

MACROECONOMIC UNCERTAINTY AND ITS FISCAL EFFECTS: AN ANALYSIS FROM NATURAL LANGUAGE PROCESSING AND DYNAMIC STOCHASTIC GENERAL EQUILIBRIUM MODELS (DSGE)

Cássio da Nóbrega Besarria Edilean Kleber da Silva B. Aragón Maria Daniella de Oliveira Pereira da Silva Wellington Charles Lacerda Nóbrega

Abstract

This work aims to analyze the effects of macroeconomic uncertainty shocks in an economy with fiscal rules. This objective will be achieved through three complementary steps. The first step seeks to measure macroeconomic uncertainty by analyzing the textual sentiment of Brazilian public debt reports. From this stage, a dictionary of terms specific to the debt context is developed and used to parameterize the Macroeconomic Uncertainty Index (MUI). Subsequently, we developed a DSGE model and estimated it using Bayesian inferential techniques. The results of this step points to a considerable influence of fiscal rule usage to control the adverse effects of macroeconomic Uncertainty Index with the structural relations of the economy, derived from the DSGE model, in an Autoregressive Vectors approach with agnostic sign identification. The results of this stage also show that a macroeconomic uncertainty shock has typical recessive effects, with a reduction in production and consumption and an increase in public debt.

Keywords: Processamento de Linguagem Natural. Sentiment Analysis. Macroeconomic Uncertainty. DSGE.

JEL Code: C02, C63, E62, H63



1 Introduction

The adoption of fiscal rules is associated with stricter fiscal austerity stances and policies that, in general, tend to control deficits and public debt. In addition, the usage of fiscal policy, based on a rule, prevents the burden of transferring current public spending from being passed on to governments and future generations and anchors the expectations of economic agents in relation to the expected results of public accounts. Although there is a vast literature that shows the positive effects of conducting fiscal policy subject to fiscal rules, maintaining this type of austerity policy at a time of increasing economic uncertainty becomes a challenge.

Despite the inherent difficulties in measuring uncertainty, studies have been developed addressing this variable in several ways. Studies such as those of Bloom (2009); Born and Pfeifer (2014); Basu and Bundick (2017) and Bloom et al. (2018) treat uncertainty as a second-stage shock in general equilibrium models, specifically as an increase in the total productivity volatility of factors of production. Other studies have investigated uncertainty using econometric techniques (Jurado, Ludvigson and NG 2015) and even using alternative approaches based on the estimation of feeling based from textual analysis (Baker, Bloom and Davis 2016; Montes, Nicolay and Acar 2019). The development of these indicators opens space for a new field of investigation, based on: Is it possible to measure economic uncertainty? What are its macroeconomic effects? Are there ways or instruments that can be used to reduce the adverse effects of uncertainty on the economy?

This work seeks to answer these questions and contribute with a literature that shows, in general, that the increase in uncertainty negatively affects the economic environment, causing contraction in economic activity and worsening of public accounts. In Brazil, this is still an embryonic discussion, which began to take a more prominent place in 2011, when there was a change in the fiscal policy¹ conduct behavior, promoting economic uncertainty increase. Since then, there has been an increase in surveys related to of fiscal policy conduct and increased uncertainty in Brazil.

¹ At this point, according to Pastore, Gazzano and Pinotti (2014), the year 2011 was marked by a regime change economic policy that, in practice, consisted of a departure from the premises of the macroeconomic tripod.



Regarding studies on fiscal policy conduction, we highlight the work of Cavalcanti et al. (2018) and Jesus, Besarria and Maia (2020). These, in general, assess the effects of monetary policy shocks when the government follows fiscal rules in order to ensure fiscal sustainability. This debate took into account the new fiscal regime proposed for the Brazilian economy in 2016, defined based on Constitutional Amendment No. 95/2016 (Brazil, 2016) and the economic and social impacts of fiscal austerity policies, in the form of spending rules. Accordingly, both studies found that the adoption of some type of fiscal rule makes public debt less sensitive to monetary policy shocks.

In parallel, we highlight the evolution of the uncertainty theme in Brazil, highlighting the works of Godeiro and Lima (2017), Barboza and Zilberman (2018), Barbosa (2018), Silva, Besarria e Silva (2019) and Montes, Nicolay and Acar (2019), which will be further discussed in Section 2. In addition, the recent attention given to alternatives for measuring the adverse effects of uncertainty on the economy by the Monetary Authority, in its information reports (Brasil, 2018; Brasil, 2019), reinforces the equal and topicality of the theme in question. However, this research differs from the others in that it aggregates these two occurring in the same proposal and, in addition, it uses the Natural Processing Language (NPL)² approach to develop an indicator of macroeconomic uncertainty, using the monthly Public Debt Reports, published by the National Treasury, something unprecedented in national literature.

That said, we developed the Macroeconomic Uncertainty Indicator (IIM) for the Brazilian economy using text mining and sentiment analysis techniques, based on the vector space model approach, using a specific dictionary specific to the debt context. public, composed of unigrams, bigrams and trigrams³. In this context, the process of extracting and parameterizing the information collected in sentiment analysis is based on machine learning (Machine Learning) and is grounded on specific economic analysis dictionaries. In general, the indicator

² The Natural Language of Processing (NLP) consists of a branch of linguistics, computer science and artificial intelligence that seeks to investigate problems related to the generation and automated understanding of human languages. LNP techniques allow the conversion of qualitative information (such as texts, for example) into numerical values, structuring them in matrix form, thus enabling the later use of econometric models.

³ *n*-*grams*: Refers to a continuous sequence of n items in a text. The n-gram of size one (1) is denoted by a unigram, for example: "debt" is a unigram. On the other hand, a size two (2) n-gram is called a biggram, with "public debt" as an example. Finally, a n-gram of size three (3) is denoted by trigram, for example, "sustainable public debt".



developed imposes low computational cost and was able to assimilate uncertainty perception increase due to already known episodes of economic crises, highlighting that the indicator was able to assimilate the increase in uncertainty due to the outbreak of coronavirus pandemic (Covid-19). In addition, when confronted with the Economic Policy Uncertainty Index (IIPE), proposed by the Getúlio Vargas Foundation (FGV) and the Economic Policy Uncertainty Index (EPU), developed by Baker, Bloom and Davis (2016), it appears that the indicator built in the present research proved to be able to assimilate the moments of increase in uncertainty in a similar way as the already consolidated indicators.

As a result, we investigated the relationships between macroeconomic uncertainty and the real and fiscal variables of the economy. This step was carried out in two stages: first, a theoretical and then an empirical approach. Regarding the theoretical approach, an artificial economy was developed using Dynamic Stochastic General Equilibrium models (DSGE models), based on Schmitt-Grohé and Uribe (2003), Galí (2008), Cavalcanti and Vereda (2015) and Cavalcanti et al. (2018), estimating its parameters using Bayesian inference technique. The idea is to obtain parameters that can reflect the Brazilian economy characteristics and then specify a macroeconomic uncertainty shock, treated as a second moment shock on the economy's productivity, according to Bloom (2009), Born and Pfeifer (2014), Basu and Bundick (2017) and Bloom et al. (2018). In general, the theoretical model observed results corroborate those found in the literature and point to a reduction in economic activity, consumption, capital stock and demand for work, as well as an increase in public debt, due to the uncertainty macroeconomic increase.

Still in relation to the artificial economy (DSGE model), a comparative analysis was carried out taking into account the implementation of a spending rule, based on the alternative proposed by EC No. 95/2016. The results show that the adoption of a fiscal rule is able to mitigate the adverse effects of uncertainty on public accounts. In addition, this result was also corroborated by calculating the fiscal variables volatility, which were less volatile when the government follows a clear spending rule, to the detriment of the scenario in which public spending is conducted in a discretionary manner.

Finally, the results above were used as a motivation for the restrictions that were imposed in the empirical model. The proposal is to estimate a model of autoregressive vectors



with signal restrictions (SVAR), as described by Uhlig (2005), with the signs impositions based on structural relations derived from the theoretical responses of the DSGE model. Thus, a minimum set of restrictions were imposed on the empirical model, thus giving the model greater flexibility in capturing the other effects. An advantage of this strategy is that it allows comparison between the impulse response functions obtained in the empirical model and those obtained in the theoretical model and, therefore, have an indication if the responses obtained from our identification scheme produce similar results to those obtained from the DSGE model. In general, the SVAR results showed that the uncertainty shock has typical contractionary effects on the economy dynamics, with reduced consumption, capital accumulation, hours of work and output. In addition, there is also a deterioration in public accounts, with an increase in debt. These results are in line with the structural responses of the theoretical model.

In this way, this monograph contributes to two fundamental aspects of public finance. First, by developing an indicator of macroeconomic uncertainty, which can serve as an input to decision making. Second, for investigating and pointing out the effects of increased uncertainty on the real and fiscal variables of the economy in a structural model, taking into account the adoption of fiscal spending rules. Thus, the present work shows that the increase in uncertainty negatively affects both economic activity and public accounts and that the adoption of a fiscal rule can reduce the contractionary effects derived from the increase in uncertainty. Taken as whole, this discussion can have positive effects by contributing to better fiscal policy planning in times of uncertainty.

In addition to this introduction, the present work proceeds as follows: Section 2 presents a brief bibliographic review of the literature related to the theme; Section 3 lays out the methodology used to construct the proposed uncertainty index; Section 4 describes a structural model in order to investigate the theoretical responses of the real variables of the economy in the face of macroeconomic uncertainty increase; in Section 5, the empirical exercise performed is presented, using the indicator constructed as a proxy for economic uncertainty; finally, in Section 6 the final considerations and discussions are carried out. Additionally, the work has an Appendices section, where additional information is available.



2 Lirerature review

In order to investigate the effects of increased uncertainty on the economy, Bloom (2009) develops a dynamic structural model based on a second-moment shock specification (variance) to model macroeconomic uncertainty. The results of the theoretical model point to a reduction in investment, employment and output; results corroborated by empirical analysis performed through VAR models, using data from the United States of America (USA). One of the main contributions of Bloom (2009) is the description of the channel linking increased uncertainty to the economy, real-options. According to the author, this transmission mechanism is explained by the fact that the increase in uncertainty induces entrepreneurs to temporarily postpone decision-making regarding investment, production and hiring, which has negative effects on output and employment.

