, at the same time, it would maintain a theoretical (and/or empirical) relation with the monetary policy inertia, as we assume an inverse relation between both variables, i.e. an increase of monetary policy inertia is translated into a decrease of monetary policy velocity, and vice versa.

We are particularly interested in determining whether an increase (or decrease) of the monetary policy velocity is accompanied by financial effects in Brazil, which we represented by the *cyclical* behavior of the Brazilian stock market (Ibovespa). Based on the literature regarding monetary policy smoothing, more aggressive basic interest rate changes (higher monetary policy velocity) could negatively affect financial markets because it would create augmented economic and financial uncertainties. Nevertheless, it is important to consider the potential case in which countries experiencing expressively high monetary policy inertia indeed perform pro-cyclical interest rate adjustments, i.e., a decrease (or an increase) of the real basic interest rate when it should have increased (or decreased) facing inflationary developments, thereby contrasting with the Taylor principle (Taylor, 1993) of a counter-cyclical and efficient monetary policy. Thus, if a country is under an extremely high degree of monetary policy inertia[1] – thereby with a consequent inefficient real interest rate path – a marginal reduction of the nominal interest rate inertia (i.e., a marginal gain of monetary policy velocity) could be optimistically perceived by the public such that there would be positive effects on the stock market. Such a hypothesis has not been regarded in previous studies.

We estimate several regressions by means of the Generalized Method of Moments (GMM), which allows to control for potential problems of endogeneity in regressors, omitted variables and outliers (Hansen, 1982; Cragg, 1983; Johnston, 1984). We use monthly data from February 2003 to December 2016, thus comprising the largest time sample currently available for all the variables adopted. Furthermore, this work performs an analysis through a Markov switching approach (Hamilton, 1989) in order to allow for different structural regimes and asymmetric effects of monetary policy velocity levels. We find that an increase in monetary policy velocity was followed by higher Ibovespa index levels in relation to its trend. When we further control for potential outliers and asymmetric effects, the estimated Markov-switching regressions indicate that there exist different potential effects of such a velocity on Brazil's stock market. Specifically, the positive effects were constrained to cases in which the Ibovespa cycle presented less inertia over time.

1. Theoretical motivation and the concept of monetary policy velocity

The potential causes and effects related to monetary policy velocity can be indirectly assessed in the literature about monetary policy gradualism or inertia. The smoothing nature of basic interest rate adjustments in the US economy was identified as a direct consequence of findings on monetary policy rules, which had its initial step in Taylor (1993). In the latter, the

[1] And this seems to be the case in Brazil (Moreira, 2015).

estimated mechanism of reaction of Federal Reserve rates to cyclical movements in the economy was based on a non-inertial rule. In other words, the previewed basic interest rate responses to output and inflation deviations were faster than would occur under an inertial rule. However, further estimates and studies showed that assuming an inertial or smoothing component for estimating Taylor rules was associated with a better fit to data (Clarida et al., 1999; Rudebusch, 2006), and it was generally related to a monetary policy with an inertial coefficient around 0.8.

Another related issue concerns the motivation for gradualism or an inertia in monetary policy. There exist mainly three explanatory arguments. First, some works suggest a motivation for maintaining financial stability (Rudebusch and Svensson, 1999; Sack and Wieland, 1999). As the basic interest rate is a key factor in determining several other prices in financial markets, such as exchange rates and bond and stock prices, avoiding intense and frequent changes – or mitigating volatility – of the former seems to be an appropriate strategy for central banks with regard to financial markets.

Second, there exists an argument for anchoring long-term interest rate expectations (Rotemberg and Woodford, 1999; Woodford, 2003). Here, the main idea is associated with the transmission effects from short-term interest rates to longer-term rates, which are especially relevant in investment decisions. If the central bank adjusts the short-term interest rate in the same direction (increasing, decreasing or maintaining its level) over several rounds before changing direction, it allows the public to anchor its expectations for the long-term interest rate by inferring several further future adjustments of the short-term rate. According to this motivation, such a strategy gives more efficacy to monetary policy, as it can strongly influence long-term interest rates, even with small changes in current short-term rates.

Lastly, there is a tradition of thought according to which an adequate strategy to deal with uncertainty is to make decisions more parsimoniously (Brainard, 1967; Bernanke, 2004). Monetary policy is inevitably surrounded by several sources of structural uncertainty, such as time lags between facts, data availability, and monetary decisions, as well as uncertainties concerning the future impacts of current interest rates adjustments. As central banks have to decide on interest rate levels on the basis of forward expectations about future effects and scenarios, a more gradualist monetary policy is a rational proposition from such a line of arguments. In order words, central banks give a high value to the option of waiting.

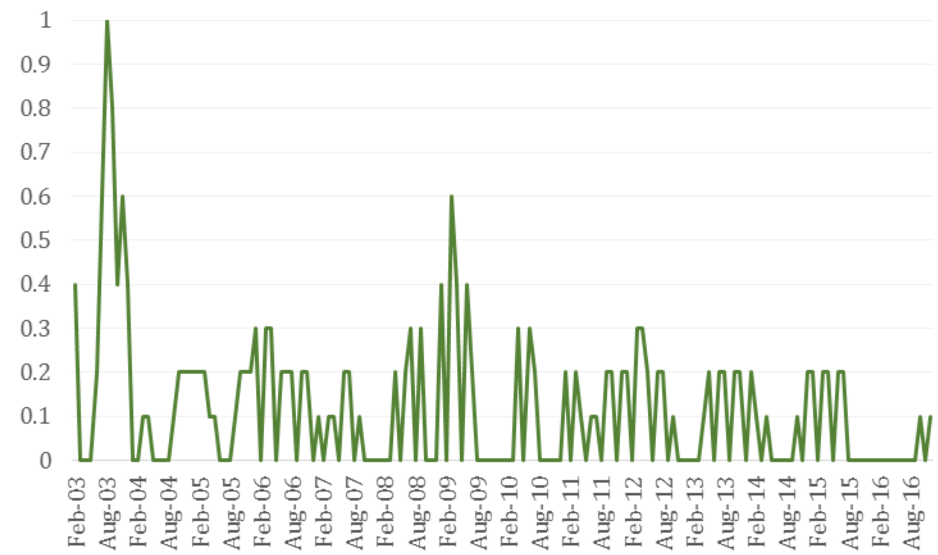
In turn, a first operational problem emerges if one aims to apply a monetary policy inertia coefficient to other empirical studies, e.g., if one is testing for potential macroeconomic or financial effects of monetary policy inertia shocks. To make it possible, it is necessary to first estimate that inertial coefficient by Ordinary Least Squares (OLS) or GMM regressions, such as commonly found in the related literature. In sequence, it would be required to estimate the inertia component path over time, based on some statistical filter, such as a Kalman filter. Of course, these procedures make it more difficult to accomplish the aforementioned aim.

