Pontifícia Universidade Católica do Rio de Janeiro

Renata Carreiro Avila

Fiscal Policy Risk and the Yield Curve: an Alternative Measure

Dissertação de Mestrado

Dissertation presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor : Prof. Carlos Viana de Carvalho
Co-advisor: Prof. Marcelo Cunha Medeiros

Rio de Janeiro
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Abstract

Carreiro Avila, Renata; Viana de Carvalho, Carlos (Advisor); Cunha Medeiros, Marcelo (Co-Advisor). **Fiscal Policy Risk and the Yield Curve: an Alternative Measure**. Rio de Janeiro, 2023. 52p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Does fiscal policy risk affect the yield curve in an emerging economy? How can we adequately measure this kind of uncertainty? Exploiting the case of Brazil, we estimate a novel, news-based measure of fiscal policy risk using natural language processing. We show that increases in fiscal policy risk are associated to increases in the levels of long maturities in the yield curve, in the term spread and to a depreciation of the exchange rate. The effects are robust to a series of alternative specifications of the text-based index, suggesting that fiscal risk is a relevant phenomenon in the Brazilian setting.

Keywords

Fiscal Policy; Risk and Uncertainty; Text Data; Yield Curve.

Resumo

Carreiro Avila, Renata; Viana de Carvalho, Carlos; Cunha Medeiros, Marcelo. **Risco Fiscal e Curva de Juros: uma Medida Alternativa**. Rio de Janeiro, 2023. 52p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Risco fiscal afeta a curva de juros no contexto de economias emergentes? Como medir adequadamente esse tipo de risco? Explorando o caso do Brasil, estimamos uma medida alternativa de risco fiscal com base em notícias, utilizando processamento de linguagem de texto. Encontramos que aumento em risco fiscal gera aumento em taxas de juros longas, no prêmio a termo e depreciação na taxa de câmbio. Os efeitos são robustos a uma série de especificações alternativas do índice de risco fiscal, sugerindo que se trata de um fenômeno relevante no cenário brasileiro.

Palavras-chave

Política Fiscal; Risco; Incerteza; Dados de texto; Curva de Juros.

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List of Abreviations

BCB - Central Bank of Brazil
CDS - Credit Default Swap
COPOM - Monetary Policy Committee (Brazil)
LRF - Fiscal Responsibility Law
LDA - Latent Dirichlet Allocation
NLP - Natural Language Processing

1
Introduction

In emerging economies, fiscal policy can be a relevant source of risk and economic uncertainty. The lack of fiscal discipline is often the root of macroeconomic instabilities, with Latin America being a notorious ground for fiscal policy related domestic crisis, materialized in multiple episodes of sovereign debt defaults, increasing fiscal deficits and hyperinflation (Esquivel et al., 2021). Recently, the Covid-19 pandemic has also led to dramatic increases in fiscal spending and debt levels in many countries[1], raising concerns over the impacts that such changes in fiscal regimes may entail to the economy.

In this paper, we undertake an empirical approach to analyze the effects of fiscal policy risk. We estimate a novel measure of fiscal policy risk using textual data from newspaper articles. We exploit the case of Brazil to study the relationship between fiscal policy risk and yield curve movements in an emerging economy, where this source of risk is deemed non-negligible. We find significant relationships between fiscal risk and increases in long-term yields and the term spread, as well as the exchange rate.

Brazil is a prominent example of a country that has recently faced repeated primary deficits and deterioration of public accounts. Despite legal constraints imposed by the Fiscal Responsibility Law (LRF) on both federal and subnational governments as of 2000, the conduction of fiscal policy in the last decades has been marked by instability, worsening of fiscal balances and even government maneuvers to artificially meet fiscal policy targets (Ayres et al., 2021). Since 2014, fiscal policy malfeasance in Brazil has led to the impeachment of a president, the downgrade of the country's sovereign bonds by major rating agencies and record debt levels.

Based on the LRF, the fiscal policy framework in Brazil establishes three main rules mandating the responsible management of public finance: a primary fiscal target set for the year, the "golden debt rule", which forbids public debt issuance to finance current expenses; and the more recent spending cap (Constitutional Amendment n. 95/2016), which limits growth in government spending to the rate of inflation of the previous year. The spending cap was created as an attempt to enhance credibility of the fiscal framework given

[1]IMF Global Debt Database, introduced in Mbaye et al. (2018)

the fragility of the primary budget target, which was altered in 55% of the years since its inception. However, the spending ceiling has also recently lost credibility, with six Constitutional Amendments having been created to exempt some categories of public expenditures from the cap. At the onset of 2023, uncertainty remains over fiscal accounts in Brazil.

Furthermore, the Monetary Policy Committee of the Central Bank of Brazil (BCB) often points, in its minutes and statements, that fiscal policy risk and uncertainty is a relevant determinant of risk premium, asset prices and de-anchoring of inflation expectations. The monetary authority often emphasizes that the fiscal scenario and the sustainability of fiscal policy are taken into account in the balance of risks considered for the monetary policy decisions. In this sense, fiscal policy risk also represents information to market participants that can be channelled, in particular, to movements in longer-term interest rates in the yield curve.

One challenge stands out: fiscal policy risk is an elusive concept and one hard to measure. Despite the importance of the topic in an emerging market setting, there is no clear universal measure of fiscal policy risk or uncertainty in the economic literature. In the case of Brazil, the 5-year Credit Default Swap (CDS) is a traditional measure of country risk, as it represents the premium paid for protection against insolvency of Brazilian sovereign assets. However, the CDS is based on spreads paid on external debt, which comprises no more than 10% of total public debt in Brazil in the last decades, according to the National Treasury Statistics.[2]

In this way, while the CDS is a straightforward proxy for country credit risk and a major driver of the Brazilian yield curve (Fernandes et al., 2021), it may not reflect concerns over domestic fiscal policy and idiosyncratic issues pertaining to it. A similar argument can be made with respect to the Emerging Markets Bond Index Plus - Brazil (*EMBI+Br*), which tracks the spread of actively traded and dollar denominated external debt instruments with respect to US Treasuries of similar maturity.

Another potential source of information on fiscal policy risk are market forecasts and their volatility. In our setting, however, the *Focus* survey of professional forecasters conducted by the BCB collects fiscal policy variables only as year-end aggregates. In addition, there is no ‘top ranking’ incentive associated to the fiscal expectations. This potentially casts doubts on the quality of forecasts and the frequency of their attentive update relative to inflation and interest rate forecasts, for which institutions are ranked each

[2]In the time frame contemplated in the exercises in the next sections, the average share of external debt over total public debt is only 4.92%.

month based on least average error.[3]

We could also consider uncertainty measures to be informative of fiscal policy risk, such as the Economic Policy Uncertainty Index of Baker et al. (2016). Their seminal work has shown that the EPU is significantly related to economic activity, and an equivalent measure is available for Brazil. However, a category-specific index is not available for fiscal policy, thus making the Brazil EPU less adequate to proxy for the particular effect of fiscal policy uncertainty. Nevertheless, we stress that multiple works have found that policy uncertainty impacts economic activity (Born & Pfeifer, 2014; Fernández-Villaverde et al., 2015; Basu & Bundick, 2017), and, in particular, news on economic uncertainty can have significant effects on long-run interest rates in the yield curve (Hansen et al., 2019).

In this paper, we use an alternative data source to measure fiscal policy risk: text data from newspaper articles. In line with the growing economic literature exploring text-based data (Gentzkow et al., 2019), we posit that news are a promising alternative to overcome the aforementioned difficulties. Not only are they available at a higher frequency, but they can contain inherently rich information on the state of the economy and signals of economic sentiment (Nyman et al., 2021; Bybee et al., 2021). Importantly, news can convey information relevant to market behavior even when lower-frequency macroeconomic aggregates and "hard data" expectations are not necessarily updated, either due to implementation lags or because long-term conjectures simply did not materialize.

In this way, our main contribution consists on using news to create a novel estimate of fiscal policy risk using natural language processing. With this alternative metric, we investigate whether fiscal policy risk influences yield curve movements in an emerging economy setting. We exploit the case of Brazil to assess how risk and uncertainty related to national fiscal policy affect yield curve premium. Beyond country credit risk and overall economic uncertainty sentiment, we investigate whether perceived risk related to fiscal policy conduction is a relevant determinant of the yield curve.

To build our novel index, we combine a dictionary-based approach with machine learning through sentiment analysis. We find that fiscal risk is indeed associated to increases in yield levels for several maturities, to rises in the term-premium and to a depreciation of exchange rates.

This paper draws inspiration on the literature that examines the consequences of non-negligible fiscal risk and its impacts on monetary policy

[3]A survey specific for expectations on fiscal policy variables, *Prisma*, was established by the Ministry of Finance in mid-2016. Yet the historical information is considered still too short to yield meaningful time series for econometric analysis.

(Arellano, 2008; Arellano et al., 2020; Bi, 2012; Bi et al., 2018). Recently, such framework has been applied to monetary policy in the Brazilian context (Amaral & Carvalho, 2021; Carvalho & Mendonça, 2022), finding that economies subject to fiscal risk can face high interest rates co-existing with high inflation if the monetary authority does not account for risk in the policy asset. Although we do not employ similar theoretical models, we contribute by providing evidence that fiscal risk also matters in another dimension important to monetary policy conduction: by affecting interest rates of longer maturities and the size of the term spread.

This paper is also inserted in the prolific strand of the literature that exploits text-based data and economic activity (Gentzkow et al., 2019), for instance, to predict or explain economic outcomes (Larsen & Thorsrud, 2019; Bybee et al., 2021; Kalamara et al., 2022), predict asset prices (Loughran & McDonald, 2011; Manela & Moreira, 2017; Hassan et al., 2020), and capture economic uncertainty (Baker et al., 2016; Larsen et al., 2021). In particular, we exploit text data to construct an uncertainty measure specific to fiscal policy-related risk, and find that it is significantly associated to yield curve and exchange rate variation in the Brazilian scenario.

The paper is structured as follows. Section 2 explains the news data used in this study. It also discusses the methodology devised to built the main fiscal risk index using natural language processing, and the ultimate content and validation of the resulting series. Chapter 3 presents the empirical specification used in estimations and the main results relating fiscal risk to the yield curve and the exchange rate movements. It also presents several robustness tests given by alternative versions of either the fiscal risk index or the empirical specification. Finally, Section 4 concludes.