Carrière-Swallow and Céspedes (2013) investigated the effects of global uncertainty shocks on consumption and investment for a group of forty (40) countries. For this, they estimated VAR models for each nation taking into account real variables, stock market and prices. The uncertainty shocks were treated as increases in the implicit uncertainty in the US stock options. The results showed that the effects of increased uncertainty are assimilated differently between the countries studied. Indeed, developed economies do exhibit a drop in investment and consumption, consistent with the literature. On the other hand, the effect on emerging economies is more severe, with a sharp drop in investment and private consumption, which are also relatively more persistent.

Jurado, Ludvigson and NG (2015) develop a measure of uncertainty for the US economy based on econometric modeling, starting with the assumption that the most relevant information for the decision-making process is the effective difficulty in predicting the economy, in contrast to the increase in volatility. When comparing the performance of the indicator with some commonly used proxies, such as the stock market's volatility, it was possible to verify that the index proposed by Jurado, Ludvigson and NG (2015) was more efficient in capturing the negative correlation between uncertainty and industrial sector production, proving to be more effective in predicting economic recessions.



The uncertainty shock effects investigation through dynamic models found controversial results, mainly with regard to the non-reduction of working hours in the face of an increase in uncertainty, a fact widely verified through empirical models (VAR). In this sense, Born and Pfeifer (2014); Basu and Bundick (2017); Bloom et al. (2018) developed DSGE New-Keynesian models with imperfect markets and nominal rigidity to investigate the effects of uncertainty shocks, specified as second-moment shocks, on macroeconomic variables.

In general, the introduction of the aforementioned characteristics provided more adherence to the empirical results of the models, where the results show that the increase in uncertainty has contractionary effects on capital, labor, consumption and output through precautionary mechanisms and real-options. In regard to government intervention, Basu and Bundick (2017) argues that the position of the monetary authority plays a fundamental role in periods of uncertainty, by reducing interest rates and stimulating economic activity. However, the limitations imposed by zero lower bound restriction, according to the author, aggravated the uncertainty in the USA in 2008 by limiting the role of the EDF. On the other hand, Bloom et al. (2018) argue that given the greater caution of economic agents, especially firms, the economy's response to expansionary policies can be substantially mitigated due to increased uncertainty.

Directing the discussion to the Brazilian context, it is possible to identify some work that address the theme of uncertainty, such as: Godeiro and Lima (2017), Montes, Nicolay e Acar (2019), Barboza and Zilberman (2018), among others. The work of Godeiro and Lima (2017) makes an adaptation of the uncertainty measure proposed in Jurado, Ludvigson e NG (2015) for Brazil. The estimated indicator showed a significant increase between 2008/2009 as a result of the subprime crisis and between 2011/2012 due to the change in conduct of macroeconomic policy in Brazil. Furthermore, through temporal causality tests, a negative correlation was found between the indicator and macroeconomic variables such as industrial production, indicating that an environment of greater uncertainty causes a decrease in output.

Montes, Nicolay e Acar (2019) uses text mining techniques to analyze whether the National Treasury's communication is capable of affecting the perception of uncertainty regarding public debt. First, a communications clarity indicator is created from the minutes of the tax authority's communication, based on the text reading ease approach of Flesch (1948).



Then, the relationship between clarity and uncertainty in the press releases is evaluated through various methodologies. The results suggest that clarity in fiscal announcements reduces uncertainty about public debt, indicating that fiscal announcements should be made as clearly as possible in order to reduce uncertainty. Barboza and Zilberman (2018) investigates empirically, making use of SVAR models, the effects of uncertainty on economic activity. For this, they use some proxies for uncertainty, such as the FGV / IBRE Economic Uncertainty Index and the volatility of the Bovespa Index, among others. The results suggest significant effects of uncertainty on economic activity, in particular, on investment. In addition, it was also possible to identify that internal sources and uncertainty have a greater effect compared to external sources of uncertainty.

3 Development of the macroeconomic uncertainty index (MUI)

The elaboration of the Macroeconomic Uncertainty Index (MUI) is based on the Vector Space Model⁴, developed by Salton, Wong e Yang (1975). In practice, this method consists of using the Natural Processing Language to lay out and measure the weights of words in a document, based on the product of local and global parameters. In general, the weight of the *i*-th term on the *j*-th document can be broken down into three different types of weights: local, global and normalization, according to:

$$L_{i,j} G_i N_j \tag{1}$$

where $L_{i,j}$ is the local weighting of the *i*-th term in the *j*-th document, G_i is the global weighting of the *i*-th term and, finally, N_j is the normalization factor for the *j*-th document. The local weighting is a function of the repetition frequency of the *i*-th term in each "*j*" document in the sample, on the other hand, the global weighting refers to the number of records of the *i*-th term in the entire sample. Finally, the normalization factor is used to compensate for discrepancies related to differences in size between documents.

⁴ Vector Space Model - algebric model of textual documents representation.

Public Finance Notebooks – Special Edition, Brasília, v. 02, n. 1, p. 1-55, apr. 2021

Furthermore, unlike some studies found in the literature, the present work expands the investigation of unigrams for analysis of the so-called n-grams, which consist of sentences composed of n sequential words derived from a sample set of texts, that is, sentences composed of n words. In practice, this approach is a Markov chain, in which each selection of a specific term depends only on the previous word. The main advantage of this approach is the fact that it provides more refined information of the analyzed texts and its implementation logic is compatible with the Vector Space Model.

In the present work, the estimation of the terms weight used as an estimation metric the approach proposed by Chisholm and Kolda (1999), which uses a counting algorithm based on frequency weighted in logarithmic terms as follows:

$$P_{i,j} = \begin{cases} \frac{1 + \log(Tf_{i,j})}{1 + \log(\alpha_j)} \times \frac{\log N}{df_i}, & se \quad Tf_{i,j} \ge 1, \\ 0, & se \quad Tf_{i,j} = 0 \end{cases}$$
(2)

where $P_{i,j}$ denotes the weight of the *i*-th *n*-gram in the *j*-th document; $Tf_{i,j}$ s the total occurrences of the word/sentence *i* in a *j* document; $\alpha_{i,j}$ denotes the mean of terms⁵ registered in the *j*-th document; *N* is the total number of documents in the sample and, finally, df_i ounts the total number of documents with at least one occurrence of the *i*-th term.

Finally, the estimate of the textual sentiment was elaborated from the frequency record of each term of uncertainty in the monthly reports of the Brazilian public debt. In other words, the value of the textual sentiment in the period j is given by the sum of the weight (calculated from the Equation 2) of all terms i in this document and so on, according to the following equation:

⁵ The mean of terms $(\alpha_{i,j})$ corresponds to the ratio of the sum of the frequency of the words in the dictionary that are present in *j*-th text and the number of words in the dictionary (n) also present in the *j*-th text, that is: $\alpha_j = \frac{1}{n} \sum_{i=1}^n f P_j$.



$$MUI_j = \sum_{i=1}^{N} P_{i,j} \tag{3}$$

where MUI_j denotes the textual feeling of the *j*-th text and $P_{i,j}$ denotes the weight of the *i*-th *n*gram in the *j*-th document. In this way, the Macroeconomic Uncertainty Index (MUI) consolidated from the sum of the specific weight of each uncertainty term for each *j* document, results in a time series subject to quantitative analysis and composed of the same number of observations in the reports used to generate it.

3.1 Textual estimation procedure

The Macroeconomic Uncertainty Index was built based on the Federal Public Debt Monthly Reports⁶, available on the website of the tax authority, that is, the National Treasury⁷. These documents are made available in *Portable Document Format* (PDF), on a monthly basis and in two languages: Portuguese and English. The choice of this specific document was due to the close relationship between the result of economic policy, be either monetary or fiscal, and the expectations of economic agents, according to Barro (1974) and Sargent and Wallace (1981). In addition, the monthly report was used because it is one of the Treasury's publications⁸ with relevant sample and periodicity for the analysis and consequent development of the indicator.

The disclosure of the reports began in November 2000, in Portuguese, and in March 2003 in English. In the present study, we opted to use the English version of the report, mainly due to the fact that the most notorious and accepted dictionary used in Sentiment Analysis is produced in this language, proposed by Loughran and McDonald (2011)⁹. Thus, the sample

⁶ The report presents information on issues, redemptions, stock, maturity profile and average cost, among others, for the Federal Public Debt, including debts internal and external responsibility of the National Treasury.

⁷ The monthly public debt reports are available available on the site of the National Treasury, more specifically: <u>http://www.tesouro.fazenda.gov.br/en/monthly-debt-report</u>.

⁸ The National Treasury also publishes an annual version of the Debt Report, available at: <u>http://www.tesouro.fazenda.gov.br/en/annual-debt-report.</u>

⁹ The word lists for Sentiment Analysis from Loughran and McDonald (2011) are available at: <u>https://sraf.nd.edu/textual-analysis/resources/.</u>



used for the construction of the macroeconomic uncertainty indicator is composed of 208 monthly observations, which cover the period between march 2003 and june 2020.

It is worth mentioning that the textual sentiment analysis developed will use, in addition to the list of uncertainty terms proposed by Loughran and McDonald (2011), words (unigrams) and sentences (bigrams or trigrams) related to a specific language used in the context of public debt, therefore, procedures for creating and validating a specific dictionary were applied and will be presented in Subsection 3.2.

After collecting the debt reports on National Treasury's website, some steps of the processing of the documents sets were carried out in order to extract as much information as possible from the linguistic corpus, thus minimizing the information loss resulting from sample manipulation. It is important to note that, in all stages of this work, the R software was used through its Integrated Development Environment (IDE), R-studio.

Firstly, it was necessary to import the contents of the reports into the internal memory (working environment) of the statistical software. This procedure was performed through an R package that performed the reading and subsequent import of the text contained in the reports into memory. It is important to note that in the analysis period, there were changes in the layout¹⁰ of the reports made available by the Treasury; however, these changes did not affect the efficiency of the document conversion algorithm.

Then, the most refined treatment of the content of the texts contained in the reports was carried out. In this step, double spaces, stop words¹¹, punctuation, numbers, line breaks, page breaks, paragraph marks and standardization of all characters to lowercase occurred. For information purposes, before the cleaning mentioned above, the *corpus* presented a total of 886,594 words, with 41,073 different terms, after the application of the textual cleaning techniques, the *corpus* presented 471,754 words in total and 3,968 different terms. After that, the frequency of the words and *n*-grams was verified, both registered in the form of a *Term*

¹⁰ Specifically, the layout changes took place on: March 2004, January 2007, January 2011 and January 2015.

Stop words - These are words with a high frequency of appearance in a text, however, they add little or no information to the analysis, thus considered irrelevant for discussion and then removed from the linguistic Corpus.



