Macroeconomic uncertainty and its fiscal effects: an analysis from natural language processing and dynamic stochastic general equilibrium models (DSGE)

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Resumo

Este artigo tem como objetivo mensurar a incerteza macroeconômica no Brasil e avaliar os efeitos de choques de incerteza em uma economia com regras fiscais. Esses objetivos foram alcançados por meio de três etapas complementares. Primeiramente, utilizamos uma técnica de aprendizado de máquina para estimar um indicador de incerteza com base na comunicação do Tesouro Nacional. Em seguida, analisamos os efeitos de choques de incerteza em uma economia com regras fiscais por meio de um modelo DSGE. Na última etapa, usamos nosso indicador como *proxy* de incerteza e as relações estruturais da economia (modelo DSGE) para gerar um esquema de identificação para estimar um modelo SVAR. Nossos achados apontam para uma influência considerável da adoção de regras fiscais no controle dos efeitos adversos da incerteza macroeconômica sobre o endividamento público.

Palavras-chave: Processamento de Linguagem Natural. Mineração de Texto. Incerteza Macroeconômica. DSGE.
JEL Code: C02, C63, E62, H63

Abstract

This paper aims to measure macroeconomic uncertainty in Brazil and assess the effects of uncertainty shocks in an economy with fiscal rules. These objectives were achieved through three complementary steps. First, we used a machine learning technique to estimate an uncertainty indicator based on the communication of the National Treasury. Then, we analyzed the effects of uncertainty shocks in an economy with fiscal rules through a DSGE model. In the last step, we used our indicator as uncertainty proxy and the structural relations of the economy (DSGE model) to generate an identification scheme to estimate a SVAR model. Our findings point to a considerable influence of fiscal rule adoption in controlling the adverse effects of macroeconomic uncertainty on public indebtedness.

Keywords: Natural Language Processing. Text Mining. Macroeconomic Uncertainty. DSGE.
JEL Code: C02, C63, E62, H63

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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 production factors. Other studies have investigated uncertainty using econometric techniques (Jurado et al., 2015) and even using alternative approaches based on the estimation of feeling based from textual analysis (Baker et al., 2016; Montes et al., 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 policy[1] conduct behavior, promoting economic uncertainty increase. Since then, there has been an increase in surveys related to fiscal policy conduct and increased uncertainty in Brazil.

Regarding studies on fiscal policy conduction, we highlight the work of Cavalcanti et al. (2018) and de Jesus et al. (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 (BRASIL, 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 with the works of Godeiro and Lima (2017); Barboza and Zilberman (2018); Barbosa (2018); Silva et al. (2019) and Montes et al. (2019). 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 (BACEN, 2018); (BACEN, 2019), reinforces the importance 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 literature.

That said, we developed the Macroeconomic Uncertainty Indicator (MUI) for the Brazilian economy using text mining and sentiment analysis techniques, based on the vector space model

[1] At this point, according to Pastore et al. (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, fact also corroborated by the study carried out by Frascaroli and Nobrega (2019).

[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.

approach, using a specific dictionary to the public debt context, composed of unigrams, bigrams and trigrams[3]. In this context, the process of extracting and parameterizing the information collected in sentiment analysis is based on machine learning and is grounded on specific economic analysis dictionaries. In general, the indicator 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 (EUI-BR), proposed by the Getulio Vargas Foundation (FGV) and the Economic Policy Uncertainty Index (EPU), developed by Baker et al. (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 paper 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

[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".

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 a whole, this discussion can generate 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 lays out the methodology used to construct the proposed uncertainty index; section 3 briefly 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[4]; in section 4, the empirical exercise performed is presented, using the indicator constructed as a proxy for economic uncertainty; finally, in section 5 the final considerations and discussions are carried out. Additionally, the work has an Appendices section, where additional information is available.

2 Development of the macroeconomic uncertainty index (MUI)

The elaboration of the Macroeconomic Uncertainty Index (MUI) is based on the Vector Space Model[5], developed by Salton et al. (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:

$$\mathrm{L}_{i,j}\ \mathrm{G}_i\ N_j \tag{1}$$

where $\mathrm{L}_{i,j}$ 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.