2
Data and Methodology

2.1
Text Data

To construct a series that proxies for fiscal policy risk, we use news articles data from three major Brazilian newspapers: Estadão, Folha de São Paulo and Valor Econômico. The dataset was assembled in Ladalardo & Medeiros (2022) following the transparency policies of the websites in question, and the authors collected articles contained in sections of Economics, Politics, Markets and related topics.[1] Figure 2.1 presents the number of articles and word counts in the dataset, which goes from January 2008 to November 2022.

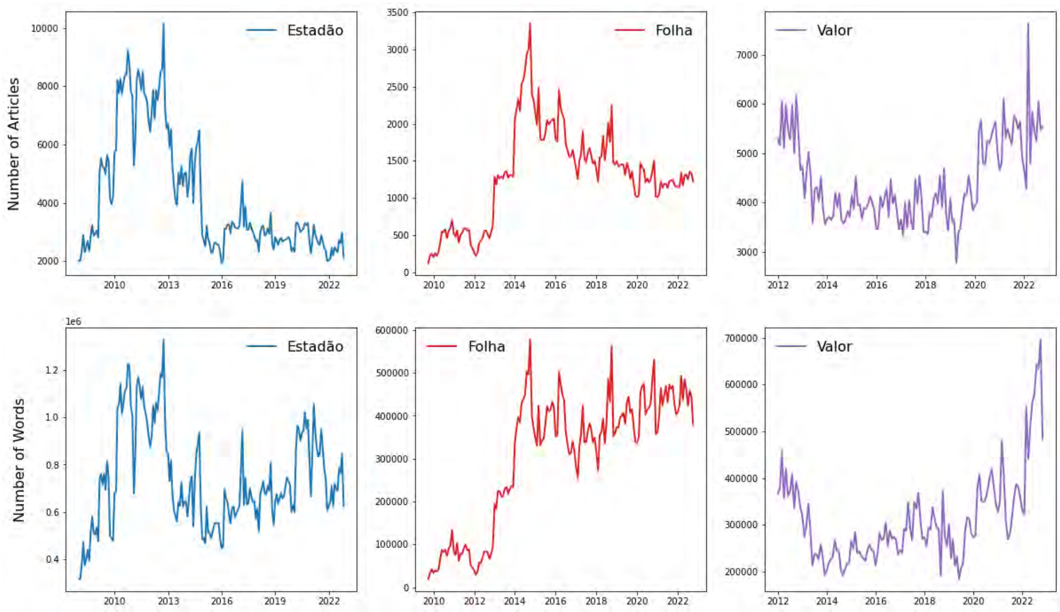
To extract meaningful information from the news articles, we transform unstructured text to structured data and represent the resulting high-dimensional array in a space of smaller dimensions. In this sense, we conduct a series of pre-processing and cleaning steps on the raw text data.

Firstly, we tokenize text by parsing it into individual elements, separated by white spaces or punctuation. Secondly, we remove stopwords - words that are very common in natural language and represent the bulk of frequency in a text, but usually lack in semantic meaning, such as prepositions, articles and pronouns. We also remove digits and other non-alphabetic characters. Then, we apply lemmatization to reduce words to their canonical form. Next, we generate the set of all unique terms in the sample, considering phrases of one or two words; namely uni-grams and bi-grams, where the latter are all pairs of ordered adjacent terms. After pre-processing, this unique set of terms is the corpus vocabulary.

In order to provide a descriptive representation of words and thus information contained in our dataset, we represent text as a numerical array by generating the "bag-of-words" representation, also known as the Document-Term Matrix. We index each unique term in the whole corpus by $v \in \{1, ..., V\}$, where V is the total number of unique terms. We index each

[1]As explained in Ladalardo & Medeiros (2022), Estadão articles are in the sections "Economia", "Política" and "Internacional"; Folha de São Paulo includes "Política", "Mercado" e "Mundo"; and all articles in Valor Econômico.

Figure 2.1: Articles and Words



time-ordered news document by $d \in \{1, ..., D\}$, and compute the count $x_{d,v}$ of occurrences of term v in document d.

To obtain time series of term frequencies and to reduce the computational cost of the high-dimensional calculation, we aggregate term counts $x_{d,v}$ for all news documents in a day t for $t \in \{1, ..., T\}$, where T is the total number of days in the sample. Therefore, we generate a Document-Term Matrix $\mathcal{M}_{\mathbf{T},\mathbf{V}}$ where entries are the counts of each unique term in the corpus occurring in a particular day in the sample. In this process, we also remove rare terms by excluding those that appear in less than 10% of all articles across a single newspaper[2].

2.2 Methodology

In the construction of our indicator of fiscal policy risk, we opt for the combination of a dictionary boolean method and sentiment analysis. As discussed in Gentzkow et al. (2019), dictionary-based methods heavily weight prior information, and can be most appropriate when the mapping of interest is weaker in the data and does not match the factor structure of unsupervised models. Our setting is similar to the one in Baker et al. (2016), which motivates our choice of methodology: we lack an actual baseline measure of fiscal policy risk in news articles in order to train a supervised model, and a topic model is unlikely to endogenously select fiscal policy risk as a topic.

[2] For this threshold, we follow the choice in Ladalardo & Medeiros (2022) for excluding rare words

Firstly, we must select, from the large and diverse body of news, articles that are thematically relevant to our application, that is, capturing information on fiscal policy risk and uncertainty. To that end, we construct a fiscal policy dictionary and validate it by a data driven procedure. We use the broad terms “fiscal” and “debt” to select columns in the Document-Term matrix containing those expressions, and extract those that are most related to fiscal policy. The use of the Document-Term matrix, with column terms derived after text cleaning and processing, allows us to build the dictionary with bi-grams, capturing information more specific and particular to our fiscal policy context. It also ensures that punctuation, plurals and other word variations do not influence the selection of terms.

Then, we look at specific days around known events related to fiscal policy news and uncertainty in the Brazilian scenario. For instance, we look at days surrounding developments in the process of the impeachment of former president Dilma Rousseff, the approval of the “Precatórios” Constitutional Amendment signed by Finance Minister Paulo Guedes, and a notorious speech given by then president elect Luis Inácio ’Lula’ da Silva in November 2022 that upset markets over fiscal responsibility concerns. We enhance the set of terms in the dictionary with some expressions that are specific to these days, while confirming that the majority of terms in the dictionary are indeed frequent around these events. Table 2.1 shows the resulting fiscal policy dictionary and Figure 2.2 depicts the time series of selected term counts.

Table 2.1: Fiscal Dictionary

court-ordered debt	debt gdp	debt increase
debt interest	debt payment	debt restructuring
fiscal FRL	fiscal adjustment	fiscal austerity
fiscal brazil	fiscal budget	fiscal ceiling
fiscal crisis	fiscal deficit	fiscal effort
fiscal end	fiscal government	fiscal measure
fiscal maneuver	fiscal policy	fiscal problem
fiscal reform	fiscal responsibility	fiscal result
fiscal risk	fiscal rule	fiscal situation
fiscal stimulus	fiscal target	government debt
gross debt	hit ceiling	public debt
responsibility law	spending cap	

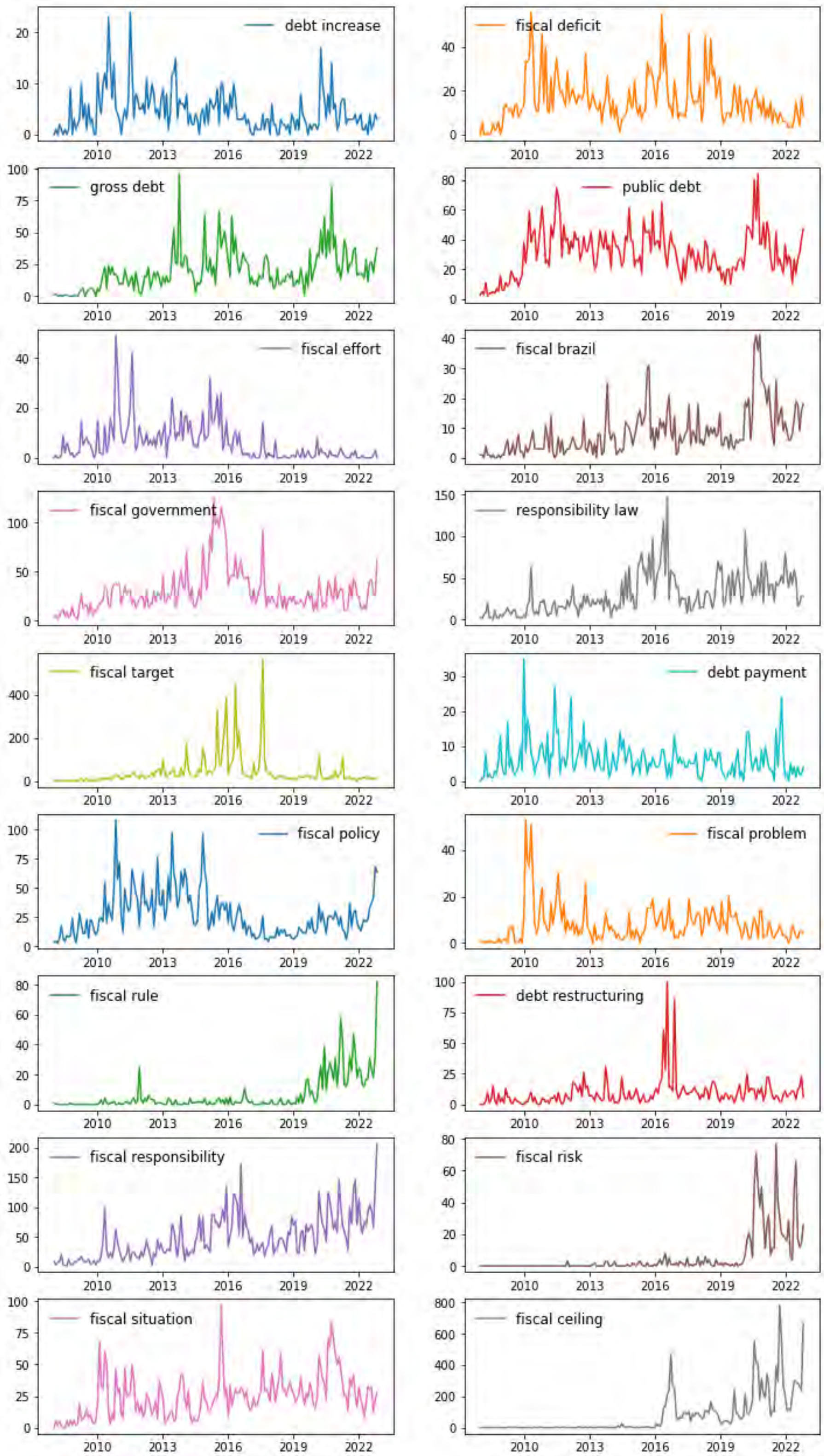
The table contains the English translation of Portuguese terms used in the dictionary search. Portuguese version available in the Appendix. We note that the dictionary search is conducted with the clean set of lemmas after the pre-processing steps, such that the final terms may differ from the exact words that appears in the written news text.