In contrast, if we look mainly at a concept of monetary policy velocity, those operational problems disappear, as we can calculate a monetary policy velocity index by a normalization of the absolute changes of the policy rate. Moreover, this new index maintains a logical and inverse relation with a measure of gradualism. The higher (lower) the monetary policy velocity, the lower (higher) the monetary policy inertia over time. Such a proposition emerges naturally. An additional advantage of working empirically with a concept of monetary policy velocity, instead of monetary policy inertia, is related to empirical controversies regarding the latter. According to some authors, such as Rudebusch (2006), the estimated high monetary policy inertia for several countries could be a result of monetary policy responses to serially correlated shocks and/or of omitted variables in estimated reaction rules. Our index is not sensible to this criticism. Therefore, our measure of monetary policy velocity (mpv_t) is based on:

$$mpv_t = \frac{\sqrt{[(i_t - i_{t-1})^2]}}{max\ \Delta i_{0,t+n}} \tag{1}$$

where i_t stands for the interest rate target in period t. It is noteworthy that our measure imposes a normalization of the policy target change $(i_t - i_{t-1})$, as it is related to the maximum absolute policy target change over the entire sample ($max\ \Delta i_{0,t+n}$). Figure 1 presents the time behavior of such a measure from February 2003 to December 2016 in Brazil, based on the annual Selic rate target (i.e., the Brazilian basic nominal interest target, which is adjusted by the Brazilian Central Bank). As we can observe, the periods of maximum monetary policy velocity in Brazil occurred during 2003, as a consequence of the confidence crisis generated by uncertainties about the new Brazilian President, Lula da Silva, and the subprime crisis (2008-2009), which also contributed to increased monetary policy velocity in Brazil.

Figure 1 – *Monetary policy velocity in Brazil, February 2003 – December 2016*



Source: see section 4.

2. A background model

Let us start by defining a *loss function* to the central bank, such as:

$$L_t = (\pi_t)^2 + \lambda(y_t)^2 + \phi(\Delta i_t)^2 \tag{2}$$

Equation (2) describes the preferences of the central bank when the monetary instrument is adjusted, that is, when the basic interest rate is changed over time (Clarida et al., 1999; Rudebusch and Svensson, 1999). While the two first components are common in the literature (i.e., the goals of reducing inflation and output deviations from their desired levels), the last one refers to the preference for monetary policy smoothing. The smaller the basic interest rate variation, the lower the social loss, because it avoids uncertainty and volatility in financial markets.

In turn, let us consider the way in which stock prices are determined. In finance (Balke and Wohar, 2006), it is conventional to regard the price of a specific stock (p_t) as the discounted value (or present value) of the sum of its expected future dividends (d_{t+j}), given a discount rate ($\beta < 1$), so that:

$$p_t = E_t \sum_{j=1}^{n} \beta^j d_{t+j} + u_t \tag{3}$$

The discount rate is usually interpreted as the basic interest rate (i_t), so that $\beta^j = 1 / i^j$, while u_t represents a white noise residual. Based on (3), we can assume that the higher the variability of the discount rate, *coeteris paribus*, the higher the variability of the stock price, or:

$$\sigma^2_{p_t} = \sigma^2_{E_t \sum_{j=1}^{n} \beta^j} + \varepsilon_t \tag{4}$$

In (4) we express the relationship between the basic interest rate variance ($\sigma^2_{E_t \sum_{j=1}^{n} \beta^j}$), which is also an expected component, and the stock price variance ($\sigma^2_{p_t}$). In turn, an increase of the latter means that financial investors have more uncertainty regarding the fundamental value of the stock, thereby inducing a selling process into the market. So:

$$p_t = E_t \sum_{j=1}^{n} \beta^j d_{t+j} - \tau\, \sigma^2_{E_t \sum_{j=1}^{n} \beta^j} + \mu_t \tag{5}$$

Expression (5) describes the transmission channel by which an increase of the expected interest rate variance is followed by a reduction in stock prices ($\tau > 0$). The first component on the right-hand side represents the present value of the expected future dividends, and it could be explained through idiosyncratic and macroeconomic factors influencing such a future cash flow; on the other hand, μ_t stands for the forecast error. Now, if we interpret monetary policy velocity (mpv_t) as a proxy for $\sigma^2_{E_t \sum_{j=1}^{n} \beta^j}$, we have a specification of the cause-and-effect relationship underlying our subject:

$$p_t = E_t \sum_{j=1}^{n} \beta^j d_{t+j} - \tau\, mpv_t + \mu_t \tag{6}$$

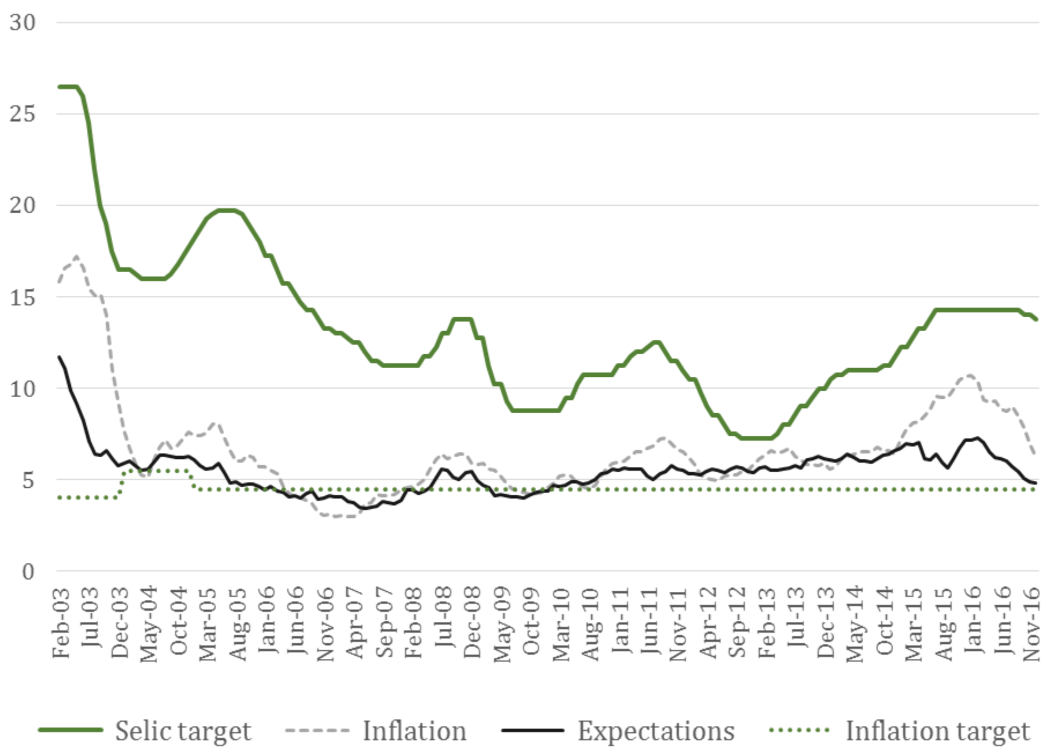
The advantage of using mpv as a proxy for interest rate variance results from statistical and operational problems regarding measures for the latter. In general, a suitable estimate for $\sigma^2_{E_t \sum_{j=1}^{n} \beta^j}$ should be conducted with a form of a Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model, thereby requiring several procedures in order to generate an adequate specification, besides the fact of potential divergent estimates if one desires to reproduce such findings. In contrast, if we can use a monetary policy velocity index, such as (1), those issues are avoided and a more parsimonious procedure is achieved.