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:

$$\mathrm{P}_{i,j} = \begin{cases} \frac{1+\log(\mathrm{T}f_{i,j})}{1+\log(\alpha_j)} \times \log\frac{N}{\mathrm{d}f_i}, & \text{if} \quad \mathrm{T}f_{i,j} \geq 1, \\ 0, & \text{if} \quad \mathrm{T}f_{i,j} = 0 \end{cases} \tag{2}$$

where $\mathrm{P}_{i,j}$ denotes the weight of the i-th n-gram in the j-th document; $\mathrm{T}f_{i,j}$ is the total occurrences of the word/sentence i in a j document; $\alpha_{i,j}$ denotes the mean of terms[6] registered in the j-th

[4] Due to page limit establish by the conference rules, we choose to omit the DSGE model description which can be made available under solicitation.

[5] *Vector Space Model* - algebric model of textual documents representation.

[6] 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: $\alpha_j = \frac{1}{n}\sum_{i=1}^{n} fP_j$.

document; N is the total number of documents in the sample and, finally, df_i counts 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:

$$\mathrm{MUI}_j = \sum_{j=1}^{N} P_{i,j} \tag{3}$$

where MUI_j denotes the textual feeling of the j-th text and $\mathrm{P}_{i,j}$ 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.

2.1 Textual estimation procedure

The Macroeconomic Uncertainty Index was built based on the Federal Public Debt Monthly Reports[7], available on the website of the tax authority, that is, the National Treasury[8]. 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 publications[9] 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)[10]. Thus, the sample used for the construction of the macroeconomic uncertainty indicator[11] is composed of 204 monthly observations, which cover the period between April 2003 and March 2020.

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. 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.

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

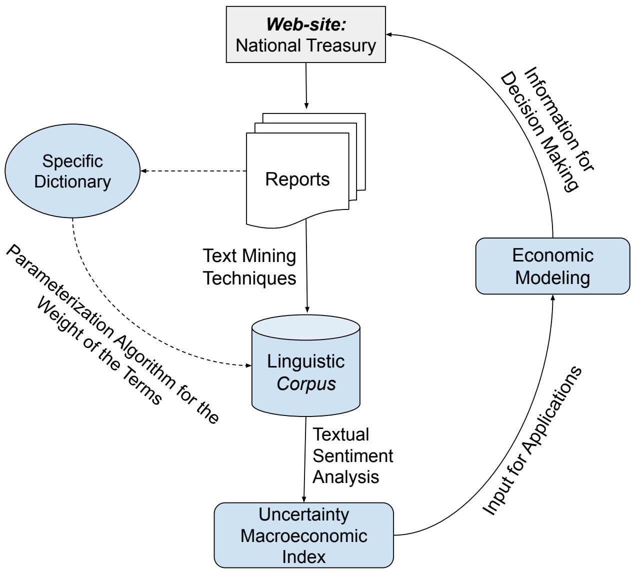
[8] The monthly public debt reports are available in *Portable Document Format* (PDF) on the *site* of the National Treasury, more specifically: `http://www.tesouro.fazenda.gov.br/en/monthly-debt-report`.

[9] The National Treasury also publishes an annual version of the Debt Report, available at: `http://www.tesouro.fazenda.gov.br/en/annual-debt-report`.

[10] The word lists for Sentiment Analysis from Loughran and McDonald (2011) are available at: `https://sraf.nd.edu/textual-analysis/resources/`.

[11] It is important to note that in the analysis period, there were changes in the *layout*. Specifically, changes to the *layout* occurred in: March 2004, January 2007, January 2011 and January 2015. However, these changes did not affect the efficiency of the process of estimation.

Figure 1 – Flowchart of the Textual Estimation Process



Source: Elaborated by the Authors.