As a next step, we filter the news dataset by selecting articles that contain at least a combination of two terms from the dictionary, with the goal of ensuring that articles selected are minimally related to fiscal policy matters.[3] Furthermore, we use sentiment analysis over the selected body of news to extract articles that convey at least a minimum degree of negative sentiment. This is an important step to ensure that our measure has the correct signal, as we aim to capture articles that contain information on risk, uncertainty and general concerns over fiscal policy, and not just any article related to fiscal policy.

Many studies using natural language processing in Economics rely on measuring the 'tone' or sentiment of text (Hansen & McMahon, 2016; Hassan et al., 2020; Aruoba & Drechsel, 2022), ultimately based on the "directional" word list of positive and negative terms in Loughran & McDonald (2011), which is extensive and adapted to financial texts. In the absence of a similar word list in Portuguese language, and to overcome the difficulty of translating the 80000-length list and adapting it to the context of Brazilian newspapers' lexicon, we resort to machine learning techniques for measuring the sentiment of fiscal policy news.

[3]Using the combination - as opposed to a single mention of one expression - reduces the number of selections by around 50% and helps to ensure the relevance of the chosen subset of news regarding fiscal policy content.

Figure 2.2: Fiscal Dictionary Terms



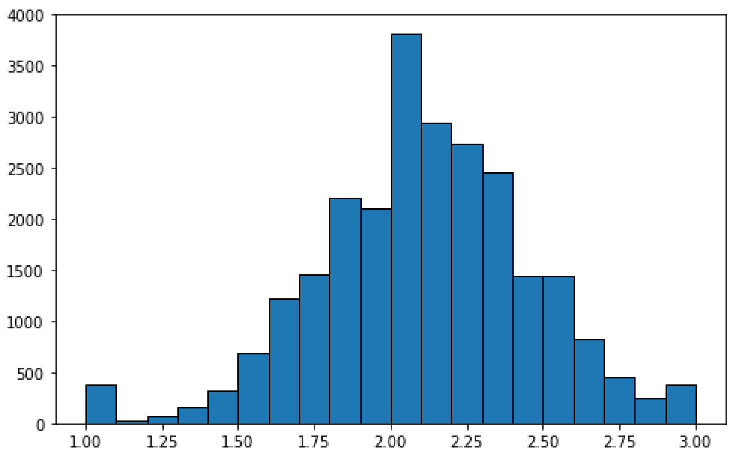
Aggregate monthly counts of selected terms in the fiscal dictionary, translated to English. Portuguese version available in the Appendix

To perform sentiment analysis, we use the BERT model (Bidirectional Encoder Representations from Transformers), a deep neural network developed and pre-trained by Google, which has been shown to achieve very high levels of accuracy in multiple natural language processing tasks (Devlin et al., 2018). In a nutshell, it uses a network architecture capable of processing input data from both left-to-right and right-to-left directions, which is crucial to incorporate overall context when it comes to sentence classification.[4]

Therefore, we use the BERT neural network to apply sentiment labels to each of the article's sentences, which are classified as either negative, neutral, or positive.[5] We attribute a score to each label and average out the scores across all sentences to assess the overall sentiment of a news article.

Having obtained a unique sentiment indicator for each news article, we select articles with a minimum level of negative sentiment. In a score range of 1 to 3, where 1 is negative and 3 is positive, we keep articles with an overall score of at most 2, representing "neutral" sentiment. As shown in figure 2.3, the distribution of article sentiment scores is slightly left-skewed, and the choice of the midpoint lies below the median of 2.10. Later in chapter 3, we discuss the threshold choice for sentiment analysis selection of articles and perform estimations with alternative scores.

Figure 2.3: Distribution of Sentiment Score - Fiscal Policy News



As in Baker et al. (2016), we generate a series of scaled article counts that fit the aforementioned criteria. For each newspaper and at a given time period, we count the number of articles containing at least two terms from the dictionary *and* with an overall sentiment score of at most 2. Each series is

[4]We refer to Vaswani et al. (2017) and Devlin et al. (2018) for a technical exposure of the Transformer architecture and its applications to NLP tasks.

[5]To classify text with these labels, we use implementations of BERT for Portuguese language available in Python, namely BERTimbau and FinBertPTBR, which can be found at the *HuggingFace* public repository.

scaled by the total number of articles in the respective newspaper by month (or week). Then, we standardize each newspaper-level to have unit standard deviation in the time interval, from 2008 to 2022. In other words, for each newspaper $i = \{1, 2, 3\}$, we calculate the scaled counts of fiscal articles X_{it}. Then, we calculate the standard deviation σ_i of each scaled article count series across all t, from which we obtain $Z_{it} = X_{it}/\sigma_i$. We conduct the process for the three newspaper sources and compute the average across the three series, obtaining $\bar{Z}_t = \frac{\sum_{i=1}^{3} Z_{it}}{3}$. We compute the mean value of $\bar{Z}_t$ across the time sample, and then obtain the normalized fiscal series $F_t = \bar{Z}_t * \frac{100}{M}$, with a mean of 100 in the time interval.

Figure 2.4 shows the resulting index and Figure 2.5, the newspaper-level standardized series:

Figure 2.4: Fiscal Risk Index

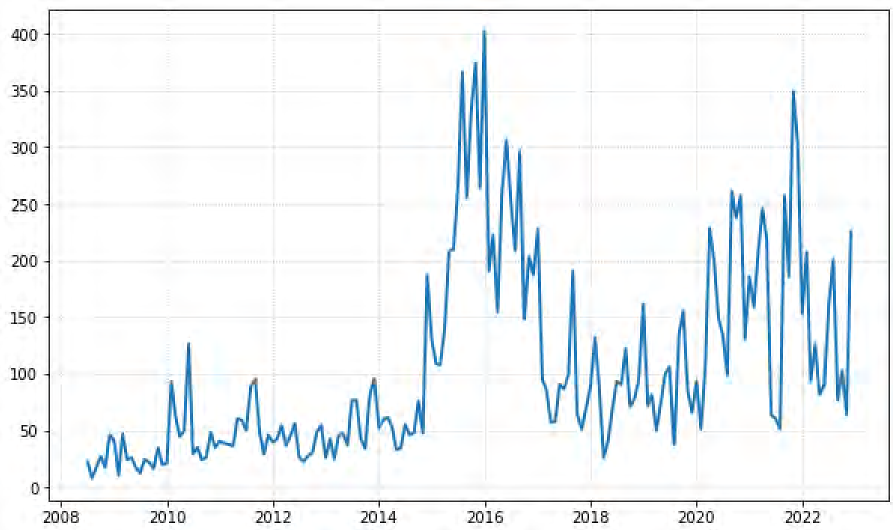
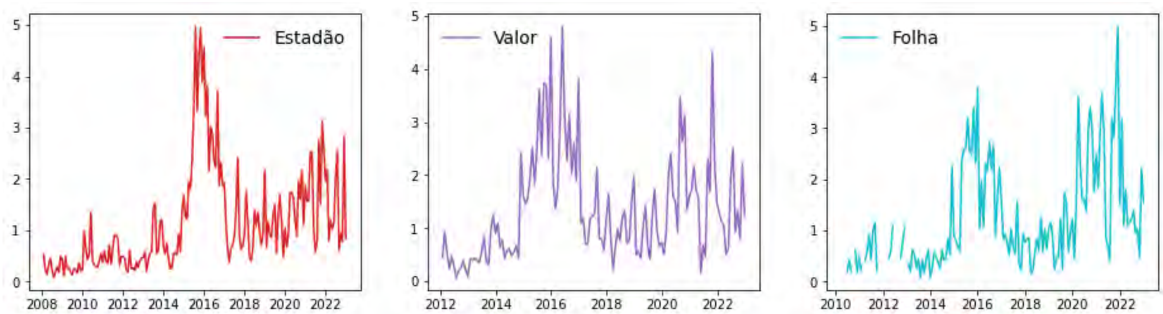


Figure 2.5: Fiscal Risk Index - Newspaper Level



We can see that the average index evolves from lower values to a more volatile behavior from 2014 onward. An evaluation based on a narrative approach shows that its peaks coincide with moments of higher fiscal policy uncertainty or the materialization of fiscal policy shocks. As explained in

Fernández-Villaverde et al. (2015), struggles about fiscal policy at different levels of government, lack of consensus of policymakers on the fiscal policy mix or its timing and unexpected variations in fiscal rules can also be read as shocks to fiscal policy volatility.

Following stable behavior in the first six years in the sample, the index reaches a first peak in November 2014, at a time when the central government proposed a bill to alter the primary surplus target for the year, after it became clear that the current deficit would not allow for the legal obligation to be fulfilled.

During 2015, the series reaches successive new peaks, as the country faced recurrent public deficits, having registered the worse results since 2002, rises in public debt and eventually the loss of investment-grade rating by Standard & Poor's and Fitch. In 2016, the index remains volatile, following the ongoing investigation of the government by the Federal Court of Accounts (TCU) over fiscal mismanagement practices, and the legal process which culminated in the impeachment of president Dilma Rousseff.

The index recedes to lower levels between 2016 and 2019, yet has notable peaks: the uncertainty over and eventual alteration of the year-end target deficit in August 2017, the flexibilization of the Fiscal Responsibility Law for states and municipalities in December 2018, and in August-September 2019, when the possibility of altering the fiscal spending ceiling in place was first considered by Jair Bolsonaro's government.

The index again soars in early 2020 with major uncertainty over the fiscal framework and macroeconomic policies in general due to the onset of the Covid pandemic. Similarly, the series displays high levels along the year following frequent discussions and internal governmental disputes on whether the fiscal spending cap should stand or not amidst the ongoing state of public calamity.

The volatile behavior is maintained in the year of 2021, due to continued attempts or threatens to bypass the fiscal target, culminating in the Constitutional Amendments n. 113 and n.114, which restructured federal debt in the form of court-ordered payments ("precatórios") and created leeway to increase fiscal spending in the following year. Finally, the series peaks again in July 2022 with yet another constitutional amendment authorizing extraordinary spending to finance cash transfers not contemplated in the fiscal spending cap, right ahead of the presidential elections, and in November 2022 after the election of president Lula and the rise in fiscal policy uncertainty.