3. A brief overview of Brazil's monetary policy path and stock market

The Brazilian inflation-targeting regime was introduced in 1999 and since then the Central Bank has performed its monetary policy mainly by adjusting the short-term interest rate, i.e., the Selic interest rate, as the instrument to control the observed inflation in relation to the inflation target. In 2003, President Luiz Inácio Lula da Silva launched his first mandate (2003-2006) but with strong uncertainty regarding what would be the effective direction of the economic policy in Brazil. As a result of such uncertainty, there was an expressive undervaluation of the domestic currency (R$) relative to the US dollar, thereby rapidly increasing inflationary expectations and the observed inflation over that first year.

The government responded to the confidence shock with an increase of the consumer inflation target, from 4% per year in 2003 to 5.5% per year in 2004, as the Central Bank argued that such an adjustment would allow the monetary policy to become less aggressive in responding to the augmented inflationary deviation. As a result, the nominal Selic target gradually decreased from 26.5% per year in February 2003 to 16% in April 2004, as the expected inflation for 12 months forward dropped from 10.9% per year in the former month to 5.6% in the latter (figure 2).

Figure 2 – *Selic target, observed inflation, expected inflation and inflation target, February 2003 – February 2017*



Source: see section 4.

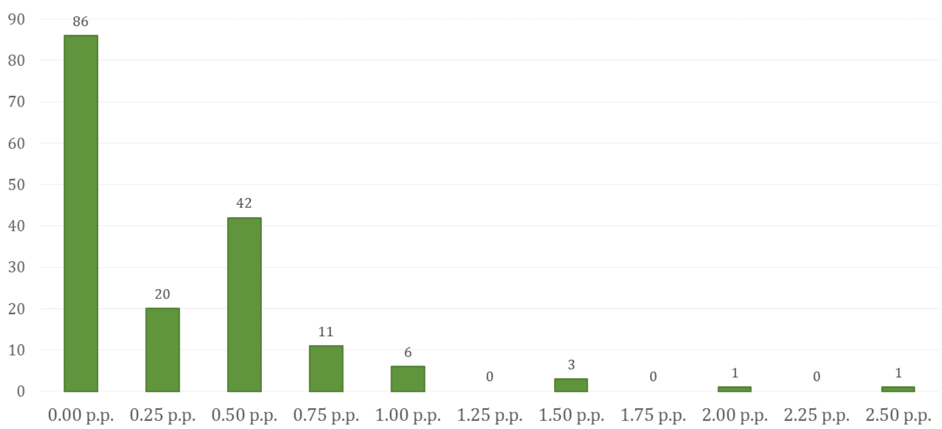
In 2005, the consumer inflation target was adjusted from 5.5% to 4.5% per year, which has been the inflation target since then. The Selic target, in turn, has presented a cycle that has responded mainly to inflationary expectations, denoting a forward perspective of the Brazilian monetary policy. However, some works have reported that Taylor rules for Brazil showed relative divergence regarding such a forward pattern, besides an expressive inertial component of the Selic effective rate as the main factor explaining monetary policy behavior in Brazil (Moreira, 2015).

Furthermore, the evident declining trend of the Selic target over the sample was not suitable if one accounted for the persistent inflation deviation, especially from August 2011 to October 2012, when the Selic target decreased from 12.5% to 7.25% per year, despite a persistent and relatively constant inflation deviation between these two moments. Such a decreasing trend of the Selic target would thus be motivated by political and judgmental factors beyond the macroeconomic fundamentals. However, a new augmented inflationary deviation from 2013 was followed by a cycle of positive changes of the Selic target, which stood at 14.25% in July 2015 and was kept at this level for 14 consecutive months.

In sum, and particularly regarding the performance of the inflation target regime in Brazil, the monetary policy has had non-trivial challenges, as we can infer from the effective inflation deviation over the sample. The mean inflation deviation from February 2003 to February 2017 stayed at 2.11 percentage points, an undoubtedly high deviation from the current target of 4.5%.

The inertial component of the monetary policy in Brazil can be assessed not only by Taylor rule estimates but also by viewing the Selic target's absolute changes in percentage points (p.p.) and the associated frequency of each observed change. Figure 3 shows such absolute changes over the sample. It is clear that, in general, Brazil's monetary policy showed a preference for smoothing the Selic target rather than adjusting it in expressive magnitudes. The Selic target stayed stable in 86 (non-consecutive) months over the sample, while it changed by0.25 p.p. in 20 months and 0.50 p.p. in 42 months. The other p.p. changes can be regarded as uncommon ones, such as 0.75 p.p. in 11 months and 1.00 p.p. in 6 months; at the limit, we had expressive p.p. changes of 1.5 three times and both 2.00 and 2.5 in only 1 month. The 2.5 p.p. adjustment occurred in August and the 2.00 p.p. occurred in September 2003, in the aforementioned context of a confidence crisis that marked the initial months of Lula's presidential mandate. In terms of the monetary policy velocity index which we propose in this work, those particular months represented the period of maximum values for such velocity in the sample.