Document Matrix, which in practice summarizes the number of occurrence of the terms (lines) per documents (columns) for the entire sample.

Subsequently, weights were calculated for the terms, according to the algorithm described in Equation 2 in Section 3. Then, the interpolation of the series generated from a simple arithmetic mean was applied, resulting in 65 quarterly observations. Finally, in order to mitigate volatility in the series trajectory, the exponential smoothing was used following the *Holt-Winters* method.

Figure 1 presents through flowcharts the most relevant points of the estimation process, used for the uncertainty indicator developed in this research, through text mining techniques and estimation of textual sentiment.





Source: Elaborated by the Authors.



3.2 Dictionary and validation of specific terms

In Sentiment Analysis, the "dictionary" represents a set of terms, previously categorized, that are capable of expressing some type of feeling. The lexicon is extremely important for the analysis because it represents the bridge between the investigated written documents and the consequent parameterization and measurement of the textual feeling.

The first dictionary used for Sentiment Analysis was Harvard-IV, focused on psychology. Notwithstanding it's importance, when directing the investigation to the economic aspect, mainly about financial markets, this dictionary became inefficient when it misclassified the feeling linked to some terms. In this context, from Harvard-IV, Loughran and McDonald (2011) structured a dictionary aimed at the financial market, classifying words into categories of feelings, such as: positive, negative, uncertainty, restriction, superfluous, among others.

In this way, the dictionary used in the present research consists of the words categorized a *priori* by Loughran and McDonald (2011) as terms capable of expressing uncertainty and, in addition, it is incorporated a list of unigrams, bigrams and trigrams which are specific to the technical language employed in the writing of public debt reports. In other words, given their specificity, some theme characteristic terms capable of expressing a feeling of uncertainty were incorporated into the dictionary.

The selection of specific terms took place after reading the public debt reports, given the uniqueness of this list of terms, the validation process chosen was the so-called "specialist validation". This procedure consists of sending a list of possible terms to be included in the dictionary to three different renowned researchers, with academic or market knowledge, in the areas related to the investigated subject, for independent evaluation and classification. The platform used for this step was a *google* form, consisting of two sections: the first, made a brief presentation of the study's motivation and exposed the response guidelines; the second, listed the list of terms, where the evaluator should, for each unigram, bigram or trigram, evaluate "yes" if this term was capable of expressing feelings of uncertainty and "no", otherwise.

After the experts' evaluation, the list of responses was converted into binary logic, in which the positive evaluation equals "1" and the negative evaluation equals "0". Then, the score for each term was calculated, given by:



$$S_i = \sum_{i=1}^N T_i \tag{4}$$

where S_i denotes the *i*-th term score, T_i is the individual assessment of the *j*-th expert referring to *i*-th term and, finally, *N* is the total number of experts.

Finally, the selection criterion for the n-grams adopted for composing the dictionary (D) an be described using the following process:

$$\begin{cases} if S_i \ge 2, & T_i \in D, \\ if \ 0 \ge S_i < 2, T_i \notin D \end{cases}$$
(5)

In other words, if two evaluators think that the *i*-th term is capable of expressing a feeling of uncertainty, it belongs to the dictionary, otherwise the term does not compose the dictionary.

The final dictionary consisted of 90 *n-grams*, of which 53 were unigrams (58.89%), 19 bigrams (21.11%) and 18 trigrams (20.00%). Among the unigrams, 38 (71.70%) were extracted from the dictionary of Loughran and McDonald (2011). The list of specific unigrams, bigrams and trigrams used in the present research are presented in Appendix A.

Figure 2 presents a visual representation through the word cloud, which shows the frequency and, consequently, the importance of the terms in the dictionary used in the present research on the discussion. In general, a term stands out according to its frequency of occurrence, thus, the larger the font (or size of the term), the more frequently it was present in the sample.



Figure 2 - Wordcloud



Source: Elaborated by the Authors.

From the figure, it is possible to observe that the unigrams: "variation", "reform", "exposure", "repurchase", among others, are placed as the most frequent terms. In relation to bigrams, the following stand out: "debt increased", "debt increase", "inflation increased", among others. Finally, among the trigrams are: "average maturity decreased", "average cost shifted", "average maturity shifted", among others. In common, all of these terms have a specific impact in the context of public debt, being, according to the judgment process described in this section, capable of expressing a feeling of uncertainty.

3.3 Results of estimation of textual sentiment

After completing the dictionary construction and validation step, the dictionary itself was used to estimate the textual sentiment and later the indicator parameterization, according to the equations 2 and 3. Figure 3 presents the temporal evolution of the Macroeconomic Uncertainty Indicator (MUI) constructed sequentially (step-by-step) from the dictionary proposed in the present research.





Figure 3 - Macroeconomic Uncertainty Index (MUI) for 1, 2 and 3-grams

Source: Elaborated by the Authors.

First, a dictionary composed of unigrams was used, the result of this estimation is represented by the dashed gray line. Then, the dictionary was expanded so that it was composed of unigrams and bigrams, this step resulted in the indicator represented by the dashed black line. Finally, the indicator was estimated using all the terms from the dictionary previously validated, that is, unigrams, bigrams and trigrams, the result of this estimation is the indicator represented by the solid black line. From the figure, it is possible to observe that the last indicator was able to better assimilate the fluctuations in uncertainty level. This result was expected since the inclusion of bigrams and trigrams sought precisely to capture more refined information that perhaps the analysis based on unigrams was not able to capture.

In general, it is possible to note that the indicators share the same trend, with emphasis on the years: 2003-2004, 2009-2010 and 2015-current. These years are related to economic crises of a national (internal) or global (external) character, a theme that has been investigated by other works over the past years, such as: Pastore, Gazzano e Pinotti (2014), Godeiro and Lima (2017), Frascaroli and Nobrega (2019), Nobrega, Maia e Besarria (2020), among others.

The behavior of the indicator between the years 2003 and 2005 can be explained due to the post-election "crisis of confidence" and the uncertainty about the economic policies to be



adopted by the then president-elect Luiz Inácio da Silva (Lula)¹². Resultado corroborado pelo encontrado em Blanchard (2004) e Favero e Giavazzi (2004), que denotam esse período como de elevado risco. A result corroborated by that found in Blanchard (2004) and Favero and Giavazzi (2004), which denote this period as being of high risk. This scenario was reversed after the announcement of a change in the fiscal rule associated with the maintenance and deepening of some of the policies adopted in the government of Fernando Henrique Cardoso (FHC), a fact which was sufficient to contain inflationary expectations and bring the economy back to the conditions leading up to that period.

Between 2008 and 2009, the indicator shows an increase and a consequent peak in the perception of risk, due to the global financial crisis due to sub-prime securities, remaining at high levels between 2010 and 2011, due to changes on the so-called "New Economic Matrix", in line with the results found by Godeiro and Lima (2017) and Silva, Besarria e Silva (2019).

Between 2011 and mid-2014, the indicator showed a slight stagnation trend, mainly due to the reduction of debt/GDP ratio. During this period, the main asset held by the Brazilian government, international reserves, played a fundamental role in the behavior of the index, since, even with the increase in public spending in President Lula's second term, DLSP presented successive reductions due to dollar appreciation and the consequent appreciation of the international reserves previously accumulated.

This situation continues until 2015, reverting to an upward trajectory with the reelection of President Dilma Vana Roussef¹³, showing this behavior until the year following the then president *impeachment*. The upward trajectory is attenuated during the government of President Michel Temer¹⁴, due to his signaling for reforms aimed at reducing the size of the government and consequently, of public spending on the economy, with emphasis on the Ceiling of Public Spending Constitutional Amendment (EC N° 95/2016) and labor reform. The trajectory started in the previous government continues during the term of the current president, Jair Messias

 ¹² First presidential term (Lula I): January 1, 2003 - December 31, 2006. Second presidential term (Lula II): January 1, 2007 - January 1, 2011.

 ¹³ First presidential term (Dilma I): January 1, 2011 - January 1, 2015. Second presidential term (Dilma II): January 1, 2015 - August 31, 2016.

¹⁴ Mandate: August 31, 2016 - January 1, 2019.



Bolsonaro¹⁵, mainly by signaling the commitment to reduce the size of the state in the economy and the approval of the Pension Reform.

Finally, given the outbreak of the new coronavirus (SARS-COV-19) that took place in the early stages of 2020 in Brazil, it is possible to note a peak in uncertainty perception. This suddenly rise in MUI can be explained by the adverse effects of the pandemic over the economy, mainly due to a reduction of individuals' income, tax revenues, GDP growth and sharply rise in unemployment.

For comparison purposes, Figure 4 compares the main indicators of economic uncertainty developed for Brazil, the Economy Uncertainty Indicator (EUI-BR) estimated by the Getúlio Vargas Foundation (FGV/IBRE) and the Economic Policy Uncertainty Index (EPU)¹⁶, developed by Baker et al. (2016), and the uncertainty indicator built in the present work.



Figure 4 - Comparison of the economic policy uncertainty index (EUI-BR / FGV) versus

Note: The series were smoothed using the Hodrick-Prescot filter.

When looking at the picture, it is possible to observe that, in general, the EUI-Br, EPU and MUI have similar trajectories. However, directing the analysis to specific periods, it is possible to verify that the indicators reacted in different intensities at some moments. For example, between 2004 and 2007, both EUI-Br and MUI showed a downward trend, however,

¹⁵ Mandate: January 1, 2019 - Current.

¹⁶ Available for consultation at: https://www.policyuncertainty.com/brazil_monthly.html.



MUI showed greater intensity compared to EUI-Br. In addition, the risk reduction after the rise resulting from the 2008 financial crisis showed similar dynamics and duration for all indicators.

It is noteworthy that the EUI-Br and the EPU are more sensitive to the European Crisis than the MUI, possibly because the latter is directed to the investigation of reports aimed at analyzing the local fiscal result, while the other indicators are constructed based on a mix of newspapers and other documents. However, the response of the indicators differs with respect to the risk perception magnitude in 2015, with the reversal of the trend being more acute in EUI-Br and EPU than in MUI, although they have the same inflection points. As highlighted earlier, this result can be associated with the signaling of governments to reduce the size of the state in the economy, as well as structural reforms aimed at reducing government spending.

Lastly, Table 1 present the estimates of the coefficient of correlation of Pearson. This measure provides a first empirical evidence of the relationship between the uncertainty and some real aggregate variables of the economy.