Firstly, it was necessary to import the contents of the reports into the internal memory of the statistical *software*[12]. Then, a more refined treatment of the text content contained in the reports was carried out. In this step double spaces, stop words[13], punctuation, numbers, line breaks, page breaks and paragraph marks were removed. We also carried out the standardization of all characters to lowercase. 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.

Subsequently, weights were calculated for the terms, according to the algorithm described in Equation 2 in subsection 2.1. Then, the interpolation of the series generated from a simple arithmetic mean was applied, resulting in 68 quarterly observations. Finally, in order to mitigate volatility in the series trajectory, the exponential smoothing was used following the Holt-Winters method.

2.2 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

[12] In all stages of this work (except for the DSGE model in which the Dynare was used), the *software* R was used through its Integrated Development Environment (IDE), the R-*studio*.

[13] 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.

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:

$$\mathrm{S}_i = \sum_{i=1}^{N} \mathrm{T}_i \tag{4}$$

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) can be described using the following process:

$$\begin{cases} \text{If } \mathrm{S}_i \geq 2, & \mathrm{T}_i \in \mathrm{D}, \\ \text{If } 0 \geq \mathrm{S}_i < 2, & \mathrm{T}_i \notin \mathrm{D} \end{cases} \tag{5}$$

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.

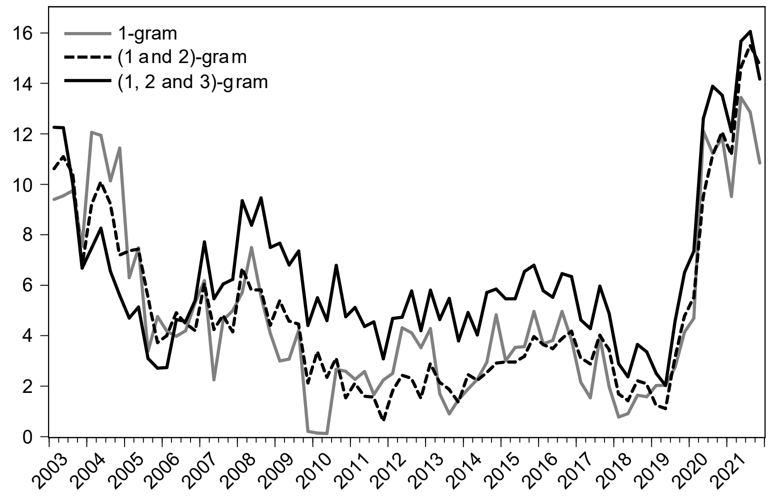
The final dictionary consisted of 90 n-grams, of which 53 were unigrams (58.89%), 19 bigrams (21.11%) and 18 trigrams (20.00%). Among the unigrams, 38 (71.70%) were extracted from the dictionary of Loughran and McDonald (2011). The list of specific unigrams, bigrams and trigrams used in the present research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

2.3 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 2 presents the temporal evolution of the Macroeconomic Uncertainty Indicator (MUI) constructed sequentially (*step-by-step*) from the dictionary proposed in the present research.

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.

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



Source: Elaborated by the Authors.

In general, it is possible to note that the indicators share the same trend, with emphasis on the years: 2003-2004, 2009-2010, 2015-2019 and 2020-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 et al. (2014), Godeiro and Lima (2017), Frascaroli and Nobrega (2019), Nobrega et al. (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)[14]. 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 subprime 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 et al. (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 Roussef[15], showing this behavior until the year following the then president *impeachment*. The upward trajectory is attenuated during the government of President Michel Temer[16], due to his signaling for reforms aimed at reducing the size of the government and consequently, of