Figure 3 – *Number of months for each absolute change of Selic target (p.p.), February 2003 – February 2017*



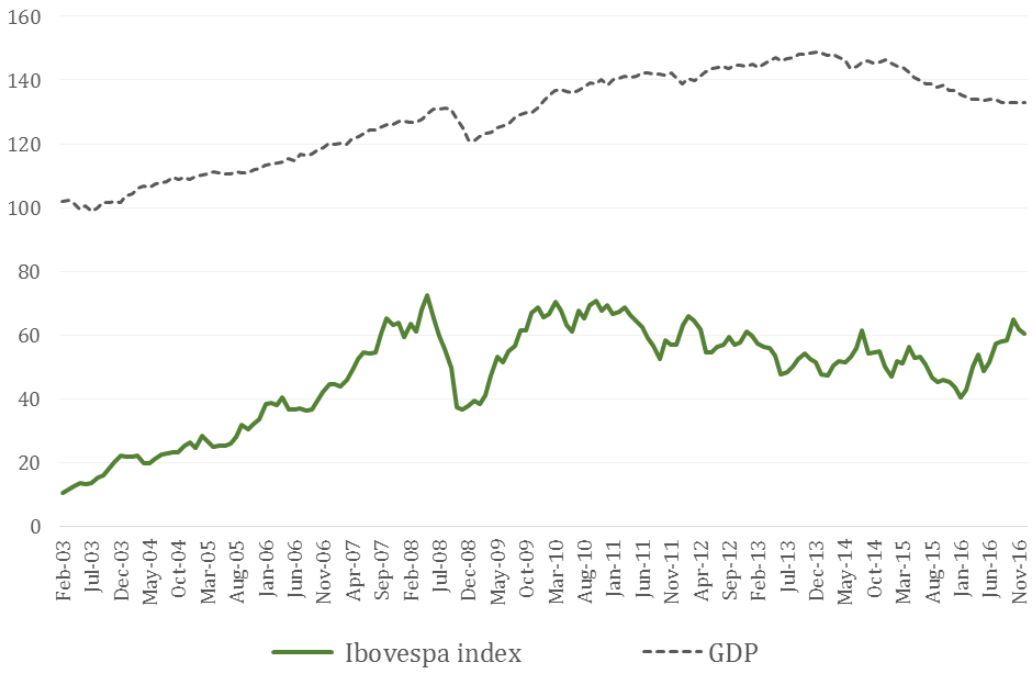
Source: see section 4.

Looking at the Brazilian stock market index (Ibovespa) during the same period, we can clearly make some preliminary associations with the previous aspects of inflation dynamics and monetary policy path. With this perspective, let us consider figure 4, in which we highlight the joint behavior of the Ibovespa and Brazil’s GDP, proxied by the monthly economic activity index of Brazil’s Central Bank (IBC-BR).

Although the variability of both variables is clearly different, with a higher magnitude for the Ibovespa, there exists a joint behavior between the time series. Under the context of the confidence crisis in 2003, both stock prices and the economic activity started from lower values and gradually assumed an increasing trend, which was disrupted only in 2008-2009 as a consequence of the recessive effects of the US subprime crisis. The economic recovery occurred in 2010 and thus the IBC-BR showed a modest positive trend from that point; since 2014 there has been a negative trend, marking the most recent recession of the Brazilian economy, contextualized by increasing fiscal risks, President Dilma Rousseff’s impeachment in 2016 and related corruption scandals.

Obviously, the Ibovespa behavior, like that of any other national stock market, cannot be explained based only on observed economic activity. Stock market prices reflect mainly the public’s expectations regarding all the factors that can affect firms’ future profits across the different economic sectors. The observed GDP behavior would then explain only a part of the cycle (or the trend) in stock prices over the short-term (or long-term). Other important macroeconomic factors, i.e., inflation, external accounts and economic policies, institutional and political risk aspects, also have to be regarded (King and Levine, 1993; Perotti and Van Oijen, 2001; Guesmi et al., 2013).

Figure 4 – Ibovespa index and Brazil’s GDP, February 2003 – February 2017



Notes: Ibovespa in thousand points; Brazil’s GDP in economic activity index.
Source: see section 4.

4. Dataset

Our econometric investigation was performed with monthly data from February 2003 to December 2016, comprising 167 observations. Regarding the Ibovespa series, our dependent variable, we were mainly interested in its cyclical behavior rather than its time trend. Thus, we applied the Hodrick-Prescott (HP) filter to the log of the Ibovespa's point level and then extracted the cycle component (*ibovc*) to use it in the regressions. Along with the monetary policy velocity (*mpv*), which is our main explanatory variable, the regressions were performed with the following time series as control variables and/or instrumental variables.

The same process we applied to extract *ibovc* was also employed to extract the output cycle component (*yc*). Thus, based on the log of the Brazilian Central Bank (BCB)'s economic activity index (IBC-BR), the HP filter yielded our output cycle measure. The nominal exchange rate (*nexch*) was defined as the price of one US dollar in terms of the Brazilian currency (Real – R$) as observed at the end of each month. The real exchange rate (*rexch*) was built on the log of the real effective exchange rate index that is calculated by the BCB and deflationated with a wholesale price index (base month: June 1994).

We also employed the deviation of the inflation rate (*infd*) accumulated in 12 months in relation to the inflation target, as a control variable, based on the Broad Consumer Price Index (IPCA-IBGE), because it has been used as the official consumer price index in Brazil since 1999. With regard to the country's fiscal dimension, we adopted the net internal public debt as a ratio to GDP (*debt*), while in relation to the external accounts the regressions applied the current account balance (*cacc*) as a ratio to GDP. Table 1 highlights the time series' descriptive statistics, while figure A1 in the appendix shows their graphical behavior.

Table 1 – *Descriptive statistics: February 2003 – December 2016*

	ibovc	*mpv*	*yc*	*nexch*	*rexch*	*infd*	*debt*	*cacc*
Mean	0.0003	0.1144	0.0000	2.3546	1.8534	2.1334	47.2979	–1.3860
Median	0.0044	0.0000	0.0015	2.2020	1.8303	1.5400	46.7700	–1.6500
Maximum	0.1272	1.0000	0.0423	4.0422	2.0576	13.2400	61.5500	1.8600
Minimum	–0.1829	0.0000	–0.0649	1.5555	1.7374	–1.5400	41.4500	–4.4400
Std. dev.	0.0533	0.1588	0.0170	0.6122	0.0750	2.8882	4.0477	1.9830

5. Results and analysis

5.1. Basics: integration order and controlling for potential endogeneity and omitted variables

Firstly, ADF, PP and KPSS tests yielded results according to which our $I(0)$ variables are *mpv*, *ibovc*, *yc* and *infd*, while the variables representing stationarity only in first difference, $I(1)$, are *debt*, *cacc*, *nexch* and *rexch* (table 2). Therefore, we estimated the GMM regressions using the first group in level values but the second group in first difference. We adopted GMM estimates because this is a better way to correct possible problems of heteroscedasticity, autocorrelation and also endogeneity (Hansen, 1982). Before applying GMM, we observed whether the instrumental variables were exogenous. As such instrumental series were defined from $t-1$ to earlier periods, we have matched this hypothesis (Johnston, 1984). Finally, an analysis of overidentification was performed (by means of the *J*-test), to test for the correct specification of the instrumental variables (Cragg, 1983; Hansen, 1982).