The description of the index's pattern and peaks suggests that, if anything, the series depicts the fiscal deterioration and the overall scenario of fiscal policy instability that has been the rule rather than the exception in Brazilian government since 2014. Furthermore, we note that our series captures movements specifically related to fiscal policy risk and moments of fiscal policy uncertainty, rather than patterns of electoral cycles or events of mainly political turmoil. For instance, a notorious event dubbed “Joesley day” in the Brazilian media, which wreaked havoc in Brazilian financial markets, occurred in May 2017, when president Michel Temer was accused of involvement in a major corruption scandal. That month, however, is not associated to a prominent peak in the fiscal risk index, given the low content of fiscal policy news.

To provide context into the subjects covered in the relevant subset of fiscal policy news, we also estimate a Latent Dirichlet Allocation topic model to create media attention series as in Bybee et al. (2021). The time series of attention to topics is available in the Appendix.

2.3 Comparison

We proceed to analyzing the correlation of our index with other indicators: the Brazilian Economic Policy Uncertainty Index (EPU), built with the methodology in Baker et al. (2016) using news from Folha de São Paulo; the 5-year CDS and the exchange rate (USDBRL).

The fiscal risk index has a correlation of 0.47 with the EPU for the Brazilian economy. While some information is clearly common to the two series, the EPU tends to peak at moments of political turmoil and corruption scandals, notably May 2017, whereas the fiscal index displays a pattern that attains more closely to periods when fiscal policy matters were the stronger concern, as discussed in the previous subsection.

The series displays correlations of 0.62 and 0.60 with the CDS and the BRL, respectively, suggesting that the fiscal risk index built with news captures information relevant to the Brazilian macroeconomic environment. We also note that the correlations of the index with the BRL and the CDS are both higher than the correlation between the two series themselves, which is 0.41 in the aggregate time frame. Interestingly, we note a pronounced difference regarding the correlation between the CDS and the BRL in the period before and after 2016, with the second window showing almost zero correlation between the two series. This resonates with the discussion on Brazilian sovereign debt being primarily domestic, making it plausible that the CDS might not have responded to domestic risk dynamics, although, at the same time, the BRL faced strong depreciation against the dollar. Despite this apparent structural break in the pattern between the two series, the Fiscal Risk

Index still displays correlations of 0.47 and 0.34, with these series, respectively, in the later time period.

Table 2.2: Correlations

	Fiscal Risk Index	BRL	CDS	EPU
Fiscal Risk Index	1.00			
BRL	0.60	1.00		
CDS	0.62	0.41	1.00	
EPU	0.47	0.36	0.56	1.00

Table 2.3: Correlations - 2008-2015

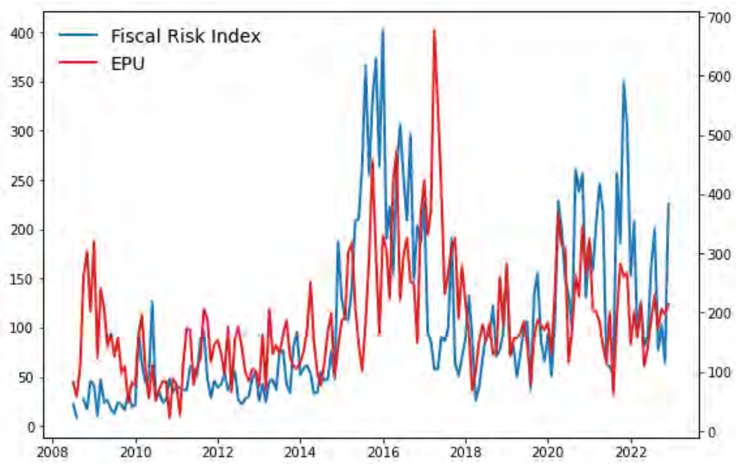
	Fiscal Risk Index	BRL	CDS	EPU
Fiscal Risk Index	1.00	0.86	0.67	0.51
BRL	0.86	1.00	0.82	0.64
CDS	0.67	0.82	1.00	0.72
EPU	0.51	0.64	0.72	1.00

Table 2.4: Correlations - 2016-2022

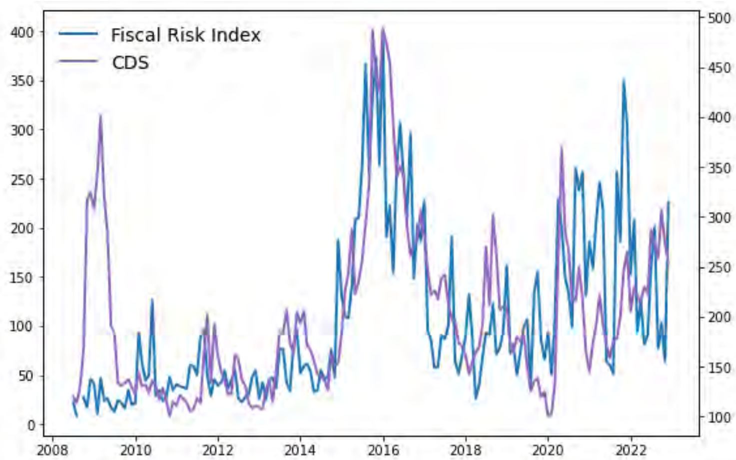
	Fiscal Risk Index	BRL	CDS	EPU
Fiscal Risk Index	1.00	0.34	0.47	0.26
BRL	0.34	1.00	0.01	-0.25
CDS	0.47	0.01	1.00	0.36
EPU	0.26	-0.25	0.36	1.00

Figure 2.6: Comparisons - Fiscal Risk Index

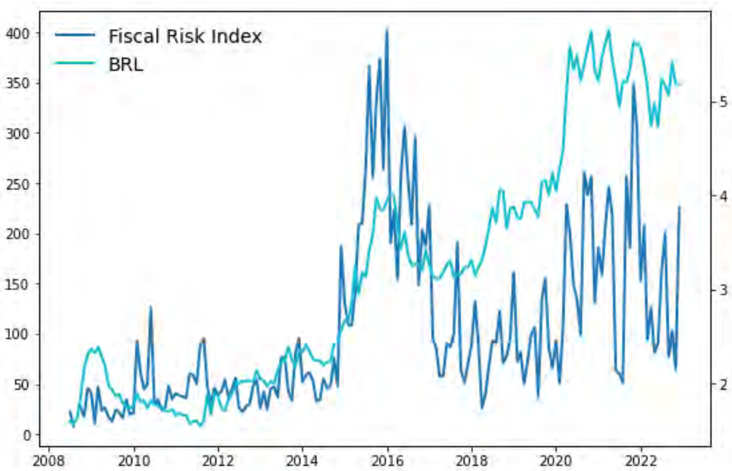
(a) EPU



(b) CDS



(c) BRL



The Fiscal Risk Index is shown in left-axis and other series are shown in the right axis.

3
Empirical Evidence

This chapter analyzes the relationship between the news-based fiscal risk index and the Brazilian yield curve. We inspect whether increases in the series are associated to increases in yield levels, and examine the effect for different maturities. In addition, we investigate whether the fiscal risk index is associated to a depreciation in the Brazilian exchange rate level.

3.1
Data Sources

In addition to text data from Brazilian newspaper articles, we use several macroeconomic variables in our estimations. The Selic interest rate and other macroeconomic aggregates of the Brazilian economy are collected from the BCB's website, the Federal Funds Effective Rate is obtained from the FRED database at the St. Louis Fed, and the Brazil 5-year CDS is obtained from Bloomberg. Exchange rate quotations for the Brazilian Real (USDBRL), other currencies and yields on government bonds of other emerging markets are collected from Thomson Reuters.

Yield curve data for Brazil is obtained from the Brazil Stock Exchange's (B3) website via webscrapping using the *rb3* R package, providing for availability of longer time series in some of the maturities considered. We collect yields from *DI x Pré* swap contracts of several maturities, which constitute a common reference for the term structure of interest rates in Brazil, given that the assets are daily traded at B3 and available at more dates compared to zero-coupon government bonds (LTNs) when it comes to the longer maturities.

The relevant time period for the estimation ranges from June 2008 to November 2022, such as to match the availability of the fiscal risk index constructed with the news dataset. We use end-of-period values for the series collected, to avoid additional serial correlation caused by the use of daily values (Bybee et al., 2021), and the results are robust to the use of average values.

3.2 Specification

To analyze the relationship between the news-based fiscal risk proxy and yield curve data, we use a reduced-form approach through linear regressions at weekly frequency, which is the highest frequency at which we can generate a meaningful fiscal index series. The variables are re-sampled to have a reference period ending Friday, including news articles.

We estimate Ordinary Least Squares (OLS) on the following specification:

$$\Delta Y_{n,t} = \beta_0 + \beta_1 \Delta FRI_t + \gamma X_t + u_t \tag{3-1}$$

where $Y_{n,t}$ is the target variable of interest, denoting the first difference of the yield with maturity n, ranging from 3 months to 10 years. FRI_t is the fiscal risk index, and is also specified as the first difference. We standardize the variation of the fiscal series such that β_1 can be interpreted as the effect over $Y_{n,t}$ of a one standard deviation increase in the fiscal risk index. X_t is a vector of controls, which includes the difference of the Selic interest rate with respect to the Fed funds, the percentage change of the BRL exchange rate, the CDS country risk and monthly dummies to control for potential seasonal patterns. We test for the stationarity of all the time series included in the regressions using Augmented Dickey-Fuller (ADF) unit root tests.[1]

In addition, we also run a similar specification to test for the relationship between the Brazilian exchange rate with respect to the US dollar and the fiscal index. In this case, the dependent variable Y_t is the Brazilian exchange rate with respect to the US dollar (USDBRL), measured in percentage changes, and the relevant controls are also measured at percentage changes.

3.3 Results: Yield Curve

Tables 3.1 through 3.5 show the results for the yield curve specification. While the fiscal risk index does not seem to have a significant correlation with the shortest yield maturities, as shown in table 3.1, it is associated to significant increases for maturities of 1 year and beyond. We note that the coefficient associated to the index is significant at the 1% level for almost all specifications, even when controlling for the CDS effect.

[1] The fiscal risk index and its first difference series, in particular, are stationary at the 1% level of confidence.