Table 1 – Coefficient of Correlation with MUI								
Variable	GDP	Debt	GFCF	Consumption				
Correlation	-0,28	0,32	-0,21	-0,20				

Source: Elaborated by the authors.

Note (*): The description of the variables can be seen in Table 5.

It is possible to observe that the MUI is negatively related to the Gross Domestic Product (GDP), Gross Fixed Capital Formation (GFCF) and to private consumption. On the other hand, the coefficient of correlation suggests a possible positive relationship between MUI and public debt. Despite of being a simple result, this result is similar to those described in Born and Pfeifer (2014), Baker, Bloom e Davis (2016), Godeiro and Lima (2017) and Basu and Bundick (2017), in which these authors found empirical evidence of a negative relationship between uncertainty and aggregate demand.

Finally, Figure 5 shows the comparison between the trajectories of the MUI and the net debt of the public sector (NDPS). Through it, it is possible to corroborate the existence of correlation between both variables, as shown in Table 1, in which moments of increase in the



perception of uncertainty are positively correlated with periods of increase in public indebtedness.

Figure 5 - Comparison of the evolution of public sector net debt versus macroeconomic uncertainty index (MUI)



Source: Elaborated by the authors.

This behavior can be explained due to the recessive effects characteristic of moments of high macroeconomic uncertainty. On the one hand, the reduction in household consumption associated with the reduction in investment acts to reduce the level of aggregate demand in the economy and, consequently, the amount of government tax revenue is also reduced. On the other hand, in periods of economic contraction, fiscal policy is commonly used as an anticyclical instrument, in order to rekindle aggregate demand and reverse the economic cycle towards growth.

In this sense, it is expected that the increase in uncertainty will negatively impact the budget balance of public accounts. Therefore, the investigation carried out in this research is justified insofar as it seeks to measure and analyze macroeconomic uncertainty through an alternative and low computational cost indicator, which can generate positive effects with regard to the understanding of the existing interactions between economic activity and uncertainty, as well as their effects on the evolution of public accounts.



4 Theoretical model

In this section, a theoretical model (DSGE) is developed to justify the signal restrictions imposed on the empirical model (section 5). The proposed model is based on Schmitt-Grohé and Uribe (2003), Galí (2008), Cavalcanti and Vereda (2015); Cavalcanti et al. (2018), among others, and depicts an infinite horizon economy, composed of three economic agents: households, firms and government. Figure 6 shows the structure of the model by means of flows.

Households are subdivided into two types, Ricardian and non-Ricardian. Ricardian households offer labor and physical capital. They consume and have access to the financial market, being able to invest in government bonds and then smooth out the consumption level between periods of time; On the other hand, non-Ricardian households also offer work and consume, however, these agents have restricted access to the bond market, thus, they do not allocate income intertemporally in an efficient way.



Figura 6 - Flowchart of the model

Source: Elaborated by the authors.



Intermediary firms operate in a monopoly market and produce a differentiated product, using the work offered by the two categories of families in the production process. Nominal rigidity is introduced in the pricing process of intermediate firms, according to Calvo (1983). On the other hand, firms producing final goods operate in a competitive market and pack goods produced by the intermediate sector in a homogeneous consumption basket.

Finally, the government is divided into two agents, the fiscal and monetary authorities. It is the responsibility of the fiscal authority to operate tax collection, government income transfers and the issuance of government bonds, the latter used to finance public expenditure. On the other hand, inflationary control is the responsibility of the monetary authority

4.1 Households

A *continuum* of families indexed by $j \in (0,1)$ is assumed, in which a ω_R portion of the families does not have access to the financial market, which are called non-ricardian or restricted families due to the limitation of intertemporal substitution of consumption and savings. On the other hand, a portion $(1 - \omega_R)$ of households has access to the credit, government securities and capital markets; these families are called Ricardian families. Families offer homogeneous work in a competitive market, so wages are identical and flexible.

4.1.1 Ricardian Households

There is a *continuum* of households indexed by $j \in (0,1)$, where a portion $(1 - \omega_R)$ is made up of Ricardian households. Each family maximizes its intertemporal utility, given by:

$$E_t \sum_{t=1}^{\infty} \beta_t \left[\log \left(C_{R,t-h} C_{R,t-1} \right) - \frac{N_{R,t}^{1+\varphi}}{1+\varphi} \right]$$
(6)

where $\beta \in (0,1)$ denotes the subjective discount factor, $C_{R,t}$ represents consumption in t, $N_{R,t}$ the hours of work offered during the period t; h is a parameter related to the consumption habit and $\varphi > 0$ is the inverse of the work elasticity of *Frisch*.



The dynamics of accumulation of physical capital (law of movement of capital) is represented by the following condition:

$$K_t = (1 - \delta^K) K_{t-1} + I_t \tag{7}$$

where δ^{K} denotes the depreciation rate of capital.

The budget constraint to which the Ricardian household is subject can be expressed by:

$$P_t(1+\tau^C)(C_{R,t}+I_t) + B_t = (1+R_{t-1})B_{t-1} + (1-\tau^W)W_t N_{R,t} + R_t^K (1-\tau^K)K_{t-1} + P_t(1-\omega_R)TRG_t$$
(8)

where B_t is government bonds held by households, I_t is the investment in t and TRG_t denotes cash transfers received by the government. W_t denotes the nominal salary, R_t is the basic interest rate and R_t^K is the return of capital. Finally, τ^C , τ^w and τ^K represent consumption, income and capital tax rates.

4.1.2 Non-ricardian households

The maximization problem faced by the non-ricardian households is similar to that faced by the ricardian families, the difference is basically the restriction on the financial market. Again, there is a *continuum* of households indexed by $j \in (0,1)$, where a portion ω_R is made up of non-ricardian households and each family maximizes its intertemporal utility, given by:

$$E_t \sum_{t=1}^{\infty} \beta_t \left[\log \left(C_{NR,t-h} C_{NR,t-1} \right) - \frac{N_{NR,t}^{1+\varphi}}{1+\varphi} \right]$$
(9)

where $C_{NR,t}$ and $N_{NR,t}$ are consumption and hours worked by non-ricardian agents in the period t, respectively. In this way, the intertemporal budget constraint of non-ricardian families is given by:



$$P_t(1+\tau^c)C_{NR,t} = (1-\tau^w)W_t N_{NR,t} + P_t \omega_R TRG_t$$
(10)

4.2 Firms

4.2.1 Production of final goods (retail firms)

The final-goods producing sector will follow Bernanke, Gertler and Gilchrist (1999), being composed of a *continuum* of retail firms, indexed by $j \in (0,1)$, which acquire the intermediate good, $Y_{j,t}$, produced by wholesale firms and transformed into a homogeneous good, Y_t , which is sold at the price P_t , according to:

$$Y_t = \left[\int_0^1 Y_{j,t}^{\frac{\Psi-1}{\Psi}} \,\partial j\right]^{\frac{\Psi}{\Psi-1}} \tag{11}$$

where $\Psi > 1$ represents the elasticity of substitution between intermediate goods.

The representative retailer maximizes its profit subject to the production function, given the price of the intermediate good and the final good. Thus, the maximization problem can be described by:

$$\max_{\Pi_t} = P_t Y_t - \int_0^1 P_{j,t} Y_{j,t} \partial j \tag{12}$$

Applying the first order condition to the problem described above and, assuming that the retail sector operates in perfect competition, where $\Pi_t = 0$, the demand curve that each retailer faces is given by:

$$Y_{j,t} = \left(\frac{P_{j,t}}{P_t}\right)^{-\Psi} Y_t \tag{13}$$



The above expression implies that the demand for the j-th intermediate good is decreasing in relation to relative prices and increasing in relation to aggregate demand. By replacing Equation 13 in 11, the corresponding price index comes down to:

$$P_t = \left[\int_0^1 P_{j,t}^{1-\Psi} \ \partial j \right]^{\frac{1}{1-\Psi}} \tag{14}$$

The Equation 14 denotes the final goods pricing rule.

4.2.2 Production of intermediate goods (wholesale firms)

The wholesale firm operates in monopolistic competition, using as inputs the aggregate labor offered by the two types of families (N) and physical capital (K), provided only by the Ricardian family. The firm's production function is a Cobb-Douglas function and can be expressed as follows:

$$Y_{j,t} = A_t K_{j,t}^{\alpha} N_{j,t}^{1-\alpha} \tag{15}$$

where α denotes the proportion of capital involved in the production process and A_t captures the technological level, which is properly specified in Subsection 4.5.

The *j*-th wholesale firm determines the optimal choice of inputs in order to minimize its total cost function, subject to the production function. The optimal quantities demanded for each production factor can be expressed by:

$$R_t^K = mc_{j,t} \left(\frac{\alpha Y_{j,t}}{K_{j,t}}\right) \tag{16}$$

$$W_t = mc_{j,t} \left(\frac{\alpha Y_{j,t}}{N_{j,t}}\right) \tag{17}$$

where λ_t is the shadow price of the production function, or, in other words, the marginal cost $(mc_{j,t})$ of the *j*-th firm, this can be expressed as:



$$mc_{j,t} = \frac{1}{A_t} \left(\frac{R_t^K}{\alpha}\right)^{\alpha} \left(\frac{W_t}{1-\alpha}\right)^{1-\alpha}$$
(18)

Furthermore, the price dynamics follow Calvo (1983), where each firm can readjust its prices with probability $(1 - \theta)$ in any period, regardless of the last adjustment, while θ producers keep their prices unchanged. In this context, the parameter θ can be interpreted as an index of price rigidity and the average duration of price contracts is $(1 - \theta)^{-1}$. In this context, the optimal price chosen by these firms satisfies:

$$\sum_{k=0}^{\infty} (\beta\theta)^{k} E_{t} \left\{ \left[(1-\Psi) + \Psi M C_{j,t+k} (P_{j,t}^{*})^{-1} \right] \left(\frac{P_{t+k}}{P_{j,t}^{*}} \right)^{\Psi} Y_{t+k} \right\} = 0$$
(19)

 $MC_{j,t+k}$ is the real marginal cost in the period t + k for the firm that readjusted its price by t. The first order condition allows you to define the equilibrium price:

$$P_{j,t}^* = \left(\frac{\Psi}{\Psi - 1}\right) E_t \sum_{t=0}^{\infty} (\beta\theta)^i M C_{j,t+k}$$
(20)

It is important to note that intermediary firms that fix prices have the same mark-up $(\Psi/\Psi - 1)$ on the marginal cost. Given the fraction θ of retailers that do not readjust their prices by *t*, the aggregate price evolves according to:

$$P_t = \left[\theta P_{t-1}^{1-\Psi} + (1-\theta)(P_t^*)^{1-\Psi}\right]^{\frac{1}{1-\Psi}}$$
(21)

Note that in the limit case, when there is no price rigidity ($\theta = 0$), the above condition results in setting prices under flexible prices. Thus, one can interpret ($\Psi/\Psi - 1$) as mark-up in the absence of friction in price adjustment frequency.