Table 2 – *Unit root and stationarity tests: February 2003 – December 2016*

	ADF				PP				KPSS		
	***t*-stat**	**Prob.**	**Specif.**	**lags (SIC)**	**Adj. *t*-Stat**	**Prob.**	**Specif.**	**Bandw.NW**	**LM-Stat**	**Specif.**	**Bandw. NW**
Mpv	−6.520	0.000	tr/cons	4	−8.850	0.000	tr/cons	4	0.064	tr/cons	6
ibovc	−4.279	0.000	none	1	−4.240	0.000	none	5	0.026	cons	9
infd	−2.193	0.490	tr/cons	13	−3.358	0.061	tr/cons	7	0.243	cons	10
yc	−4.312	0.000	none	2	−3.966	0.000	none	4	0.033	cons	9
debt	1.658	0.976	none	3	0.214	0.998	tr/cons	8	0.154**	tr/cons	10
d(*debt*)	−3.367	0.001	none	2	−9.638	0.000	tr/cons	6	0.234***	tr/cons	8
cacc	−1.122	0.237	none	3	−0.851	0.346	none	9	0.189**	tr/cons	10
d(*cacc*)	−3.849	0.000	none	2	−6.579	0.000	none	7	0.213	cons	9
nexch	−1.999	0.597	tr/cons	0	−2.068	0.559	tr/cons	5	0.357***	tr/cons	10
d(*nexch*)	−12.583	0.000	tr/cons	0	−12.636	0.000	tr/cons	5	0.038	tr/cons	5
rexch	−2.479	0.122	cons	1	−2.755	0.067	cons	0	0.348***	tr/cons	10
d(*rexch*)	−10.312	0.000	none	0	−10.198	0.000	none	5	0.052	tr/cons	2

Notes: *tr* = trend; *cons* = constant; lags in ADF tests were defined based on the Schwarz information criterion (SIC); lags in PP and KPSS tests were defined with Bandwidth (Newey-West automatic criterion) using the Bartlett kernel as the estimation method.

As we have two measures for exchange rates, i.e., nominal (*nexch*) and real (*rexch*), the GMM regressions were divided into two groups, each of them with four equations. We also applied specific dummies in order to capture possible structural breaks in uncommon periods into our time sample: on the one hand, *subprime* was specified to account for the period from October 2008 to August 2009, when Brazil's output gap dropped significantly below normal levels; on the other hand, *pol_cycle* accounted for a potential effect on Brazilian financial dynamics from the first six months of each elected presidential mandate over time, thus comprising the two initial months of Lula's mandate (2003 and 2007) and the two initial months of Dilma Rousseff's mandate (2011 and 2015).

The estimates for GMM regressions (table 3) highlight a positive and statistically significant effect of monetary policy velocity (*mpv*) on *ibovc*, meaning that, when the Brazilian Central Bank increased the velocity of absolute changes in the Selic rate target, there was a positive response of the Ibovespa around its time trend, i.e., an increase of *ibovc*. In other words, a reduction of the monetary policy inertia was accompanied by higher *ibovc* levels. Such a correlation was identified for all the GMM regressions, either with real or nominal exchange rates as control variables.

Among the control variables, the *ibovc* inertia component should also be taken into account. In all the regressions it showed high coefficients and with statistical significance at 1%, suggesting a substantial persistence of Ibovespa around its trend. In contrast, the other control variables presented sensitivity to the specification of the regressions and do not deserve much attention. However, it is noteworthy that *subprime* had a negative impact on Brazil's stock market when controlled for the real exchange rate, while *pol_cycle* had a negative impact by means of *nexch* as a control variable. Finally, the J-test demonstrated that our group of instrumental variables and equation specifications was validated (pr. > 0.10), thereby satisfying the exogeneity condition for the accuracy of the GMM estimation.

Table 3 – *GMM regressions* (*ibovc$_t$*: *dependent variable*)

	With real exchange rate (*rexch*)				**With nominal exchange rate (*nexch*)**			
	Eq.1	**Eq.2**	**Eq.3**	**Eq.4**	**Eq.1**	**Eq.2**	**Eq.3**	**Eq.4**
α	−0.007***	−0.005***	0.000	−0.005***	−0.006***	−0.004*	−0.004	−0.0050**
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.0024)
ibovc$_{t-1}$	0.962***	0.990***	0.998***	0.986***	0.951***	0.958***	0.902***	0.9733***
	(0.028)	(0.044)	(0.071)	(0.061)	(0.050)	0.043	(0.126)	(0.0331)
***d*(*exch$_{t-1}$*)**	−0.653**	−0.819**	0.144	−0.003	−0.065	−0.069	−0.006	−0.4798
	(0.280)	(0.361)	(0.343)	(0.041)	(0.069)	(0.083)	(0.066)	(0.3230)
mpv$_{t-1}$	0.066***	0.052***	0.037**	0.071***	0.062***	0.046**	0.060*	0.0584***
	(0.011)	(0.014)	(0.017)	(0.014)	(0.014)	(0.022)	(0.033)	(0.0102)
***d*(*debt$_{t-1}$*)**	0.014***	–	–	0.010	0.006	–	–	0.0202***
	(0.004)	–	–	(0.007)	(0.004)	–	–	(0.0054)
infd$_{t-1}$	–	0.000	–	–	–	0.000	–	–
	–	(0.001)	–	–	–	(0.000)	–	–
yc$_{t-1}$	–	–	0.371	–	–	–	0.788	–
	–	–	(0.503)	–	–	–	(1.026)	–
yc$_{t-2}$	–	–	−1.114**	–	–	–	−1.164	–
	–	–	(0.545)	–	–	–	(1.010)	–
subprime	–	–	−0.051***	–	–	–	−0.032	–
	–	–	(0.014)	–	–	–	(0.024)	–
pol_cycle	–	–	–	−0.019	–	–	–	−0.0243***
	–	–	–	(0.013)	–	–	–	(0.0076)
Adj. R-sq.	0.685	0.672	0.651	0.671	0.697	0.697	0.676	0.6667
Inst. Rank	21	21	20	21	21	21	20	21
***J*-stat.**	9.493	11.819	5.733	7.244	7.854	7.727	6.428	7.2832
pr. *J*-stat.	0.891	0.756	0.955	0.950	0.953	0.956	0.929	0.9493

Notes: the list of instrumental variables is *yc*(−2), *yc*(−3), *yc*(−4), *yc*(−5), *yc*(−6), d(*exch*(−2)), d(*exch*(−3)), d(*exch*(−4)), d(*exch*(−5)), d(*exch*(−6)), d(*debt*(−2)), d(*debt*(−3)), d(*debt*(−4)), d(*debt*(−5)), d(*debt*(−6)), d(*cacc*(−1)), d(*cacc*(−2)), d(*cacc*(−3)), d(*cacc*(−4)) and d(*cacc*(−5)). Eq. 3 in both cases for d(*exch*) does not use *yc*(−2) as IV. ( ) for standard errors; *** denotes significance at 1%, ** at 5%, and * at 10%.