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

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

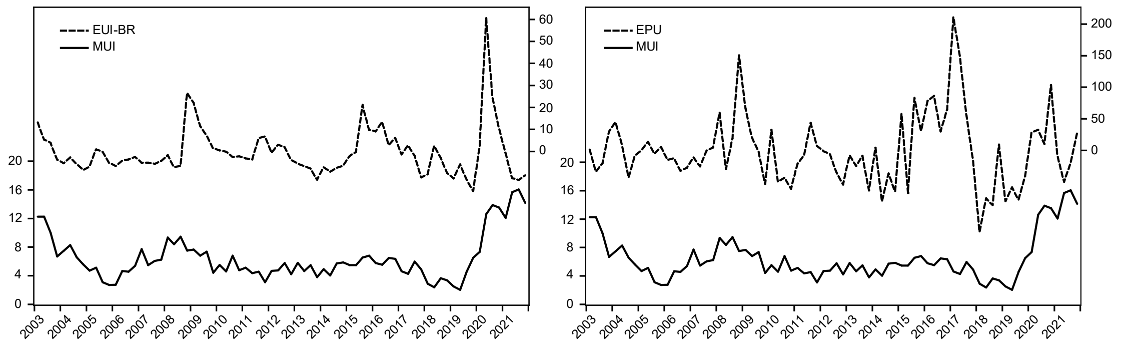
[16] Mandate: August 31, 2016 - January 1, 2019.

public spending on the economy, with emphasis on the Ceiling of Public Spending (EC No. 95/2016) and labor reform. The trajectory started in the previous government continues during the term of the current president, Jair Messias Bolsonaro[17], 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 sudden 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 sharp rise in unemployment. Over the 2021, the uncertainty perception was deepened due to the changes made on Brazil's fiscal rule through the Constitutional Amendment No. 23/2021, which gave space for some expenses to not follow the fiscal rule, rising the uncertainty about the maintenance of the rule and also fiscal sustainability.

For comparison purposes, Figure 3 compares the main indicators of economic uncertainty developed for Brazil, the Economy Uncertainty Indicator (EUI-BR) estimated by the Getulio Vargas Foundation (FGV) and the Economic Policy Uncertainty Index (EPU)[18] Developed by Baker et al. (2016), and the uncertainty indicator built in the present work.

Figure 3 – Comparison of the Macroeconomic Uncertainty Indicator (MUI) with others Uncertainty Indicators for Brazil



Source: Elaborated by the Authors.
Note: The series were smoothed using the Hodrick-Prescott 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, MUI showed greater intensity compared to IIPE-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 I present the estimates of the coefficient of correlation of Pearson. This measure provide a first empirical evidence of the relationship between the uncertainty and some real aggregate

[17] Mandate: January 1, 2018 - Current.
[18] Available for consultation at: https://www.policyuncertainty.com/brazil_monthly.html.

variables of the economy.

Table I – 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 IV.

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 suggest 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 et al. (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.

3 Theoretical Model

In this section, a briefly description of the theoretical model (DSGE)[19] is made to justify the signal restrictions imposed on the empirical model (section 4). 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.

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 a efficient way.

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.

3.1 Theoretical model results

3.1.1 Effect of an uncertainty shock on macroeconomic variables

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

[19] Due to page limit establish by the conference rules, we choose to omit the DSGE model description which can be made available under solicitation.

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)):

$$\log(A_t) = (1 - \rho_A)\log(A_{ss}) + \rho_A \log(A_{t-1}) + \sigma_{A_t}\varepsilon_t^A \tag{6}$$