4.3 Government

4.3.1 Fiscal authority

O papel desempenhado pela autoridade fiscal no presente modelo se resume a operacionalizar a arrecadação tributária e a emissão de títulos ao público, no intuito de financiar os seus gastos agregados, bem como as transferências de renda realizadas para as famílias.

The determination of the government's budget constraint, in real terms, can be represented by:

$$\frac{B_t}{P_t} + \frac{TAX_t}{P_t} = \frac{G_t}{P_t} + (1 + R_t)\frac{B_{t-1}}{\pi_t} + \frac{TRG_t}{P_t}$$
(22)

where G_t is government spending in the *t* period. Thus, government revenue, TAX_t , is given by the sum of all its sources of income, expressed by:

$$TAX_{t} = \tau^{C} (C_{R,t} + C_{NR,t}) P_{t} + \tau^{w} W_{t} (N_{R,t} + N_{NR,t}) P_{t} + \tau^{K} (R_{t}^{K} - \delta^{K}) K_{t}$$
(23)

Finally, the government's primary result, SP_t , é is denoted by the following equation:

$$SP_t = TAX_t - G_t \tag{24}$$

in the case where $SP_t < 0$, in the case where SPt < 0, the primary result will be deficitary (primary deficit), since $G_t > T_t$, that is, expenditures were higher than revenues. On the other hand, when $SP_t > 0$, it implies a primary surplus, since revenues are higher than expenses, $G_t < T_t$.

As in Cavalcanti et al. (2018), the budget deficit, D_t , is the relationship between government revenue and expenditure, as a proportion of GDP and can be expressed by:

$$\frac{D_t}{Y_t} = \frac{R_{t-1}D_{t-1}}{Y_t} + \frac{G_t}{Y_t} - \frac{TAX_t}{Y_t}$$
(25)

Public Finance Notebooks – Special Edition, Brasília, v. 02, n. 1, p. 1-55, apr. 2021

in which *coeteris paribus* a primary surplus implies in debt reduction, since $G_t < T_t$. On the other hand, a primary deficit implies an increase in debt, given that $G_t > T_t$. Finally, through Equation 25 it is also possible to observe the interaction between monetary and fiscal policy, due to the debt stock, D_{t-1} , indexed to the monetary policy instrument

4.3.2 Monetary authority

The present work admits that the monetary authority adopts the Inflation Targeting Regime (ITR) and, thus, determines the basic interest rate of the economy according to a rule of Taylor (1993). Thus, the Central Bank's reaction function assumes the following specification:

$$\frac{R_t}{R_{SS}} = \left(\frac{R_{t-1}}{R_{SS}}\right)^{\phi_R} \left[\left(\frac{\pi_t}{\pi_{SS}}\right)^{\phi_\pi} \left(\frac{Y_t}{Y_{SS}}\right)^{\phi_Y} \right]^{1-\phi_R} Z_t^R$$
(26)

where ϕ_R represents the authority's preference for maintaining a smooth trajectory for interest rates, ϕ_{π} represents the interest response sensitivity in relation to the deviation between observed and expected inflation, ϕ_Y is the interest sensitivity in relation to business cycles and, finally, Z_t^R r represents the stochastic shock of monetary policy, which follows the following specification:

$$\log(Z_t^R) = (1 - \rho_R) \log(Z_{SS}^R) + \rho_R \log(Z_{t-1}^R) + \varepsilon_t^R$$
(27)

onde ε_t^R is a *i*. *i*. *d* ~ N(0,1) process and ρ_R denotes the persistence of the monetary policy shock.

4.4 Aggregation, market clearing and equilibrium

Once the optimal behavior of the economic agents has been described, the interaction between them must be established to determine the macroeconomic balance. The homogeneous



goods aggregation is given by the weighted average of the variables, thus, the aggregate level of any variable (X_t) can be obtained from:

$$X_t = \int_0^1 X_{h,t} \partial h = (1 - \omega_R) X_{i,t} + \omega_R X_{j,t}$$
(28)

where $(1 - \omega_R)$ is the proportion of non-Ricardian families and ω_R is that of Ricardian households.

Finally, to close the model, the condition of the goods market balance is given by:

$$Y_t = C_t + I_t + G_t \tag{29}$$

The equilibrium of the model consists of the solution of the sequence of endogenous variables so that the conditions that define the equilibrium are satisfied.

4.5 Uncertainty shock specification

The specification adopted for the macroeconomic uncertainty in DSGE models is given by introducing a second moment shock over the productivity of the economy, that is, an increase in the volatility in productivity. This modeling approach for uncertainty shocks has already been adopted by other works, such as: Bloom (2009), Born and Pfeifer (2014), Basu and Bundick (2017) and Bloom et al. (2018).

The productivity shock, A_t , captures the technological level determined exogenously and follows the following movement rule, based on a first-order autoregressive process (AR(1)):

$$\log(A_t) = (1 - \rho_A)\log(A_{SS}) + \rho_A\log(A_{t-1}) + \sigma_{A_t}\varepsilon_t^A$$
(30)

Public Finance Notebooks – Special Edition, Brasília, v. 02, n. 1, p. 1-55, apr. 2021

Where ε_t^A is a *i*. *i*. *d* ~ $N(0, \sigma_A)$ process and ρ_A denotes the persistence of the technological shock. In turn, the macroeconomic uncertainty shock also follows an AR(1), process, expressed by:

$$\log(\sigma_{a,t}) = (1 - \rho_{\sigma_a})\log(\sigma_a) + \rho_{\sigma_A}\log(\sigma_{a,t-1}) + \varepsilon_t^{\sigma_a}$$
(31)

where $\varepsilon_t^{\sigma_a}$ is a *i.i.d* ~ $N(0, \sigma_a)$ process and ρ_{σ_a} denotes the persistence of shock of uncertainty.

4.6 DSGE model estimation and structural parameters calibration.

4.6.1 Data

To estimate the model, quarterly data from the Brazilian economy was used, covering the period between the first quarter of 2000 and the second quarter of 2020, totaling about 82 observations. The time series used were the real Gross Domestic Product and the real consumption of families, both collected from the National Account System (SCN), produced and made available by the Brazilian Institute of Geography and Statistics (IBGE).

4.6.2 Estimated parameters

This subsection presents the results regarding the estimation of some of the parameters of interest for the (1) DSGE model. Table 2 presents the estimated values of the parameters posterior, using Bayesian inference techniques.



Table 2 - Model Estimation Results (1) DSGE:							
			Priors	ii density		Poster	riors
Parameter	Description	Dens.	Mean	Des. P.	5%	Mean	90%
$ ho_U$	Uncertainty shock persistance	beta	0.88	0.01	0.8310	0.8311	0.8312
σ_U	Uncertainty shock scalar	beta	0.10	0.01	0.1250	0.1251	0.1252
φ	Marginal disutility of labor supply	gama	1.50	0.05	1.4969	1.4969	1.4970
ω_R	Non-ricardian family share	beta	0.50	0.05	0.6198	0.6209	0.6222
h	Consumption habits	beta	0.65	0.05	0.3231	0.3232	0.3232
$ ho_A$	Autoregressive productivity parameter	beta	0.94	0.05	0.8308	0.8316	0.8321
$ au^{C}$	Quota on family consumption	beta	0.23	0.02	0.1795	0.1796	0.1798
$ au^w$	Quota on Income	beta	0.17	0.02	0.3029	0.3033	0.3029
$ au^K$	Quota on Capital	beta	0.14	0.02	0.1406	0.1407	0.1407
ϕ_R	Interest rate smoothing term	beta	0.70	0.05	0.7433	0.7434	0.7435
ϕ_{π}	Interest sensitivity in relation to inflation deviation	gama	2.43	0.10	2.4122	2.4133	2.4144
ϕ_{Y}	Interest sensitivity in relation to the output gap	gama	0.16	0.05	0.1145	0.1147	0.1149

Source: Elaborated by the Authors.

The Bayesian estimation method requires the estimation of prior parameter declaration, as well as probability distribution approximation. Thus, for the parameters in which the value must be contained in the interval [0,1], the beta distribution was imputed. On the other hand, for the parameters that must assume strictly non-negative values, the gamma distribution was assigned.

After defining the distributions a priori, the Metropolis-Hastings algorithm was used, composed of two sequences of Monte Carlo Markov chains (MCMC) with 2,000,000



interactions, a number considered sufficient to guarantee convergence. The acceptance percentage along the chains was around 34.27%, according to Brooks and Roberts (1998). Finally, 70.00% of withdrawals were discarded before the realizations were used to calculate the empirical moments of the posterior distribution in order to ensure the prior convergence of the Markov chain before the use of information for empirical moments computing.

4.6.3 Calibrated parameters

Table 3 presents the fixed (calibrated) values for some parameters of the model. It is worth mentioning that the reference values of the calibration parameters were retrieved from works highlighted in the literature.

Parameter	Description	Value	Reference
β	Discount factor	0.9850	Cavalcanti et al. (2018)
h	Consumption persistence	0.65	Cavalcanti et al. (2018)
θ	Price rigidity parameter	0.74	Castro et al. (2015)
δ^{K}	Capital depreciation rate	0.03	Silva and Bessaria (2018)
α	Production elasticity in relation do capital	0.35	Costa (2018)
ϕ_{TRG}	GDP transfer proportion	0.01	Costa (2018)
$ ho_R$	Monetary policy shock persistence	0.79	Krause and Moyen (2016)
Ψ	Substitution elasticity between final goods	6.0	Lim and McNelis (2015)

Table 3 – Calibration parameters (Chapter 3 model)

Source: Elaborated by the Authors.

The parameters referring to the discount factor (β) and consumption habit persistence (*h*) were collected from Cavalcanti et al. (2018). The value of the parameter regarding price rigidity (θ) was extracted from the SAMBA model (Castro et al., 2015). The capital



depreciation rate (δ^{K}), the monetary policy shock persistence (ρ_{R}) and the substitution elasticity between final goods (Ψ) were collected from Silva and Bessaria (2018), Krause and Moyen (2016) and Lim and McNelis (2015), respectively. Finally, the parameters related to the production elasticity in relation to Capital (α) and the GDP transfer proportion were both borrowed from Costa (2018).