Table 3.1: Short Yields

	Yield 3m		Yield 6m		Yield 9m	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.13	0.25	0.09	0.16	0.01	0.27
	(0.68)	(0.64)	(0.80)	(2.80)	(0.90)	(0.83)
Fiscal Risk Index	0.94	0.73	1.88	1.43	2.63**	2.18*
	(0.92)	(0.93)	(1.16)	(1.11)	(1.25)	(1.26)
Selic	3.87***	3.99***	3.94***	4.10***	3.88**	4.13***
	(0.69)	(0.55)	(1.17)	(0.92)	(1.68)	(1.43)
Exchange Rate	1.14	-1.16*	2.48**	-1.11	3.85**	-0.98
	(0.83)	(0.67)	(1.24)	(0.92)	(1.68)	(1.24)
CDS		10.04***		16.20***		21.07***
		(3.24)		(4.48)		(6.48)
Num.Obs.	640	640	639	639	639	639
R2	0.116	0.180	0.094	0.199	0.092	0.191
R2 Adj.	0.112	0.175	0.089	0.180	0.088	0.186

The table reports results of regression 3-1. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable.
Heteroskedasticty and autocorrelation robust standard errors in parenthesis
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 3.2: Yield 1y

	(1)	(2)	(3)
Constant	0.53	-0.10	0.14
	(0.97)	(0.96)	(0.89)
Fiscal Risk Index	4.24***	3.37**	2.84**
	(1.41)	(1.36)	(1.37)
Selic	3.56**	3.60**	3.86**
	(1.77)	(1.77)	(1.53)
Exchange Rate		4.61**	
		(1.85)	
CDS			22.00***
			(6.12)
Num.Obs.	648	640	640
R2	0.056	0.093	0.186
R2 Adj.	0.053	0.088	0.182

The table reports results of regression 3-1. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01

In the case of the benchmark 5-year yield, a one standard deviation increase of the fiscal index is linked to a 3.75 basis point increase on average, and 3.37 when controlling for standardized deviations of the CDS. The increase

Table 3.3: Yield 3y

	(1)	(2)	(3)
Constant	0.43	-0.88	-0.49
	(1.22)	(1.07)	(1.06)
Fiscal Risk Index	6.25***	4.37***	3.93***
	(1.69)	(1.51)	(1.49)
Selic	1.10	1.32	1.79
	(1.66)	(1.63)	(1.54)
Exchange Rate		10.91***	4.63***
		(2.09)	(1.76)
CDS			27.11***
			(7.52)
Num.Obs.	623	615	615
R2	0.042	0.161	0.233
R2 Adj.	0.039	0.157	0.228

The table reports results of regression 3-1. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

in the fiscal risk series of 3 to 6.76 standard deviations at peak signifies a 11.25 to 26.25 basis points increase in the 5-year yield. Similar responses can be found for the 1-year and 3-year yields, as well as 6-year and 8-year yields, shown in table A.2 in the Appendix. For the 10-year yield, a one standard deviation increase in the fiscal risk index is associated to a rise of 4.75 basis points and 4.16 controlling for the CDS, which translates to a 12.5-32 basis points increase at peak standard deviation increase.

Table 3.4: Yield 5y

	(1)	(2)	(3)
Constant	0.49	-1.46	-2.08
	(1.35)	(1.10)	(3.12)
Fiscal Risk Index	6.13***	3.75***	3.37**
	(1.69)	(1.33)	(1.31)
Selic	0.92	0.74	0.95
	(1.53)	(1.29)	(1.19)
Exchange Rate		14.44***	9.71***
		(2.66)	(1.71)
CDS			21.78***
			(7.18)
Num.Obs.	592	584	584
R2	0.036	0.233	0.290
R2 Adj.	0.033	0.229	0.271

The table reports results of regression 3-1. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: Yield 10y

	(1)	(2)	(3)
Constant	0.02	-1.53	-1.26
	(1.25)	(1.05)	(1.02)
Fiscal Risk Index	7.14***	4.75***	4.16***
	(1.58)	(1.38)	(1.28)
Selic	0.57	0.46	0.77
	(1.40)	(1.23)	(1.20)
Exchange Rate		13.38***	8.10***
		(2.41)	(1.79)
CDS			23.40***
			(7.21)
Num.Obs.	622	614	614
R2	0.050	0.216	0.267
R2 Adj.	0.046	0.213	0.262

The table reports results of regression 3-1. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Furthermore, as shown in table 3.6, increases in the fiscal risk index are associated to rises in the yield curve term spread, as measured by the difference between the 5-year and the 3-month yield, or, alternatively, the 10-year and the 3-month yield. This is consistent with the positive and statistically significant relationship found between the fiscal index and the 5-year and 10-year yields and the lack of an effect of the series on yields shorter than one year.

Table 3.6: Term Spread

	Spread: 5y - 3m		Spread 10y - 3m	
	(1)	(2)	(3)	(4)
Constant	-1.49	-1.36	-1.55	-1.39
	(1.01)	(1.02)	(0.99)	(0.99)
Fiscal Risk Index	2.46**	2.30**	3.87***	3.53***
	(1.03)	(1.05)	(1.29)	(1.21)
Selic	-3.00**	-2.86**	-3.36***	-3.18**
	(1.24)	(1.31)	(1.24)	(1.31)
Exchange Rate	13.15***	10.42***	12.04***	9.07***
	(2.22)	(1.54)	(1.90)	(1.67)
CDS		11.90*		13.17*
		(6.89)		(7.47)
Num.Obs.	584	584	615	615
R2	0.235	0.251	0.210	0.228
R2 Adj.	0.231	0.246	0.206	0.223

The table reports results of regression 3-1. The dependent variable is the weekly first difference of the term spread. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.4 Results: Exchange Rate

Table 3.7 displays the result for the exchange rate specification. Due to higher volatility in the pattern of the exchange rate, we run this specification at monthly frequency and present weekly results in the Appendix.

The regressions suggest that increases in the Fiscal Risk Index are associated to increases in the USDBRL rate, which constitutes a depreciation of the Brazilian currency. The coefficient associated to a one-standard deviation increase in the fiscal series is statistically significant at the 5% level and comparable to the magnitude of the decrease associated to a one standard deviation increase in the Selic rate.

Table 3.7: BRL

	(1)	(2)
Constant	0.008**	-0.005
	(0.004)	(0.009)
Fiscal Risk Index	0.014***	0.007**
	(0.004)	(0.003)
Selic	-0.003	-0.006***
	(0.003)	(0.002)
CDS		0.034***
		(0.003)
Num.Obs.	173	173
R2	0.089	0.579
R2 Adj.	0.078	0.541

The table reports results of regression 3-1 in monthly frequency. The dependent variable is the end-of-period percentage change in the exchange rate. The Fiscal Risk Index and the control variables are also included as percentage variations. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.5 Robustness

3.5.1 ArCo

One potential concern with our strategy is that the significant associations found between yield curve movements and our news-based index are not explained by idiosyncratic fiscal risk shocks, but global movements that affect both financial markets in general and perspectives on national fiscal policy itself. To provide further evidence that our series proxies for Brazilian fiscal policy risk, we use the idea of the Artificial Counterfactual (ArCo) methodology from Carvalho et al. (2018) to build in-sample counterfactuals for our dependent variables of interest.

For the yields used as dependent variables in our specifications, we construct fitted series using yields from other emerging markets bonds (ex-Brazil) of the same maturity, such that the fitted series most closely follows the Brazilian yield variation. Following notation in Carvalho et al. (2018), we estimate:

$$\boldsymbol{Y}_t^{(0)} = \mathcal{M}\left(\boldsymbol{Z}_{0t}, \boldsymbol{\theta}_0\right) + \boldsymbol{v}_t, t = 1, \ldots, T \tag{3-2}$$

where $\boldsymbol{Y}_t^{(0)}$ is the target Brazilian yield, $\boldsymbol{Z}_{0t} = (z_{2,t}, z_{3,t}, ..., z_{n,t})'$ are observables of "untreated" units and $\boldsymbol{\theta}_0 = (\theta_{0,1}, \theta_{0,2}, ...\theta_{0,n})'$ are linear projection parameters. In our application, untreated units are selected emerging economies excluding Brazil. The countries considered are Chile, Colombia, Mexico, China, India, Russia and South Africa; namely the BRICS countries ex-Brazil and some Latin American peers.

The functional form for the model $\mathcal{M}$ is flexible in ArCo, and we choose the standard OLS given the absence of a high-dimensional framework to justify the use of shrinkage estimators such as LASSO. The $\hat{\boldsymbol{Y}}_t^{(0)}$ fitted series can be interpreted as the yield curve variation that can be explained by a "global factor". While we cannot control for the ArCo estimation error, we nevertheless use this proxy as a further regressor in the main specification in 3-1, to mitigate concerns that the results found in the previous sections are driven by factors other than domestic fiscal policy risk. We include graphs of the dependent variables and the ArCo proxy in the Appendix.

Tables 3.8 show the results with the 5-year and 10-year yields as dependent variables. The coefficient for the fiscal risk index is roughly unchanged and still significant at the 1% level, even when controlling for the yield curve variation that can be explained by yield curve movements of other economies. The effect is around 5bps for a unit increase in standard deviation of the fiscal index, and around 15-33 bps and 16-37 bps at peak increase, for the 5-year and 10-year yields, respectively. Even when controlling for the CDS variation, the peak effect stands at 12-27 bps and 13-29 bps.

Table 3.8: Yields with ArCo

	Yield 5y		Yield 10y	
	(1)	(2)	(3)	(4)
Constant	0.13	-0.14	-0.01	-0.24
	(1.17)	(1.03)	(1.19)	(1.08)
Fiscal Risk Index	4.93***	4.03***	5.44***	4.31***
	(1.51)	(1.47)	(1.27)	(1.26)
ArCo	0.98***	0.69***	0.97***	0.70***
	(0.11)	(0.15)	(0.11)	(0.14)
CDS		26.66***		25.55***
		(8.30)		(7.73)
Num.Obs.	554	554	543	543
R2	0.214	0.299	0.234	0.312
R2 Adj.	0.211	0.295	0.232	0.309

The table reports results of regression 3-1 with the addition of the fitted series displayed in 3-2 as a control. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We also run the exchange rate specification controlling for an ArCo series built with exchange rate levels for the other emerging markets. The effect of the Fiscal Risk index over the BRL also holds when controlling by the movement that can be explained by foreign currencies.