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

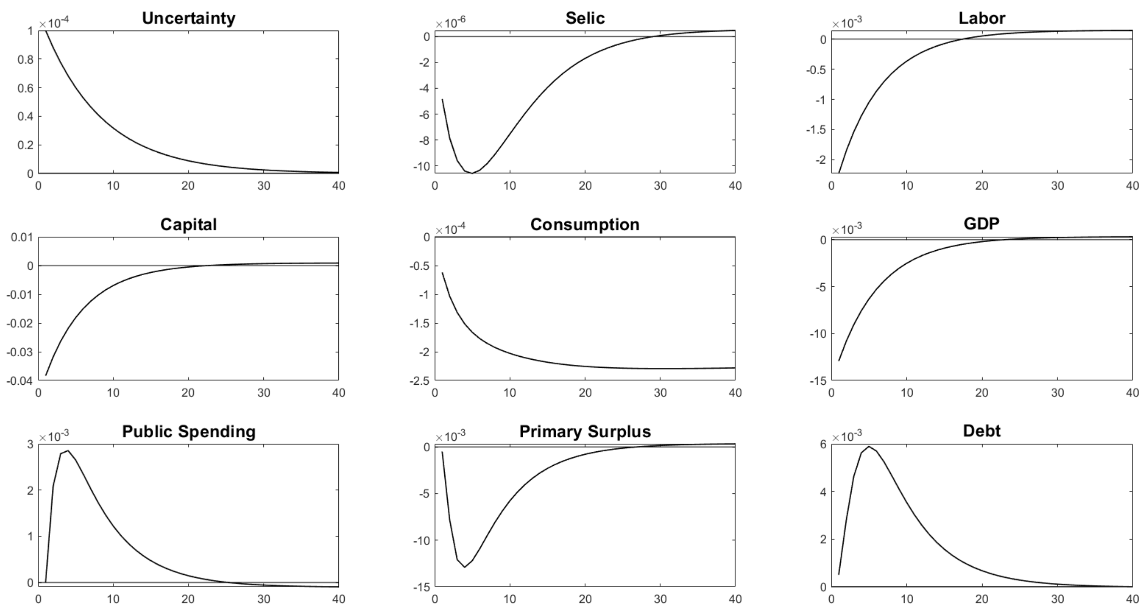
$$\log(\sigma_{a,t}) = (1 - \rho_{\sigma_a})\log(\sigma_a) + \rho_{\sigma_a}\log(\sigma_{a,t-1}) + \varepsilon_t^{\sigma_a} \tag{7}$$

where $\varepsilon_t^{\sigma_a}$ is a $iid \sim (0, \sigma_a)$ process and ρ_{σ_a} denotes the persistence of shock of uncertainty.

It is worth mentioning that the theoretical response will serve as a basis for imposing the signal restrictions of the empirical model. Figure 4 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 4 – 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 counter-cyclical 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.

3.1.2 Uncertainty shock under fiscal constraint

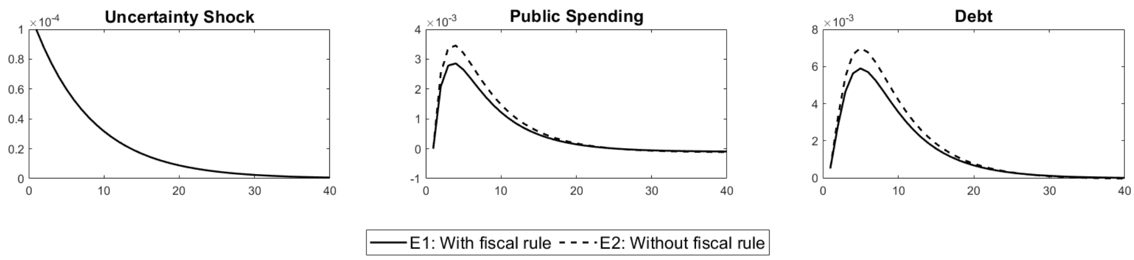
This section aims to carry out a comparative exercise of the effects of macroeconomic uncertainty shocks on public accounts, taking into account two scenarios in the conduct of fiscal spending policy: First, with the adoption of a public spending rule; second, we consider the scenario in which there 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 de Jesus et al. (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:

$$G_t = (1 + \pi_{t-1})\ G_{t-1} \tag{8}$$

Figure 5 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 5 – Theoretical model variable response function as a result of uncertainty shock under fiscal restriction



Source: Elaborated by the Authors.

The results in Figure 5 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 de Jesus et al. (2020), these results corroborate the importance of adopting spending rules to tune down the shock effects on the public debt level.

3.1.3 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 8) 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:

$$\sigma_i = \frac{1}{50} \times \sum_{t=0}^{50} \beta^t \left(\frac{\partial X_{t+j}}{\partial e_t} \right)^2 \tag{9}$$

Table II 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.

Table II – Effects of the fiscal rule on public debt and spending volatilities

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%

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.