5.2. Monetary policy cycle and potential asymmetric effects of *mpv*

It is normal to assume that *mpv* effects on stock prices are positive and higher when the Selic target level is dropping, compared to such effects when Selic rates are rising. In the latter case, we are conditioned to suppose that *mpv* effects on stock prices could be negative or, if positive, at least lower than in the former case. Therefore, if our estimation did not control for this possible asymmetry, we could incur spurious conclusions. With the aim of taking account of potential asymmetries in *mpv* effects, as well as of controlling for the Selic target cycle, we performed a Markov-Switching (MS) approach, in which we allowed for two structural regimes marked by specific and different coefficients regarding *mpv* effects on the Ibovespa cycle. We also regarded the Ibovespa cycle inertia as an endogenous component, thereby dependent on each specific regime over time.

This method is the so-called Markov switching model of Hamilton (1989), in which the estimates vary according to different regimes or structures that are regarded as random states of the economy over time. Thus, a state can be replaced by others by a stochastic process that is ruled by a Markov chain. Recently, Hamilton's framework has been applied to several economic subjects, especially related to finance series (Giesecke et al., 2011; Switzer & Picard, 2016).

Table 4 reports the estimates from MS regressions with real exchange rate and with nominal exchange rate. We found that there were qualitatively different regimes regarding the *mpv* effects on the Ibovespa cycle over time. In all estimated models (table 4), the previous positive effects are restricted to a specific regime (Regime 2), in which the Brazilian stock market cycle shows less inertia, that is, a lower value related to its autoregressive component ($ibovc_{t-1}$). Otherwise, when there was a higher Ibovespa cycle inertia, *mpv* effects on *ibovc* became negative.

Table 4 – *MS-regressions* (*$ibovc_t$: dependent variable*)

	With *rexch*			**With *nexch***		
	Eq. 1	**Eq. 2**	**Eq. 3**	**Eq. 1**	**Eq. 2**	**Eq. 3**
			Regime 1: switching regressors			
$ibovc_{t-1}$	0.791***	0.755***	0.749***	0.781***	0.744***	0.736***
	(0.092)	(0.081)	(0.079)	(0.090)	(0.080)	(0.078)
mpv_{t-1}	−0.075***	−0.067***	−0.111***	−0.071***	−0.064***	−0.065***
	(0.023)	(0.019)	(0.032)	(0.023)	(0.019)	(0.018)
			Regime 2: switching regressors			
$ibovc_{t-1}$	0.755***	0.708***	0.700***	0.747***	0.703***	0.694***
	(0.064)	(0.070)	(0.072)	(0.066)	(0.070)	(0.072)
mpv_{t-1}	0.026**	0.034***	0.061***	0.027**	0.034***	0.037***
	(0.011)	(0.011)	(0.020)	(0.012)	(0.012)	(0.012)
			Common variables			
d($exch_{t-1}$)	−0.109	−0,178	−0,196	−0.023	−0.032*	−0.032*
	(0.148)	(0.152)	(0.148)	(0.016)	(0.017)	(0.016)
yc_{t-1}	−0.170	–	–	−0.168	–	–
	(0.263)	–	–	(0.263)	–	–
$selicc_{t-1}$	−0.002*	−0.003**	−0.003**	−0.002**	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
d($debt_{t-1}$)	–	−0.000	–	–	0.001	–
	–	(0.004)	–	–	(0.004)	–
$infd_{t-1}$	–	–	0.000	–	–	−0.000
	–	–	(0.000)	–	–	(0.000)
subprime	−0.034***	−0.029***	−0.031***	−0.035***	−0.030***	−0.032***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
D-W stat	1.749	1.669	1.666	1.786	1.720	1.697
AIC	−4.444	−4.415	−4.417	−4.453	−4.428	−4.430

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%.

It is noteworthy that such results were obtained by controlling for the potential outlier problems and including the Selic target cycle as a common control variable. Firstly, the outlier problems respecting the higher Selic target changes in August (2.5 p.p.) and September 2003 (2.0 p.p.) were controlled based on their replacement by the median absolute change in our sample, thereby implying a new measurement of the *mpv* index. Secondly, we introduced a new regressor on the MS regressions, that is, the *Selic target cycle* (*selicc*). Such a variable was measured by applying the HP filter to the Selic target, so that we extracted its cycle component. Therefore, by adopting it as a regressor in our MS approach, we could control for the potential asymmetries of the aforementioned *mpv* effects.

When *selicc* increases, *ibovc* decreases in all estimated MS models, but regardless of such a correlation the true response of *ibovc* to higher *mpv* levels was conditioned on the *ibovc* inertia. In turn, through the *transition probabilities* related to each estimated mode,l we observed that Regime 2 occurred more than Regime 1. For instance, regarding the equation with the best fit to data based on AIC (Eq. 1 with nexch), the Markov switching one-step-ahead predicted probability for Regime 1 stayed at 37%, while 63% was the same probability for Regime 2. In other words, most of the time the true correlation between mpv_{t-1} and $ibovc_t$ was positive.

One way to interpret the overall result is, considering that *mpv* indeed affects the stock market cycle in Brazil in two possible ways: positively, when *ibovc* shows less inertia, i.e., *ibovc* converges more rapidly to its trend; and negatively, when *ibovc* presents more inertia, i.e., it converges more slowly to its trend. Assuming that we can associate higher *ibovc* inertia with decreasing financial uncertainty, the potential positive effects of *mpv* on *ibovc* are more common in cases when Brazil's stock market exhibits stronger instability or higher uncertainty (Regime 2). In contrast, Regime 1 is associated with moments of increased smoothing of *ibovc*, and thus higher financial stability. Under such cases, when the Brazilian Central Bank increases its *mpv* we observe negative effects on *ibovc*.

6. Robustness checks

The estimates regarding the non-linear effects of monetary policy velocity on Brazil's stock market over time were based on the HP filter so as to extract the cycle component of the Ibovespa index. However, several critics have recently addressed its application as an appropriate statistical filter. In particular, Hamilton (2018) argued that HP filtering is inconsistent with the true data-generating process due to an imposed autocorrelation between the estimated cyclical component at period *t* and its lagged and future estimated values in the sample, thus introducing spurious results.