3.5.2 Sentiment Analysis

As a further robustness test, we vary the sentiment analysis score chosen as threshold to select fiscal policy articles for entering our index count. From a baseline of 2, we augment the threshold to 2.2 such that we allow more articles to enter the computation. This represents an increase of the average number of articles selected per month from 21.2 to 32.5 in our sample. Table 3.10 shows that the results are sustained and the magnitude of the coefficient associated to the fiscal index is only slightly smaller for some specifications, and still highly statistically significant.

We also select a stricter sentiment score threshold of 1.85, yet in this case coefficients are not statistically significant for all yield specifications. This

Table 3.9: BRL with ArCo

	(1)	(2)
Constant	0.001	0.003
	(0.002)	(0.002)
Fiscal Risk Index	0.010***	0.008***
	(0.002)	(0.002)
ArCo	0.995***	0.717***
	(0.078)	(0.136)
Selic	-0.006***	-0.006***
	(0.001)	(0.001)
CDS		0.015***
		(0.005)
Num.Obs.	172	172
R2	0.659	0.707
R2 Adj.	0.653	0.700

The table reports results of regression 3-1 with the addition of the fitted series in 3-2 as a control. The dependent variable is the end-of-period percentage change in the exchange rate. The Fiscal Risk Index and the control variables are also included as percentage variations. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

is perhaps unsurprising, given that this choice results in the selection of only an average of 11.6 articles per month, and, as shown in the distribution of sentiment score in figure 2.3, the baseline threshold score of 2 is already below the median of articles.

3.6 Alternative Dictionary

As explained in section 2, our method for building the fiscal index is based on a dictionary search, which can raise concerns over misspecification bias and the heavy reliance on researcher input, as discussed in Bybee et al. (2021). In this way, we provide an alternative estimation that selects articles containing (at least two) terms from a much smaller set, that represents a more succinct version of the fiscal policy dictionary, built without drawing on particular days when known fiscal policy events occurred. The index is otherwise constructed in the same manner: we use sentiment analysis to filter articles that contain negative sentiment[2], generate a series of scaled article counts, standardize it by newspaper, average out values and normalize the series to a mean of 100 in the time interval. The “core” dictionary and the resulting time series are displayed in table 3.12 and figure A.8.

[2]We use the same threshold score of 2 as in the baseline estimation.

Table 3.10: Yields - Higher Sentiment Threshold

	Yield 1y		Yield 5y		Yield 10y	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.08	0.10	-1.41	-1.97	-1.44	-1.15
	(0.94)	(0.89)	(1.04)	(3.11)	(1.08)	(1.00)
Fiscal Risk Index	3.23**	2.85**	4.02***	3.79***	4.98***	4.53***
	(1.39)	(1.38)	(1.42)	(1.33)	(1.28)	(1.24)
Selic	3.65**	3.81**	1.03	1.14	0.76	0.99
	(1.77)	(1.56)	(1.52)	(1.27)	(1.29)	(1.20)
Exchange Rate	4.21**		14.47***	8.91***	13.68***	7.69***
	(1.65)		(2.01)	(1.66)	(1.97)	(1.74)
CDS		20.20***		23.25***		25.00***
		(5.63)		(6.62)		(7.03)
Num.Obs.	656	656	600	600	631	631
R2	0.088	0.178	0.254	0.317	0.241	0.299
R2 Adj.	0.084	0.174	0.250	0.299	0.237	0.295

The table reports results of regression 3-1. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.11: Yields - Lower Sentiment Threshold

	Yield 1y		Yield 5y		Yield 10y	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.03	0.31	-1.33	-0.85	-1.34	-1.03
	(0.98)	(0.87)	(1.10)	(3.36)	(1.06)	(1.01)
Fiscal Risk Index	2.17*	1.93	1.14	1.10	2.66**	2.28*
	(1.11)	(1.20)	(1.32)	(1.27)	(1.16)	(1.18)
Selic	4.32**	4.94***	1.86	2.50**	1.54	2.26**
	(1.94)	(1.61)	(1.24)	(1.18)	(1.21)	(1.09)
Exchange Rate	5.65***		16.32***	10.57***	15.12***	8.74***
	(1.82)		(2.38)	(1.79)	(2.15)	(1.87)
CDS		25.74***		27.07***		28.18***
		(5.01)		(5.56)		(6.12)
Num.Obs.	576	576	523	523	557	557
R2	0.104	0.230	0.286	0.373	0.256	0.334
R2 Adj.	0.099	0.226	0.282	0.355	0.252	0.330

The table reports results of regression 3-1. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 3.1: Fiscal Risk Index - Alternative Dictionary

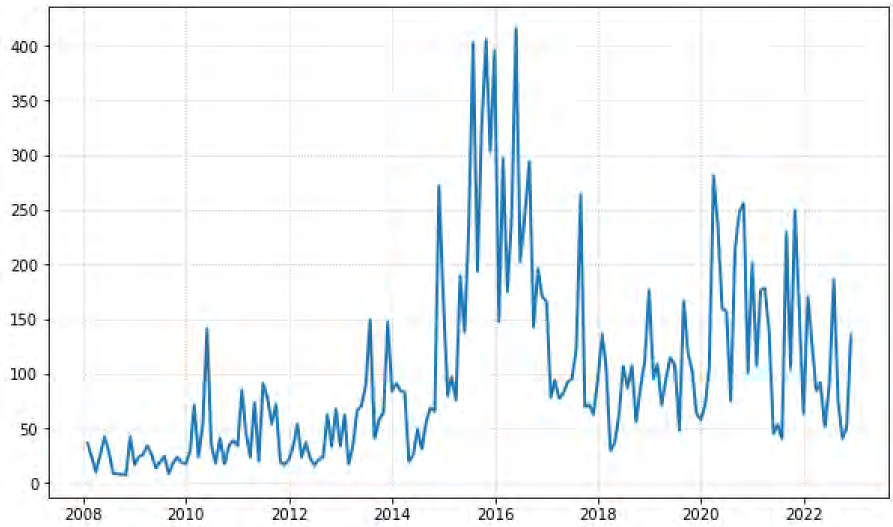


Table 3.12: Fiscal Policy Terms - Core

fiscal crisis	fiscal deficit	fiscal effort
fiscal stimulus	fiscal brazil	fiscal government
fiscal FRL	fiscal measure	fiscal target
fiscal policy	fiscal problem	fiscal reform
fiscal responsibility	fiscal result	fiscal risk

This alternative series displays a very similar behavior, with moments of higher volatility around 2015-2016 and 2020-2022, although the peaks are less pronounced in the last few years of the sample. Table 3.13 shows that the fiscal index is still significantly correlated with yield curve increases in the main regression specifications, although magnitudes are somewhat smaller and statistical significance is at the 5% level. Nevertheless, this result further illustrates that our index captures the target information on fiscal risk and uncertainty, even with reduced variability, given that the alternative dictionary leads to the selection of an average of only 8.5 articles per month.

Table 3.13: Yields - Fiscal Index with Core Dictionary

	Yield 1y		Yield 5y		Yield 10y	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.58	0.43	-0.86	-2.24	-1.27	0.19
	(0.97)	(0.91)	(1.10)	(3.15)	(1.07)	(2.83)
Fiscal Risk Index	1.88**	1.59*	3.61**	3.04**	4.15**	3.79**
	(0.90)	(0.94)	(1.61)	(1.39)	(1.70)	(1.55)
Selic	4.75***	4.50***	0.60	0.86	0.26	0.37
	(1.69)	(1.65)	(1.08)	(1.10)	(1.12)	(1.13)
Exchange Rate	3.79***	1.25		11.20***		9.76***
	(1.16)	(1.27)		(1.94)		(2.36)
CDS		12.74**	41.67***	17.34	38.94***	18.98
		(5.80)	(13.99)	(15.67)	(12.65)	(15.67)
Num.Obs.	528	528	482	482	509	509
R2	0.089	0.108	0.185	0.261	0.184	0.245
R2 Adj.	0.084	0.101	0.180	0.237	0.179	0.222

The table reports results of regression 3-1. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4
Conclusion

Fiscal policy related risk is a relevant phenomenon in many emerging economies. Brazil is a prominent case-study where fiscal policy is often shrouded in uncertainty, amidst frequent fiscal deficits, growing public debt and lack of credible rules and constraints over policy actions. This suggests, as has been acknowledged by the monetary authority, that fiscal risk can be relevant to risk premia, asset prices and overall expectations in this economy.

In this paper, we overcome the inherent difficulty of assessing the aforementioned relationship by building a novel measure of fiscal policy risk using text data and natural language processing. We find that our fiscal index is associated to increases in yield levels of maturities of 1 year and longer, the term-spread and exchange rate depreciation, suggesting that fiscal policy is a relevant source of risk premium in our setting. Although we measure a different phenomenon, our findings are broadly in line with the literature, which generally encounters significant impacts of policy uncertainty and text-based sentiment measures on asset prices and macroeconomic variables.

Some considerations are in order with respect to our analysis. As discussed, our methodology hinges on a dictionary boolean method with scaled article counts and sentiment analysis, which amounts to restrictive criteria for article selection. Alternative techniques could potentially yield smoother metrics, and therefore alter the magnitudes of effects estimated for fiscal risk on the yield curve and the exchange rate.

In addition, we note that a higher frequency estimation is intentionally prioritized to identify fiscal policy risk and concomitant yield curve movements. However, an interesting extension of this analysis would be the study of dynamic relationships between fiscal risk and yield curve factors or macroeconomic fluctuations in general, potentially using SVARs or BVARs as in Baker et al. (2016) and Bybee et al. (2021), although the short time series would pose challenges for confidence intervals sizes. The use of more granular text analysis, combined with either supervised or unsupervised methods, could provide "directional" sentiment metrics associated to fiscal policy news that would address the issues discussed. We consider these interesting directions for future research.

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A
Appendix

A.1
Media Attention in Fiscal Policy News

While we built the fiscal risk index using the methodology described in chapter 2, to provide further insight into the fiscal policy articles, we also use topic modelling by Latent Dirichlet Allocation (Blei et al., 2003) to generate a thematic summary of the news. This approach has recently seen widespread use in the economic literature (Hansen & McMahon, 2016; Hansen et al., 2017; Bybee et al., 2021).

LDA is an unsupervised clustering algorithm that maps observed variables - news articles - to latent factors, the topics, thus reducing the dimensionality of a text corpus. The topics are estimated as clusters of terms that are likely to occur together in the same article.