4 Empirical Model

4.1 Identified VAR Model with Signal Restriction

Given the endogeneity between the variables of the model, the method adopted is the Autoregressive Vectors (VAR) model, proposed by Sims (1980). Consider the following multivariate structural autoregressive model [20]:

$$AX_t = \sum_{i=1}^{p} A_i X_{t-p} + \epsilon_t \qquad \forall\, t \;=\; 0,\; 1,\; \ldots,\; T \tag{10}$$

where X_t is a column vector of endogenous variables, A is a $n \times n$ 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 $iid\ (0, \sigma)$ process. Assuming that the A matrix of the structural representation of the VAR (Equation 10) is non-singular, then the reduced form VAR model can be obtained by pre-multiplying the Equation 10 by A^{-1}, obtaining:

$$X_t = \sum_{i=1}^{p} B_i X_{t-p} + u_t \qquad \forall\, t \;=\; 0,\; 1,\; \ldots,\; T \tag{11}$$

[20] In 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.

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

To retrieve the information from the primitive system (10), by estimating the reduced model (11), 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 imposing restrictions[21] 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 10), 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 10, with this, the problem becomes the determination of the vector α associated with the vector m-dimensional, so that :

$$\alpha = \tilde{A}\alpha \tag{12}$$

where α is a A column called the impulse vector Uhlig (2005), containing the contemporary responses of the n-endogen variables to a given shock.

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

$$r_\alpha = \sum_{i=1}^{m} \alpha_i r_i(k) \tag{13}$$

Equation 13 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 III was extracted from the structural response of the theoretical model developed in section 3.

Table III – Signal Restrictions Imposed on Structural Responses

Variable	**Uncertainty Shock**
Uncertainty	"+"
Interest Rate	"-"
Inflation	"?"
Labor	"-"
Capital	"-"
Consumption	"-"
Debt	"+"
Output	"?"

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

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

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.

4.2 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 (IPC) 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 IV presents the description of the data series used in this research.

Table IV – Description of the dataset used in the research

Series	**Description**	**Unit of Measurement**	**Source**
MUI	Macroeconomic Uncertainty	Index	Elaborated by the Authors
CONSUMPTION	Consumption of Government + Famílias	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	BCB
WORK	Hours Worked in Industry	Index	IPEA
DEBT	Public Sector Net Debt	(%) per year, accumulated	BCB
CPI	Consumer Price Index (Inflation)	(%) per year, accumulated	IPEA

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[22], 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

[22] Due to page limit establish by the conference rules, we choose to omit the tables of unit roots result, which can be made available under solicitation.

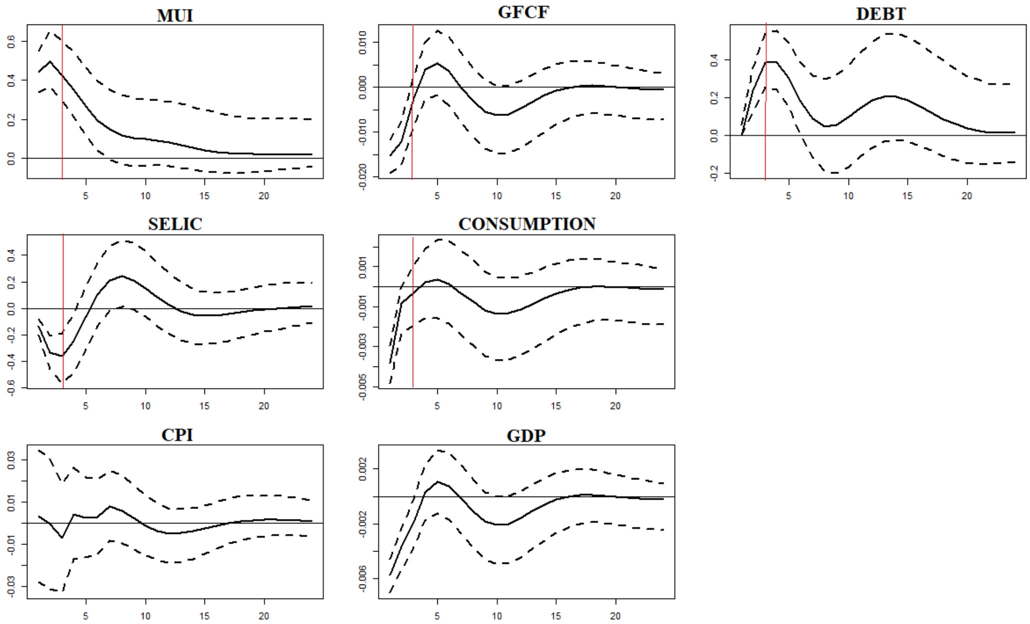
root test with structural break. Therefore, it was decided to use the Hodrick-Prescott (HP)[23] in order to eliminate deterministic terms from these, turning them into deviations in relation to the trend.