4.7 Theoretical model results

4.7.1 Effect of an uncertainty shock on macroeconomic variables

This section aims to analyze the response of some model variables due to an uncertainty shock, modeled in Equation 31. It is worth mentioning that the theoretical response will serve as a basis for imposing the signal restrictions of the empirical model. Figure 7 presents the impulse response functions due to an uncertainty shock. Through this, it is possible to observe that an increase in macroeconomic uncertainty has a contractionary impact on labor and capital accumulation in the economy, which results in a negative dynamic for aggregate consumption and a consequent reduction in the level of aggregate income in the economy.

In general, the results are in line with the literature, where shocks of volatility in productivity have negative effects on aggregate demand and, consequently, on economic activity. First, in periods of uncertainty, economic agents increase preventive savings. In turn, this increase in savings causes a consequent contraction in the level of current aggregate consumption.





Figure 7 - Impulse response function of the variables of the theoretical model due to an uncertainty shock

Source: Elaborated by the Authors.

In relation to capital accumulation and employment, the model's result can be explained through the real options channel of the uncertainty shocks, proposed by Bloom (2009). In general, the intuition behind this transmission mechanism is related to the costs faced by firms in the production process, the increase in uncertainty about the future increases the value of postponing decision making regarding the production process, causing contractionary effects on the dynamics of employment, capital and interest. Together, these effects result in an economic output contraction, in line with the theoretical results of the models developed by Born and Pfeifer (2014); Basu and Bundick (2017) and Bloom et al. (2018).

Finally, the result in public accounts is negatively affected by the uncertainty shocks. On the one hand, the economic contraction results in an increase in public spending as a countercyclical instrument, on the other hand, there is a reduction in tax revenues due to reduction in practically all components of aggregate demand. Together, these effects have a negative impact on the government's financing need (primary surplus), leading to a deficit budget and, as consequence, an increase in public debt. As the uncertainty shock dissipates, there is a tendency to gradually return to the steady state value.



4.7.2 Uncertainty shock under fiscal constraint

This section aims to carry out a comparative exercise of the effects of macroeconomic uncertainty shocks on public accounts, taking into account two scenarios in the conduct of fiscal spending policy: First, with the adoption of a public spending rule; second, we consider the scenario in which there is no adoption of a defined rule of expenditure policy, being the fiscal policy, in this case, characterized by being discretionary.

The spending rule is based on Jesus, Besarria and Maia (2020), representing EC No. 95/2016, in which current spending is determined by the immediately preceding spending period adjusted for inflation. In practice, such a rule implies a limit in public spending in real terms, according to the following principle:

$$G_t = (1 + \pi_{t-1})G_{t-1} \tag{32}$$

Figure 8 shows the dynamics of spending and public debt as a result of an uncertainty shock. In general, the results show that an increase in macroeconomic uncertainty results in an increase in spending levels and, consequently, in public debt shock, through the transmission mechanisms of this type of shock to the economy, discussed in the previous section.



Figure 8 – Theoretical model variable response function as a result of uncertainty shock under fiscal restriction

E1: With fiscal rule - - - E2: Without fiscal rule

Source: Elaborated by the Authors.



The results in Figure 8 show that the model with fiscal constraint adoption (solid line) showed a smaller increase, both in spending and in debt, compared to the model in which fiscal policy does not follow a clear spending rule. In line with the work of Cavalcanti et al. (2018) and Jesus, Besarria and Maia (2020), these results corroborate the importance of adopting spending rules to tune down the shock effects on the public debt level.

4.7.3 Volatility analysis

This section performs a volatility analysis of spending and public debt resulting from uncertainty shock, taking into account a scenario in which the government follows a spending rule (in this case, given by Equation 32) and another scenario in which public spending does not follow a defined rule.

For this, the methodology proposed by Suh (2012) was used. Formally, the volatility of any variable (σ_i) consists of the sum of the squares of the impulse response function for fifty periods after the shock, expressed as follows:

$$\sigma_i = \frac{1}{50} \times \sum_{t=0}^{50} \beta^t \left(\frac{\partial X_{t+j}}{\partial e_t}\right)^2 \tag{33}$$

Table 4 presents the volatilities result for the variables of interest. Through these, it is possible to observe that the model suggests that the adoption of a spending rule makes the volatility of both spending and debt considerably lower than the situation in which no spending rule is followed.

		_	-
Volatility	With rule	Without rule	Difference
σ_g (Spending)	$10^{-7} 1.7880$	$10^{-7} 2.5190$	40.91%
σ_D (Debt)	10 ⁻⁷ 1.3225	$10^{-7} 1.7190$	29.98%

Table 4 - Effects of the fiscal rule on public debt and spending volatilities

Source: Elaborated by the Authors.



The results point to a 40% higher volatility in public spending in the scenario where there is no adoption of a fiscal rule. This behavior can also be observed in relation to debt, where the failure to adopt an expense rule resulted in a 29% higher volatility than in the case where an expense rule is adopted. As a whole, the model shows that the adoption of a fiscal rule makes public accounts more robust in the face of macroeconomic uncertainty shock, corroborating the results from the impulse response function

5 Empirical model

5.1 Identified VAR model with signal restriction

Given the endogeneity between the variables of the model, the method adopted is the Auto-regressive Vectors (VAR) model, proposed by Sims (1980). Consider the following multivariate structural autoregressive model¹⁷:

$$AX_{t} = \sum_{i=1}^{p} A_{i}X_{t-p} + \epsilon_{t} \quad \forall t = 0, 1, ..., T$$
(34)

where X_t is a column vector of endogenous variables, A is an $n \times n$ matrix of contemporary impacts, A_i denotes $n \times n$ matrices of lagged endogenous variables and ϵ_t denotes the residual term, which follows a *i.i.d* ~ (0, σ) process. Assuming that the A matrix of the structural representation of the VAR (Equation 34) is non-singular, then the reduced form VAR model can be obtained by pre-multiplying the Equation 34 by A^{-1} , obtaining:

¹⁷In general, linear regression models or VAR are suitable when the data series has an integration order of zero (I(0)), otherwise, if all series are first order integers (I(1)), the results obtained may be illegitimate, since econometric relationships are found between variables without any causal relationship, exclusively because they present non-stationarity or common tendency, this process is called spurious regression.



$$X_{t} = \sum_{i=1}^{p} B_{i} X_{t-p} + u_{t} \quad \forall t = 0, 1, ..., T$$
(35)

where $B_i = A^{-1}A_i$, $u_t = A^{-1}\epsilon_t$ and $\Omega = E[u_t u_t']$ is the variance-covariance matrix of the model's residuals.

To retrieve the information from the primitive system (34), by estimating the reduced model (35), it is necessary to impose some restrictions on the first system coefficients, in order to make them identified. An alternative is to use the decomposition of *Cholesky* (recursive) to identify the constraints. As proposed by Sims (1980), this method consists of imposing¹⁸ on the contemporary impact matrix, in order to make it a lower triangular matrix, this allows to obtain the values of the structural primitive shocks (ϵ_t) through the residuals estimated in the vector u_t .

In this context, Uhlig (2005) developed an identification strategy in which it is unnecessary to impose restrictions on the entire *A* matrix of contemporary impacts, known as the VAR model with agnostic sign identification.

The method in question consists of showing that the contemporary relation matrix A (Equation 34), such that $\hat{\Sigma} = AA'$, can then be defined as $A = \tilde{A}Q$, where Q is an orthogonal matrix and \tilde{A} is the decomposition of *Cholesky* of the residual variance matrix ($\hat{\Sigma}$). Taking the identification of a column α from the matrix A in Equation 34, with this, the problem becomes the determination of the vector α associated with the vector m-dimensional, so that:

$$\alpha = \tilde{A}\alpha \tag{36}$$

onde α é uma coluna de *A* denominada por Uhlig (2005) de vetor de impulso, contendo as respostas contemporâneas das *n*-variáveis endógenas a um determinado choque.

Uhlig (2005) demonstrated that, given the impulse vector, it is possible to calculate the appropriate response assuming that $r_i(k)$ is the impulse-response in the k of the *i*-th shock

¹⁸ For the case of a primitive system with p equations, $(p^2 - p)/2$ restrictions are imposed to make the system identifiable.



obtained by decomposing *Cholesky*. Thus, the impulse-response function for k periods can be represented by:

$$r_{\alpha} = \sum_{i=1}^{m} \alpha_i r_i(k) \tag{37}$$

Equation 37 shows that it is possible to identify the impulse vector corresponding to the investigated shock. However, the restrictions imposed *per se* do not imply sufficient conditions for the correct identification of shocks. In this way, the strategy to identify the signal restrictions presented in Table 5 was extracted from the structural response of the theoretical model developed in Section 4.

Variable	Uncertainty
variable	Shock
Uncertainty	"+"
Interest Rate	<u>،،</u>
Inflation	<i>"</i> ?"
Labor	۰۰_››
Capital	۰۰_>>
Consumption	۰۰_>>
Output	<i>"</i> ?"
Debt	"+"

Tabele 5 - Signal restrictions imposed on structural responses

Source: Elaborated by the authors.

Note: Positive (+), negative (-) and free (?) Response in the constraint horizon (k).

In short, through the identification of signal restriction, it is possible to identify the impulse response signals of some model variables based on economic theory, thus imposing a smaller number of restrictions compared to the standard VAR and, finally, not imposing any



restriction on the variable of interest to which it is intended to analyze the effect of the shock in question

5.2 Dataset

_

The time series referring to Gross Fixed Capital Formation (GFCF), Household Consumption, Government Consumption and Gross Domestic Product (GDP) were collected through the website of the Brazilian Institute of Geography and Statistics (IBGE). The data referring to the Consumer Price Index (CPI) and the Hours Worked in Industry (LABOR) were obtained from the virtual platform of the Institute for Applied Economic Research (IPEA). Finally, the information regarding the Selic Rate (SELIC) and Public Sector Net Debt (DEBT) was extracted through the Time Series Management System (SGS) of the Central Bank of Brazil. The Table 6 presents the description and the Figure 10 (Appendix B) presents the temporal evolution of the data series used in this research.