Each topic β_k, for $k = 1, ..., K$, is as a V-dimensional vector estimated as a probability distribution over all terms in the corpus. The model also generates, for each article d, a probability distribution over topics $\theta_d \in \Delta^K$, which determines how each article d allocates attention to each topic. LDA performs Bayesian estimation of the overall likelihood, placing Dirichlet priors over β and θ.[1]

Using the LDA estimated topic-specific term probabilities, we construct media attention series to each topic to provide a descriptive summary of fiscal policy news following Bybee et al. (2021). The estimated attention that article d allocates to topic k can be represented as the frequency with which its terms are assigned to k:

$$\hat{\theta}_{t,k} = \frac{\sum_{i=1}^{N_t} \mathbb{I}\left(\hat{z}_{t,i} = k\right)}{\sum_{q=1}^{K} \sum_{i=1}^{N_t} \mathbb{I}\left(\hat{z}_{t,i} = q\right)},$$

Therefore, to aggregate media attention allocation to topic k in a particular time-period τ, we have:

$$\hat{\theta}_{\tau,k} = \frac{\sum_{t\in\tau} \sum_{i=1}^{N_t} \mathbb{I}\left(\hat{z}_{t,i} = k\right)}{\sum_{t\in\tau} \sum_{q=1}^{K} \sum_{i=1}^{N_t} \mathbb{I}\left(\hat{z}_{t,i} = q\right)}.$$

[1]For further details on LDA estimation, we refer to Hansen et al. (2019) as well as the original paper (Blei et al., 2003).

Figure A.2 shows the attention to selected topics in the fiscal policy news subset. It is clear that the algorithm can capture themes relevant to the conduction of national fiscal policy, such as the Pension Reform, the impeachment of Dilma Rousseff, debt management between the Treasury and the National Development Bank, and the alterations of the fiscal spending "ceiling" during the government of Jair Bolsonaro, as well as topics related to inflation and surge of taxes and fuel prices.

Note that, prior to running LDA in the corpus, we also apply a further data-driven stopwords removal to the set of fiscal policy news by dropping terms with the lowest term frequency-inverse document frequency (tf-idf) score as in (Gentzkow et al., 2019). The score is given as follows: we define the term-frequency for each unique term v accross the entire corpus as below, where $x_{v,d}$ is the word count for term v in document v:

$$tf_v = 1 + log\left(\sum_d x_{d,v}\right)$$

Furthermore, let t_v be the number of documents that contain the term v, and T the total number of documents. The inverse document frequency is defined as:

$$idf_v = log\left(\frac{T}{t_v}\right)$$

Note that words that occur in fewer documents have a higher idf_v. We can then calculate a score for each term in the corpus as:

$$\text{tf-idf}_{d,v} = tf_v \times idf_v$$

The score is such that common words that appear in most documents will have lower scores, while words that appear frequently in some documents but not in others will have higher scores. We fix a threshold below which to drop terms that are considered very common in our dataset, providing another round of stopwords removal. In our application, this results in the exclusion of words such as "Brazil", "fiscal" and "government".

Figure A.1: Media Attention Series

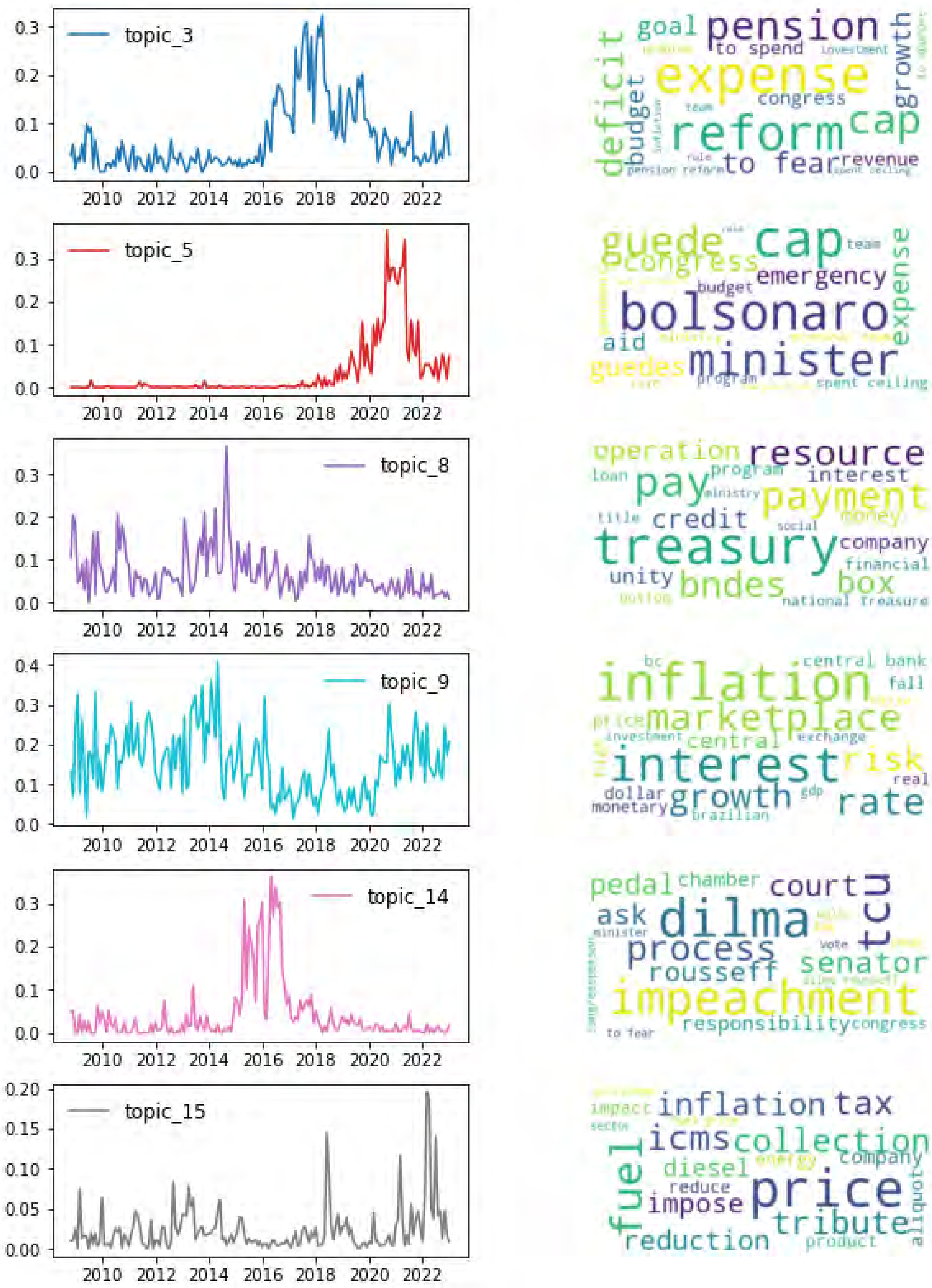
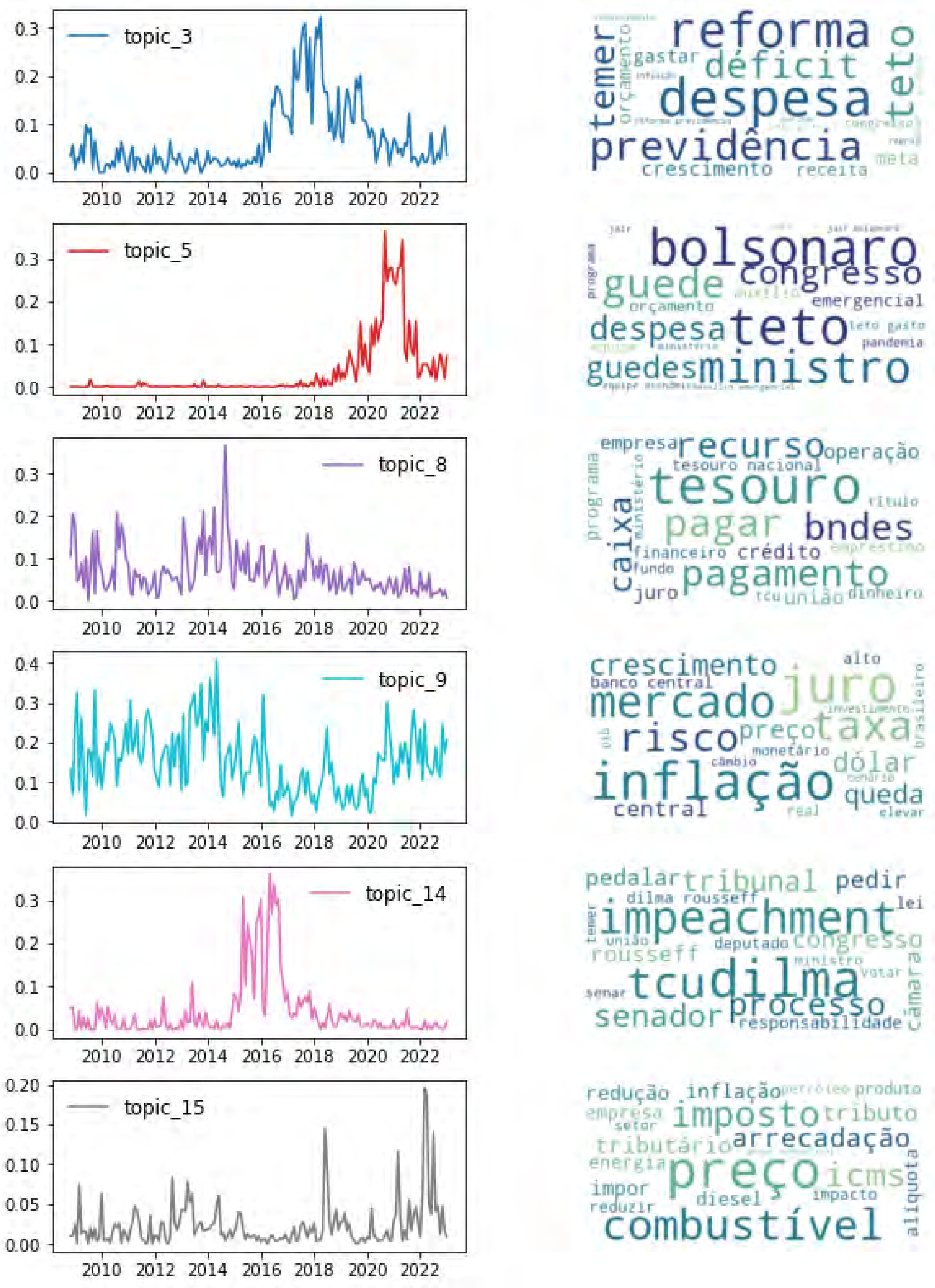