Therefore, in order to perform a robustness exercise on the previous estimates, we calculated the deviation of the Ibovespa index from its trend (the cyclical component) based on the residual of the Hamilton autoregressive procedure.[2] We also applied the latter to the output cycle component as it was used as a control variable in the following estimates.

Table A1 in appendix reports the estimates from MS regressions with real and nominal exchange rates. A first finding was that, despite the difference between HP and Hamilton

[2] Basically, the residual of the following equation: $x_t = \alpha + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \beta_3 x_{t-3} + \beta_4 x_{t-4} + \varepsilon_t$. According to Hamilton (2018) ε_t can be used as a substitute for the cycle component extracted by the HP filter.

procedure estimates, we still qualitatively confirmed the existence of different regimes of the *mpv* effects on the Ibovespa cycle. In all estimated models, there exist positive effects which are restricted to a specific regime (Regime 2), which is marked by less inertia in the Ibovespa cycle, in spite of the non-statistical significance of the latter; on the other hand, negative effects of *mpv* on *ibovc* under Regime 1 were also identified, representing periods of increased instability or inertia of the Ibovespa cycle.

One could try to diminish the importance of these results based on Hamilton's procedure by stressing that the lack of a statistically significant *ibovc* inertia constrains the previous interpretation (based on HP filtering). Thus, it can be useful to regard the regime probabilities in figure A2 appendix, which shows such probabilities over the entire sample. As in MS regressions based on HP filtering, using Hamilton's approach did not change the predominance of Regime 2, in which we observe a lower coefficient for AR(1) in comparison to Regime 1. Taking into account two moments of extreme instability in Brazil's stock market is helpful in this interpretation. Let us consider what happened in the stock market in the periods of October 2008 and August 2015. These were two moments of strong undervaluation and of uncertainties surrounding Brazil's stock market: the former due to the main effects of the subprime crisis on domestic assets; and the latter due mainly to fiscal and political uncertainties in the country. In both periods we observe that Regime 1 assumed a higher probability of occurrence, thereby suggesting the negative effects of an increase in *mpv* on stock prices, as we pointed out in the previous section when associating *ibovc* inertia with the non-linear effects of *mpv*. In sum, even with a non-statistical significance of the AR(1) component based on Hamilton's approach, we can still interpret the regime change as a consequence of a transition between moments of higher or lower instability of the Brazilian stock market.

This means that non-linear effects of *mpv* on the Ibovespa cycle can be regarded as robust in the face of Hamilton's critique. Therefore, a more aggressive monetary policy can achieve positive effects on stock prices, especially when the market is on a stable path. Otherwise, in particular periods of financial turbulence, an increase of monetary policy smoothness (i.e., a decrease of velocity) is accompanied by higher stock prices.

7. Concluding remarks

Our work made some contributions to the literature on monetary policy inertia. We proposed an easier and a feasible procedure to assess such inertia by means of a concept and a measurement process of monetary policy velocity. The latter is not subject to criticism on spurious estimates for Taylor rules (Rudebusch, 2006), because our monetary policy velocity index can be calculated directly based on absolute changes of the policy rate.

When should central banks increase their monetary policy velocity? It is a general question and our empirical results cannot be adopted to offer a precise answer. However, regarding the recent Brazilian experience as a special case, our empirical findings has shown that the Brazilian Central Bank influenced the stock market cycle by manipulating monetary policy velocity.

Specifically, our GMM regressions showed that an increase of *mpv* was accompanied by higher Ibovespa index levels in relation to its trend. When we further controlled for potential outliers and asymmetric effects, the estimated MS regressions indicated that there existed different potential effects of *mpv* on *ibovc*. Mainly, the previous positive effects were conditioned to cases in which *ibovc* presented less inertia over time, which was the more frequent regime. This result corroborated the evidence in Silva et al. (2015) and Moreira (2015), which indicated pro-cyclical effects of an increase in monetary policy inertia in Brazil (i.e., a reduction of monetary policy velocity in our perspective). Otherwise, when *ibovc* had higher inertia, an increase of *mpv* was followed by negative effects on *ibovc*, thereby suggesting that in periods of uncommon financial stability the Brazilian Central Bank should reduce *mpv* rather than increase it.

Our empirical findings can be additionally robust relative to Hamilton's (2018) concerns on HP filtering. Measuring *ibovc* through Hamilton's autoregressive procedure, we found the same qualitatively different regimes, thereby corroborating the robustness of our results.

Finally, in terms of potential ways for extending research, we suggest the application of our monetary policy velocity concept and index to studies regarding other countries, either by time series or panel data methods. It is a relevant step if one aims to test our results for a more general case.

References

Balke N.S. and Wohar M.E. (2006), "What Drives Stock Prices? Identifying the Determinants of Stock Price Movements", *Southern Economic Journal*, 73, pp. 55-78.

Bernanke B. (2004), "Gradualism", Remarks at an economics luncheon co-sponsored by the Federal Reserve Bank of San Francisco and the University of Washington, Seattle, May 20, 2004.

Brainard W. (1967), "Uncertainty and the Effectiveness of Policy", *American Economic Review*, 57, pp. 411-425.

Clarida R., Galí J. and Gertler M. (1999), "The Science of Monetary Policy: A New Keynesian Perspective", *Journal of Economic Literature*, 37(4), pp. 1661-1717.

Cragg J.G. (1983), "More Efficient Estimation in the Presence of Heteroscedasticity of Unknown Form", *Econometrica*, 51, pp. 751-763.

Giesecke K., Longstaff F., Schaefer S. and Strebulaev I. (2011), "Corporate Bond Default Risk: A 150-year Perspective", *Journal of Finance Economics*, 102, pp. 232-250.

Guesmi K., Nguyen D.K., and Teulon F. (2013), "Further Evidence on the Determinants of Regional Stock Market Integration in Latin America", *The European Journal of Comparative Economics*, 10 (3), pp. 397-413.

Hamilton J.D. (2018), "Why You Should Never Use the Hodrick-Prescott Filter", *Review of Economics and Statistics*, 100 (5), pp. 831-843.

Hamilton J.D. (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle", *Econometrica*, 57, pp. 357-384.

Hansen L.P. (1982), "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, 50, pp. 1029-1054.

Johnston J. (1984), *Econometric Methods* (3rd ed.), Singapore: McGraw-Hill Book Co.

King G.R. and Levine R. (1993), "Finance and Growth: Schumpeter Might be Right", *The Quarterly Journal of Economics*, 108 (3), pp. 717-737.

Moreira R.R. (2015), "Reviewing Taylor Rules for Brazil: Was There a Turning-Point?", *Journal of Economics and Political Economy*, 2, pp. 276-289.