	1		
Series	Description	Unit of Measurement	Source
MUI	Macroeconomic Uncertainty	Index	Elaborated by the Authors
CONSUMPTION	Consumption of Government + Households	Millions of R\$	IBGE
GFCF	Gross Fixed Capital Formation	Millions of R\$	IBGE
GDP	Gross Domestic Product	Millions of R\$	IBGE
SELIC	Interest Rate (Selic)	(%) per year, accumulated	BACEN
LABOR	Hours Worked in Industry	Index	CNI
СРІ	Consumer Price Index (Inflation)	(%) per year, accumulated	FGV

Table 6 - Description of the Dataset Used in the Research



DEBT	Public Sector Net Debt	(%) PIB	BACEN

Source: Elaborated by the authors.

Note (*): The accumulation of the series refers to the last 12 months.

The series collected from IBGE cover a quarterly period, while the others were available on a monthly basis. For the latter, an interpolation using an average was applied to convert them into quarterly values. The variable referring to aggregate consumption (CONSUMPTION) was generated from the sum of household and government consumption. Finally, after transforming the data, the final sample used in the estimation covered the period between the second quarter of 2003 and 2020, totaling 69 observations. This time window was motivated mainly due to the publication of public debt reports in English, which conditioned the construction of the uncertainty indicator and, consequently, the investigation period of this work.

It is worth mentioning that the series referring to GDP, GFCF, CONSUMPTION and IPC presented seasonal behavior, the adjustment was made using the X - 13 ARIMA method. To test for the presence of a unit root in the data series, the unit root tests of Dickey and Fuller (1979); Phillips and Perron (1988); Kwiatkowski et al. (1992) and the unit root test in the presence of a structural break of Zivot and Andrews (1992) were performed. Based on the result of the unit root tests (Tables 8 and 9 in Appendix B), it was not possible to reject the null hypothesis, of unit root, for the level variables, except for the variable referring to the uncertainty and inflation indicator, the result is corroborated by the unit root test with structural break. Therefore, it was decided to use the *Hodrick-Prescott* (HP)¹⁹ in order to eliminate deterministic terms from these, turning them into deviations in relation to the trend.

5.3 Empirical model results

In this section, the evidence found, for Brazil, of the effects of uncertainty macroeconomic shocks on selected variables is analyzed using an autoregressive vector model developed by Sims (1980) specified with agnostic identification, as proposed by Uhlig (2005).

¹⁹ The parameter *lambda* used in the HP filter was the standard for quarterly series, that is: $\lambda = 1.600$.



In the present exercise, the macroeconomic uncertainty indicator developed and exposed in Section 3 will be used as *proxy* for macroeconomic uncertainty. It is worth mentioning that the imposition of signals for the SVAR model was based on a theoretical DSGE model, exposed in Section 4.

Figure 9 presents the impulse-response function of the model variables due to a shock of macroeconomic uncertainty. Through the picture, it is possible to observe that, in general, the responses of the variables are in line with the responses specified in the theoretical model. Initially, the uncertainty shock raises the perception of macroeconomic uncertainty for approximately 10 periods. The increase in uncertainty causes a reduction in consumption in the first quarter after the shock, this movement is mainly explained by precautionary reasons. In other words, given the increase in uncertainty, economic agents increase precautionary savings and, consequently, reduce present consumption.



Figure 9 – Impulse-response function of the model with signal restriction (k = 3)

Source: Elaborated by the Authors.

(*) Note: The restrictions were imposed for three periods (k = 3). The three lines correspond to: quantile 16.00 %, the median and quantile 16.00 % of the posterior distribution, respectively. The SVAR Model was estimated with one (1) lag.



In relation to gross fixed capital formation and labor, the shock of uncertainty has a contractionary effect on both. As previously discussed, this result is explained by the channel real options described by Bloom (2009), in which the increase in uncertainty about the future negatively affects investment and productive decisions by entrepreneurs, since the decision-making regarding investment and production entail costs, often sunk, which, once taken, are unlikely to be reversed without the incursion of high costs and losses. Together, the contraction in consumption, capital accumulation and labor negatively affect the dynamics of the economy's output. Finally, the increase in uncertainty causes a worsening of the fiscal scenario in the first period after the shock. This behavior can be explained by the reduction in tax revenues linked to components of aggregate demand, which had their respective trajectories negatively influenced by the uncertainty shock, thus resulting in an increase in public debt.

5.4 Robustness analysis

The present section aims to evaluate the robustness of the results discussed in the previous section, thus, the model was estimated again considering some changes in its specification. Thus, the signal restrictions were relaxed for less restricted models (k = 2 and 1) in order to verify whether the responses found are sensitive to the restrictions. The figures referring to the impulse response function of these models (Figures 11 and 12) are available on Appendix C.

In general, the results of the new estimated models did not show significant changes in relation to those presented in the previous section, remaining also in line with the results of the theoretical model. In other words, due to a shock of macroeconomic uncertainty, there was a contraction in consumption, accumulation of capital, labor and, finally, the product of the economy and an increase in public debt.

6 Concluding remarks

This monograph sought to investigate the effects of increased uncertainty on the real and fiscal variables of the economy, taking into account the adoption of a fiscal rule. First,



based on the natural language processing, an indicator of macroeconomic uncertainty for Brazil was developed, based on techniques of Textual Sentiment Analysis of the Monthly Public Debt Reports, released by the National Treasury. Subsequently, in order to investigate the effects of an increase in macroeconomic uncertainty on the economy, an artificial economy (DSGE model) was built, taking into account the adoption or not of a spending rule.

he results, both by the theoretical and the empirical approach, point to the contractionary effects of an uncertainty shock on the dynamics of the economy, causing a contraction of consumption, capital accumulation and employment and, consequently, a drop in aggregate demand which has a negative impact on the domestic output of the economy. Concomitantly, the reduction in government revenues associated with the taxation of components of aggregate demand and the countercyclical use of public spending leads to a deficit in the government budget, implying an increase in government liabilities.

These results help to explain the negative results observed in the Brazilian economy in the recent period, due to the increased uncertainty arising from the Covid-19 pandemic. It is important to emphasize that this performance could be worse, if there was no anchorage or ceiling for public spending. As observed in the DSGE model, the adoption of this rule reduced the uncertainty contractionary effects on public accounts. However, under the circumstances of increased uncertainty, failure to comply with the spending rule stipulated by EC No. 95/2016, becomes a subject of active debate, both from an economic and a social perspective.

It is important to emphasize that the main contributions of this work, in regard to public finances, can be summarized in two complementary aspects. First, by developing an indicator of macroeconomic uncertainty, it provides inputs for decision making both in the current scenario and in future perspectives. Second, by investigating and pointing out the effects of increased uncertainty on the real and fiscal variables of the economy in a structural model, showing that increased uncertainty negatively affects both economic activity and public accounts and that the adoption of a fiscal rule can reduce the adverse effects of increased uncertainty on public accounts. Taken as a whole, this discussion can have positive effects by contributing to better planning and consolidation of fiscal policy in times of uncertainty.

For future research, with regards to the uncertainty indicator construction, we suggest the specific dictionary temporal optimization through machine learning techniques, in order to



increase indicator accuracy. In addition, the index can be constructed based on more than one report, becoming an indicator of economic policy uncertainty built through a mix of reports, such as debt and COPOM minutes, for example. In addition, we intend to analyze the effects of economic uncertainty in scenarios that take into account different public debt maturity structures. In this sense, it is expected that the uncertainty shock will also affect the term structure of the interest rate and the dynamics of the spread between short and long term interest.



Bibliography

BAKER, S. R.; BLOOM, N.; DAVIS, S. J. Measuring Economic Policy Uncertainty*. **The Quarterly Journal of Economics**, v. 131, n. 4, p. 1593–1636, nov. 2016.

BARBOSA, R. B. **Impacto de Choques de Incerteza sobre a Situação Fiscal no Brasil**. Brasília: Secretaria do Tesouro Nacional (XXIII Prêmio Tesouro Nacional), 2018.

BARBOZA, R. D. M.; ZILBERMAN, E. Os Efeitos da Incerteza sobre a Atividade Econômica no Brasil. **Revista Brasileira de Economia**, v. 72, n. 2, p. 144–160, 2018. ISSN 0034-7140.

BARRO, R. J. Are government bonds net wealth? Journal of political economy, **The University of Chicago Press**, v. 82, n. 6, p. 1095–1117, 1974.

BASU, S.; BUNDICK, B. Uncertainty Shocks in a Model of Effective Demand. **Econometrica**, v. 85, n. 3, p. 937–958, 2017. ISSN 0012-9682.

BERNANKE, B. S.; GERTLER, M.; GILCHRIST, S. The financial accelerator in a quantitative business cycle framework. **Handbook of Macroeconomics**, v. 1, n. PART C, p. 1341–1393, 1999.

BLANCHARD, O. **Fiscal Dominance and Inflation Targeting**: Lessons From Brazil. 46p. Working Paper, 2004.

BLOOM, N. The Impact of Uncertainty Shocks. **Econometrica**, v. 77, n. 3, p. 623–685, 2009.

BLOOM, N. *et al.* Really Uncertain Business Cycles. **Econometrica**, v. 86, n. 3, p. 1031–1065, 2018.

BORN, B.; PFEIFER, J. Policy risk and the business cycle. Journal of Monetary Economics, v. 68, p. 68–85, 2014. ISSN 03043932.

BANCO CENTRAL DO BRASIL. Relatório de Inflação - Boxe: Condicionamentos internamente consistentes para câmbio, incerteza econômica e risco-país. Brasília: **Banco Central do Brasil**, v. 20, n. 1, p. 73–75, 2018.

_____. Relatório de Inflação - Boxe: Incerteza e atividade econômica. Brasília: **Banco Central do Brasil**, v. 21, n. 3, p. 59–63, 2019.

BRASIL. **Emenda Constitucional Nº 95**, de 15 de dezembro de 2016. Altera o Ato das Disposições Constitucionais Transitórias, para instituir o Novo Regime Fiscal, e dá outras providências. Brasília: [s.n.], 2016.



BROOKS, S. P.; ROBERTS, G. O. Convergence assessment techniques for Markov chain Monte Carlo. **Statistics and Computing**, Springer, v. 8, n. 4, p. 319–335, 1998.

CALVO, G. A. Staggered prices in a utility-maximizing framework. **Journal of monetary Economics**, Elsevier, v. 12, n. 3, p. 383–398, 1983.

CARRIÈRE-SWALLOW, Y.; CÉSPEDES, L. F. The impact of uncertainty shocks in emerging economies. **Journal of International Economics**, v. 90, n. 2, p. 316–325, jul. 2013. ISSN 00221996.

CASTRO, M. R. *et al.* SAMBA: Stochastic analytical model with a bayesian approach. **Brazilian Review of Econometrics**, v. 35, n. 2, p. 103–170, 2015.