4.3 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). In the present exercise, the macroeconomic uncertainty indicator developed and exposed in section 2 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 3.

Figure 6 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.

Figure 6 – 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.

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.

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

[23] The parameter *lambda* used in the HP filter was the standard for quarterly series, that is: $\lambda = 1,600$.

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.

4.4 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 $k = 1$) 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 7a and 7b) are available on Appendix B.

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.

5 Final Considerations

This paper 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.

The 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 counter-cyclical 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. In this sense, over the year of 2021, the uncertainty perception was deepened due to the changes made on Brazil's fiscal rule through the Constitutional Amendment No. 23/2021, which gave space for some expenses to not follow the fiscal rule, rising the uncertainty about the maintenance of the rule and also fiscal sustainability.

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.

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APPENDIX A – Dictionary

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.

2 2-grams

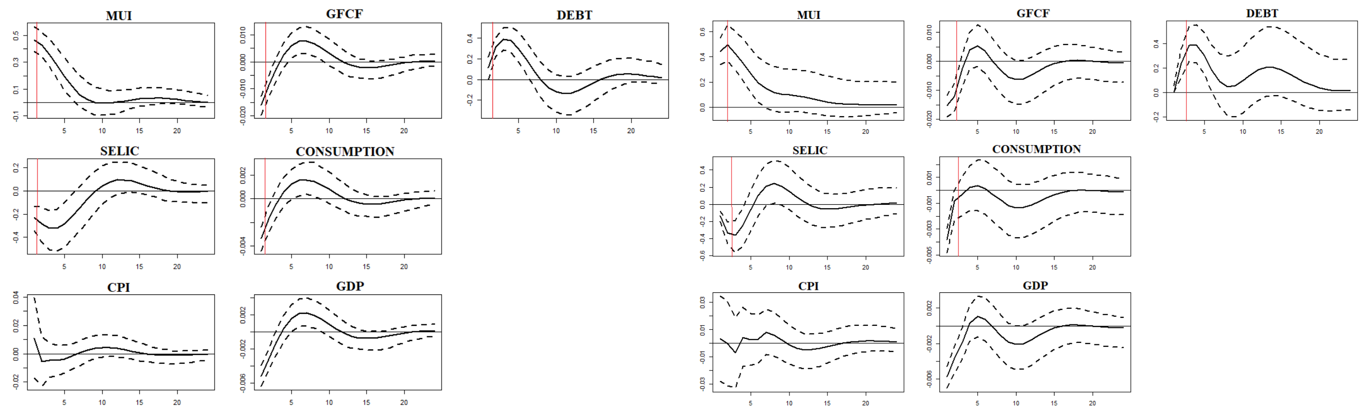
additional costs; agrarian debt; bonds renegotiation; concentrating; maturities; concentration maturities; concentration maturity; cost appreciation; cost increased; cost increases; costs rose; credit default; debt exceeded; debt increase; debt increased; debt refinancing; debt renegotiation; increased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

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 – Robustness Analysis

Figure 7 – Robustness Analysis - Impulse Response Function of the Model with Signal Restriction



(a) $k = 1$ (b) $k = 2$

(*) Note: The restrictions were imposed for three periods ($k = 2$). 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.