Perotti C.E. and Van Oijen P. (2001), "Privatization, Political Risk and Stock Market Development in Emerging Economies," *Journal of International Money and Finance*, 20 (1), pp. 43-69.

Rotemberg J.J. and Woodford M. (1999), "Interest Rate Rules in an Estimated Sticky Price Model", in Taylor J. (ed.), *Monetary Policy Rules* (pp. 57-126), Chicago: University of Chicago Press.

Rudebusch G.D. (2006), "Monetary Policy Inertia: Fact or Fiction?", *International Journal of Central Banking*, 2, pp. 85-135.

Rudebusch G. and Svensson L. (1999), "Policy Rules for Inflation Targeting", in Taylor J. (ed.), *Monetary Policy Rules*, Chicago: University of Chicago Press.

Sack B. and Wieland V. (1999), "Interest-Rate Smoothing and Optimal Monetary Policy: A Review of Recent Empirical Evidence", *Journal of Economics and Business*, 52, pp. 205-228.

Silva M.J., Brasil G.H., and Moreira R.R. (2015), "Dynamic Relations of the Inertia of Monetary Policy: Application to the Brazilian Case by a Kalman Approach", *International Journal of Monetary Economics and Finance*, 9 (1), pp. 1-24.

Switzer L.N. and Picard A. (2016), "Stock Market Liquidity and Economic Cycles: A Non-linear Approach", *Economic Modelling*, 57, pp. 106-119.

Taylor J.B. (1993), "Discretion versus Policy Rules in Practice", *Carnegie Rochester Conference Series on Public Policy*, 39 (1), pp. 195-214.

Woodford M. (2003), *Interest and Prices: Foundations of a Theory of Monetary Policy*, New Jersey: Princeton University Press.

Appendix

Figure A1 – *Time series' graphical behavior: February 2003 – December 2016*

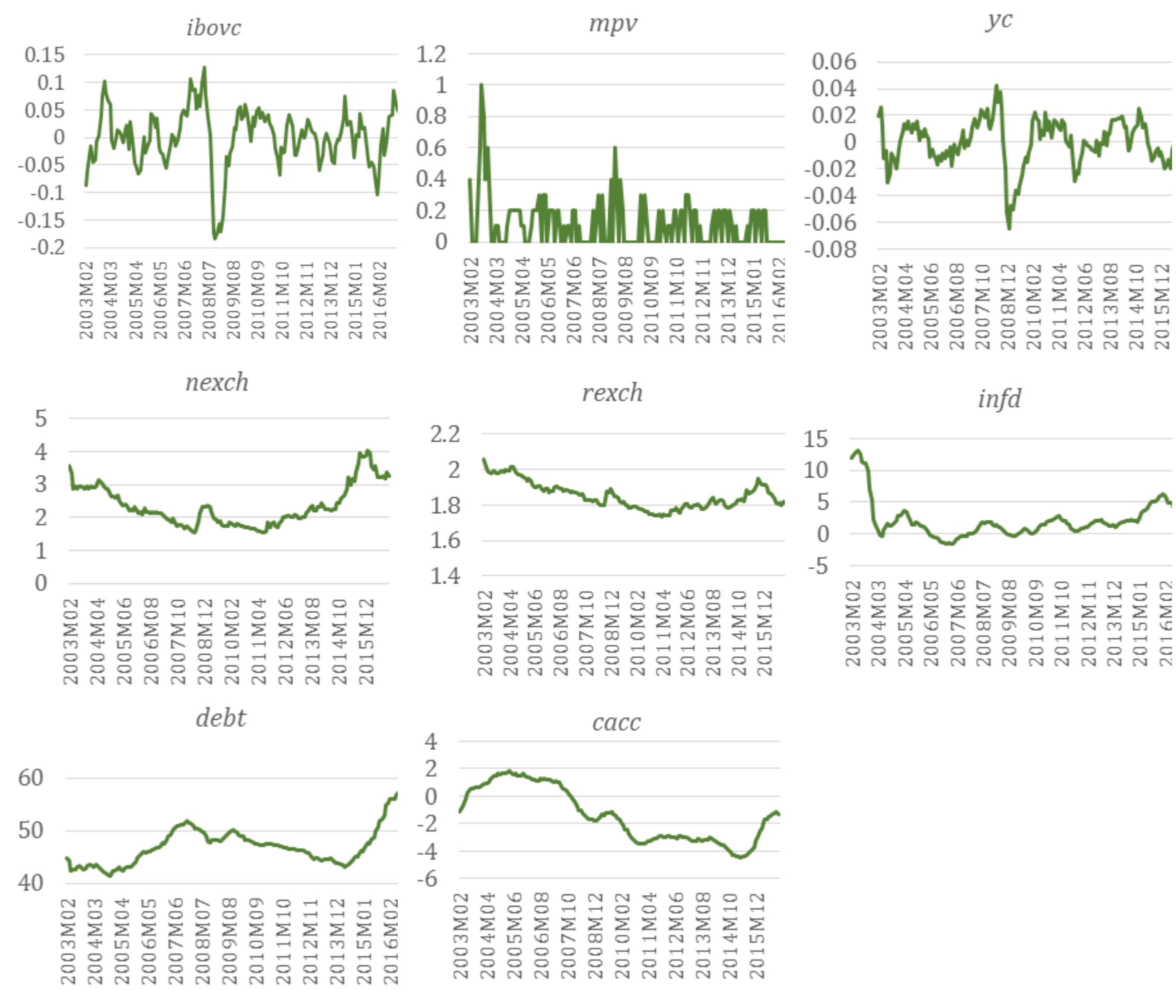


Table A1 – *MS regressions based on Hamilton's approach to measure ibovc$_t$*

	With *rexch*	With *nexch*
Regime 1: switching regressors		
ibovc$_{t-1}$	0.136	0.132
	(0.155)	(0.168)
mpv$_{t-1}$	–0.121***	–0.120***
	(0.036)	(0.035)
Regime 2: switching regressors		
ibovc$_{t-1}$	–0.208	–0.208
	(0.160)	(0.169)
mpv$_{t-1}$	0.048*	0.049*
	(0.025)	(0.025)
Common variables		
d(exch$_{t-1}$)	0.022	0.000
	(0.191)	(0.024)
yc$_{t-1}$	0.004	0.001
	(0.253)	(0.254)
d(debt$_{t-1}$)	0.003	0.003
	(0.005)	(0.005)
infd$_{t-1}$	–0.000	–0.000
	(0.000)	(0.000)
D-W stat	1.966	1.968
AIC	–4.297	–4.297

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%.

Figure A2 – *Markov switching filtered regime probabilities*