CAVALCANTI, M. A. *et al.* The macroeconomic effects of monetary policy shocks under fiscal rules constrained by public debt sustainability. **Economic Modelling**, v. 71, p. 184–201, apr. 2018.

CAVALCANTI, M. A. F. H.; VEREDA, L. Fiscal Policy Multipliers in a DSGE Model for Brazil. **Brazilian Review of Econometrics**, v. 35, n. 2, p. 197, 2015.

CHISHOLM, E.; KOLDA, T. G. New term weighting formulas for the vector space method in information retrieval. Technical Report, [S.1.], 1999.

COSTA, C. Understanding DSGE models: Theory and Applications. Vernon Press, 2018.

DICKEY, David A.; FULLER, Wayne A. Distribution of the estimators for autoregressive time series with a unit root. **Journal of the American statistical association**, v. 74, n. 366a, p. 427-431, 1979.

FAVERO, C.; GIAVAZZI, F. Inflation Targeting and Debt: Lessons from Brazil. Working Paper, 2004.

FLESCH, R. A new readability yardstick. **Journal of Applied Psychology**, v. 32, n. 3, p. 221–233, 1948.

FRASCAROLI, B. F.; NOBREGA, W. C. L. Inflation Targeting and Inflation Risk in Latin America. **Emerging Markets Finance and Trade**, Routledge, v. 55, n. 11, p. 2389–2408, 2019.

GALÍ, J. **Monetary Policy, Inflation, and the Business Cycle**: An Introduction to the New Keynesian Framework. Princeton: Princeton University Press, 2008. 216 p.

GODEIRO, L. L.; LIMA, L. R. R. d. O. Measuring Macroeconomic Uncertainty to Brasil. **Economia Aplicada**, v. 21, n. 2, p. 311, 2017.



JESUS, D. P. de; BESARRIA, C. D. N.; MAIA, S. F. The macroeconomic effects of monetary policy shocks under fiscal constrained: An analysis using a DSGE model. **Journal of Economic Studies**, v. 47, n. 4, p. 805–825, 2020.

JURADO, K.; LUDVIGSON, S. C.; NG, S. Measuring Uncertainty. American Economic Review, v. 105, n. 3, p. 1177–1216, mar. 2015.

KRAUSE, M. U.; MOYEN, S. Public Debt and Changing Inflation Targets. American Economic Journal: Macroeconomics, v. 8, n. 4, p. 142–176, oct. 2016.

KWIATKOWSKI, D. et al. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? **Journal of econometrics**, Elsevier, v. 54, n. 1-3, p. 159–178, 1992.

LIM, G. C.; MCNELIS, P. D. Macroeconomics at the Zero Lower Bound: QuasiFiscal Monetary Policy vs. Quasi-Monetary Fiscal Policy. Working Paper, 2015.

LOUGHRAN, T.; MCDONALD, B. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. **The Journal of Finance**, **Wiley Online Library**, v. 66, n. 1, p. 35–65, 2011.

MONTES, Gabriel Caldas; NICOLAY, Rodolfo Tomás da Fonseca; ACAR, Tatiana. Do fiscal communication and clarity of fiscal announcements affect public debt uncertainty? Evidence from Brazil. **Journal of Economics and Business**, v. 103, p. 38-60, 2019.

NOBREGA, W. C. L.; MAIA, S. F.; BESARRIA, C. D. N. Interação entre as Políticas Fiscal e Monetária: uma Análise sobre o Regime de Dominância Vigente na Economia Brasileira. **Análise Econômica**, v. 37, n. 74, p. 7–34, 2020.

PASTORE, A.; GAZZANO, M.; PINOTTI, M. **Inflação e Crises**: O Papel da Moeda. 1. ed. [S.l.]: Elsevier Brasil, 2014.

PHILLIPS, P. C. B.; PERRON, P. Testing for a unit root in time series regression. **Biométrika**, v. 75, n. 2, p. 335–346, 1988. ISSN 00063444.

SALTON, G.; WONG, A.; YANG, C. A Vector Space Model for Automatic Indexing. **Communications of the ACM**, v. 18, n. 11, p. 613–620, 1975.

SARGENT, T. J.; WALLACE, N. Some Unpleasant Monetarist Arithmetic. Federal Reserve Bank of Minneapolis Quarterly Review, v. 5, n. 3, p. 1–17, 1981.

SCHMITT-GROHÉ, S.; URIBE, M. Closing small open economy models. Journal of international Economics, Elsevier, v. 61, n. 1, p. 163–185, 2003.



SILVA, M. E. A. da; BESSARIA, C. D. N. Política Monetária e Preço dos Imóveis no Brasil: Uma Análise a partir de um Modelo DSGE. **Revista Brasileira de Economia**, v. 72, n. 1, p. 117–143, 2018.

SILVA, P. H. N.; BESARRIA, C. D. N.; SILVA, M. D. d. O. P. da. **Mensurando o sentimento de incerteza da política econômica**. São Paulo: ANPEC - Associação Nacional dos Centros de Pós-Graduação em Economia, 2019.

SIMS, C. A. Macroeconomic and Reality. Econometrica, v. 48, p. 1–48, 1980.

SUH, H. **Macroprudential Policy**: Its Effects and Relationship to Monetary Policy. FRB of Philadelphia working paper, 2012.

TAYLOR, John B. iDiscretion versus Policy Rules in Practice, **j Carnegie Rochester Conference Series on Public Policy**, December, v. 39, p. 195-214, 1993.

UHLIG, H. What are the effects of monetary policy on output? Results from an agnostic identification procedure. **Journal of Monetary Economics**, v. 52, n. 2, p. 381–419, mar. 2005.

ZIVOT, E.; ANDREWS, D. W. K. Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. **Journal of Business & Economic Statistics**, v. 10, n. 3, p. 251–270, 1992. ISSN 0735-0015.



Appendix A - Public debt-specific dictionary

A.1. 1-Grams

almost; alteration; alterations; anticipate; anticipated; appear; appeared; appearing; approximate; approximately; assumed; assuming; assumption; contingency; exposure; fluctuated; fluctuations; may; might; nearly; possibilities; possible; possibly; predictability; preliminary; revised; risk; risks; roughly; somewhat; suggesting; suggests; variation; variations; varied; varying; volatile; volatility; deficit; economic; economy; reform; regulation; repurchase; renegotiation; exposure; default; rollover.

A.2. 2-Grams

additional costs; agrarian debt; bonds renegotiation; concentrating; maturities; concentration maturities; concentration maturity; cost appreciation; cost increased; cost increases; costs rose; credit default; debt exceeded; debt increase; debt increased; debt refinancing; debt renegotiation; increased cost; increased costs; inflation increased; maturing loss; maturing lower; maturity drop; maturity loss; maturity lost.

A.3. 3-Grams

agrarian debt renegotiation; average cost increased; average cost increases; average cost shifted; average maturity declined; average maturity decreased; average maturity diminished; average maturity dropped; average maturity shifted; average term dropped; exchange exposure increased; featuring shorter maturities; featuring smaller average; federal debt increased; floating rate increased; outstanding debt increased; rolled exclusively swaps; short term variations.



APPENDIX B - Trajectory and econometric tests applied to the time series used in the SVAR model



Figure 10 - Trajectory of the SVAR model variables



	Table 7 - Descriptive statistics of variables							
	CONS.	DEBT	GFCF	LABOR	MUI	CPI (DUTPUT	SELIC
Mean	230823.71	41.53	54375.01	302.84	6.25	0.45	276418.98	11.62
S.D.	29013.11	7.38	9772.25	23.20	1.70	0.21	28399.12	3.46
V.C.	12.57	17.77	17.97	7.66	27.20	47.52	10.27	29.76
Median	243633.40	41.11	52580.16	302.70	6.07	0.44	289756.70	11.22
Max	265021.20	54.30	71696.99	335.60	11.88	1.10	311701.10	19.69
Min	172984.50	30.38	38728.43	252.80	3.59	-0.04	218159.10	6.40
Kurtosis	-1.00	-1.31	-1.1	5 -0.68	8 1.33	0.68	-0.8	5 -0.27
Asymmetry	-0.69	0.07	0.1	1 -0.54	1.03	0.37	-0.72	2 0.43

Source: Elaborated by the authors.

Table 8 - Unit root tests (ADF, PP, KPSS)

Variable	ADF Statistic	ADF Critical Value	Statistic PP	PP Critical Value	Statistic KPSS	KPSS Critical Value	Result
GDP	-2.141	-2.89	-2.569	-2.91	0.551	0.463	Unit Root
SELIC	-3.167	-2.89	-1.25	-2.91	0.399	0.463	Unit Root
СРІ	-3.776	-2.89	-6.134	-2.91	0.142	0.463	Stationary
LABOR	-0.919	-2.89	-0.641	-2.91	0.17	0.463	Unit Root
MUI	-3.012	-2.89	-3.588	-2.91	0.204	0.463	Stationary
GFCF	-1.81	-2.89	-1.855	-2.91	0.284	0.463	Unit Root
CONSUM.	-2.854	-2.89	-2.834	-2.91	0.589	0.463	Unit Root
DEBT	-0.866	-2.89	-1.420	-2.91	0.186	0.463	Unit Root

Source: Elaborated by the authors.



Variable	Statistic	Critical	Break	Results
	ZA	Value		
GDP	-2.9657	-4.42	2011Q1	Non Stationary
SELIC	-2.1582	-4.42	2006Q4	Non Stationary
СРІ	-7.0098	-4.42	2015Q3	Stationary with Break
LABOR	-2.9333	-4.42	2014Q3	Non Stationary
MUI	-3.2335	-4.42	2004Q2	Non Stationary
GFCF	-2.9856	-4.42	2011Q2	Non Stationary
CONSUM.	-3.1702	-4.42	2011Q2	Non Stationary
DEBT	-4.0497	-4.42	2014Q1	Non Stationary

Table 9 - Unit root with structural break tests

Source: Elaborated by the authors.







(*) Note: Restrictions were imposed for a period (k = 1). The three lines corresponding to: quantile 16.00%, median and quantile 16.00% of the posterior distribution, respectively. The SVAR model was estimated with one (1) lag.

Figure 12 - Impulse-response function of the model with signal restriction (k = 2)





(*) Note: Restrictions were imposed for a period (k = 2). The three lines corresponding to: quantile 16.00%, median and quantile 16.00% of the posterior distribution, respectively. The SVAR model was estimated with one (1) lag.