Figure A.2: Media Attention Series - Portuguese



Media attention series and most frequent words in Portuguese language

A.2 Tables

Table A.1: Fiscal Policy Terms - Portuguese

ajuste fiscal	aumento dívida	austeridade fiscal
crise fiscal	déficit fiscal	dívida bruta
dívida governo	dívida pública	dívida pib
esforço fiscal	estímulo fiscal	fiscal brasil
fiscal encerrar	fiscal governo	fiscal LRF
fiscal orçamento	fiscal teto	furar teto
juro dívida	lei responsabilidade	medida fiscal
meta fiscal	pagamento dívida	pedalar fiscal
política fiscal	precatório dívida	problema fiscal
reforma fiscal	regra fiscal	responsabilidade fiscal
renegociação dívida	resultado fiscal	risco fiscal
situação fiscal	teto gastos	

Table A.2: Yield 6y and 8y

	Yield 6y		Yield 8y	
	(1)	(2)	(3)	(4)
Constant	-1.494	-1.177	-1.511	-1.194
	(1.033)	(1.003)	(1.030)	(0.998)
Fiscal Risk Index	4.381***	3.846***	4.310***	3.775***
	(1.432)	(1.384)	(1.390)	(1.328)
Selic	0.656	0.952	0.580	0.878
	(1.349)	(1.286)	(1.264)	(1.231)
Exchange Rate	13.979***	8.235***	14.132***	8.339***
	(2.314)	(1.765)	(2.421)	(1.756)
CDS		25.085***		25.283***
		(6.854)		(7.093)
Num.Obs.	640	640	639	639
R2	0.222	0.278	0.224	0.281
R2 Adj.	0.218	0.273	0.220	0.276
RMSE	28.39	27.34	28.42	27.36

The table reports results of regression 3-1. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Yields: 1y, 5y and 10y - Monthly

	Yield 1y		Yield 5y		Yield 10y	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.57	-1.96	-0.84	5.29	-0.85	9.79
	(4.33)	(14.42)	(4.83)	(11.98)	(4.78)	(12.05)
Fiscal Risk Index	14.05**	14.24**	11.96**	10.88**	9.82**	8.38*
	(5.71)	(5.76)	(4.67)	(5.22)	(4.36)	(4.80)
Selic	19.48***	18.31***	12.32*	7.60*	11.35	6.04
	(3.91)	(3.60)	(6.89)	(4.34)	(6.91)	(4.76)
Exchange Rate	2.22	-4.06	25.66***	8.83	28.85***	10.99*
	(5.04)	(5.06)	(6.10)	(5.80)	(6.23)	(6.03)
CDS		8.26		23.07***		25.02***
		(6.05)		(8.38)		(7.85)
Num.Obs.	172	171	172	171	172	171
R2	0.206	0.257	0.239	0.325	0.254	0.341
R2 Adj.	0.191	0.185	0.225	0.259	0.241	0.277

The table reports results of regression 3-1 in monthly frequency. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: BRL Weekly

	(1)	(2)
Constant	0.002**	0.001
	(0.001)	(0.001)
Fiscal Risk Index	0.002*	0.000
	(0.001)	(0.001)
Selic	-0.001	-0.001*
	(0.001)	(0.001)
CDS		0.014***
		(0.001)
Num.Obs.	668	668
R2	0.007	0.391
R2 Adj.	0.004	0.388

The table reports results of regression 3-1 in monthly frequency. The dependent variable is the end-of-period percentage change in the exchange rate. The Fiscal Risk Index and the control variables are also included as percentage variations. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Yield 6y and 8y - Higher Sentiment Threshold

	Yield 6y		Yield 8y	
	(1)	(2)	(3)	(4)
Constant	-1.424	-1.098	-1.390	-1.067
	(1.023)	(0.996)	(1.039)	(0.990)
Fiscal Risk Index	4.732***	4.360***	4.644***	4.273***
	(1.405)	(1.358)	(1.368)	(1.300)
Selic	0.941	1.156	0.866	1.083
	(1.394)	(1.320)	(1.327)	(1.236)
Exchange Rate	14.099***	7.704***	14.335***	7.888***
	(1.914)	(1.740)	(1.959)	(1.740)
CDS		26.392***		26.591***
		(6.539)		(6.886)
Num.Obs.	656	656	655	655
R2	0.243	0.306	0.247	0.311
R2 Adj.	0.240	0.302	0.244	0.307

The table reports results of regression 3-1 in monthly frequency. The dependent variable is the weekly first difference of yields. The Fiscal Risk Index is included as a first difference, as well as the control variables. The independent variables are standardized such that coefficients can be interpreted as the effect of a unit standard deviation increase over the dependent variable. Heteroskedasticty and autocorrelation robust standard errors in parenthesis.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.3 Figures

Figure A.4: Fiscal Risk Index - Weekly

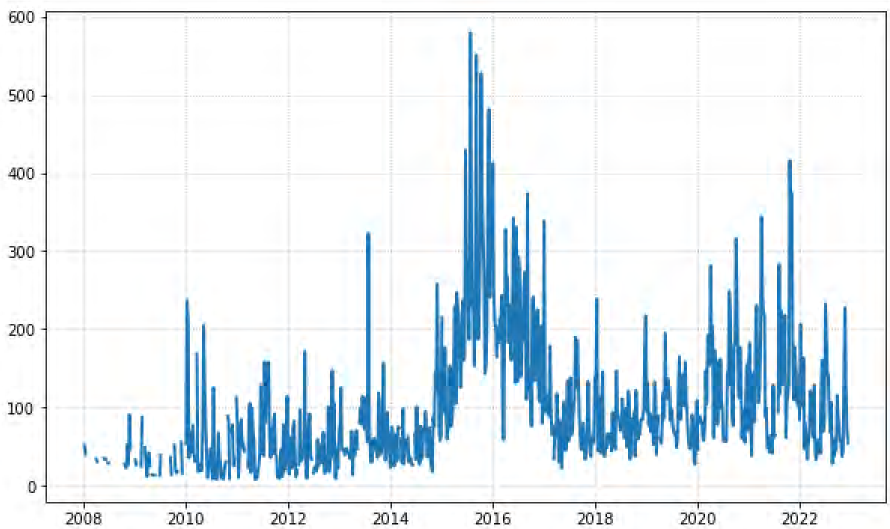
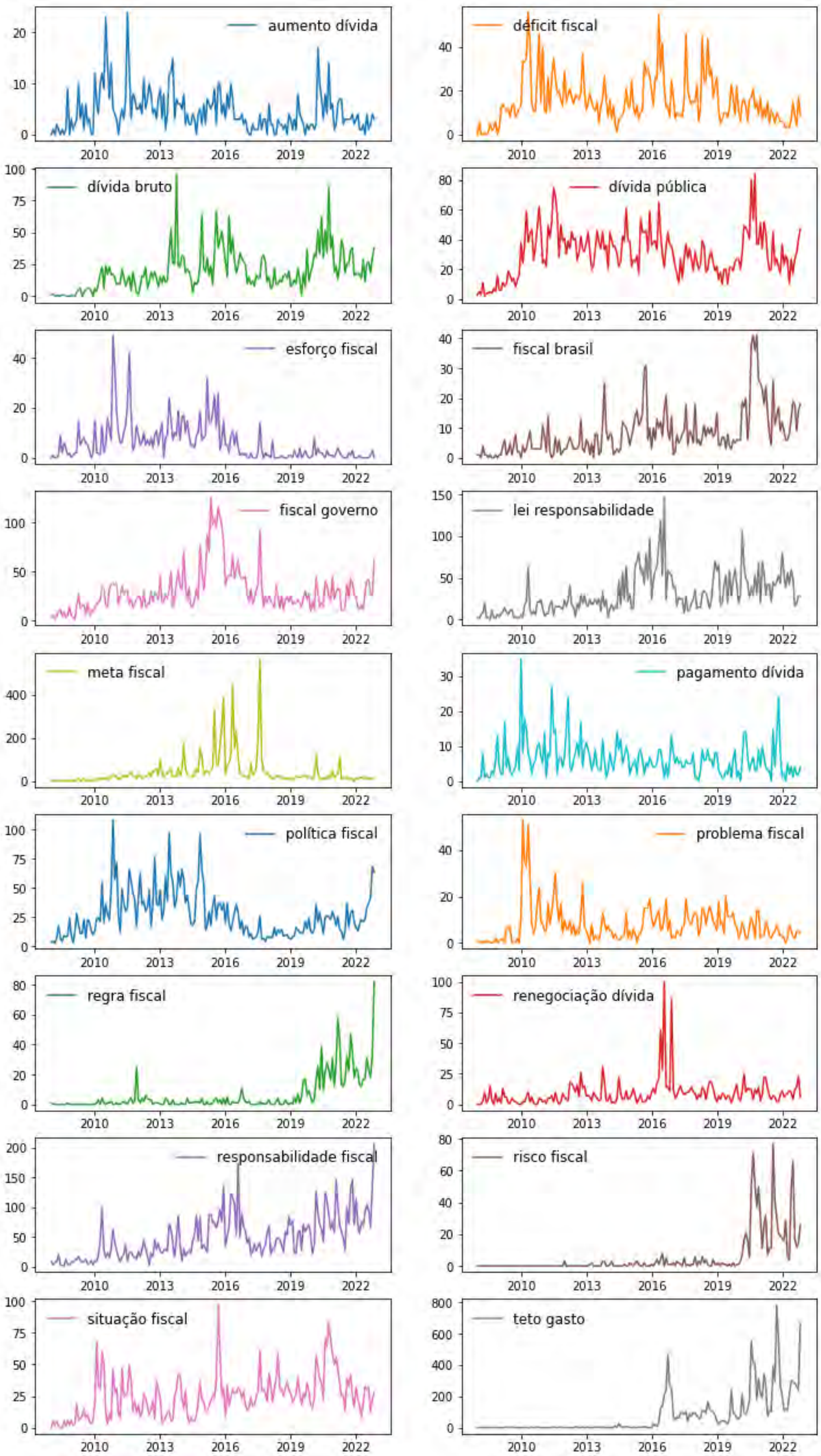


Figure A.3: Fiscal Dictionary Terms - Portuguese



Aggregate monthly counts of selected terms in the fiscal dictionary in original Portuguese language

Figure A.5: Fiscal Risk Index - Weekly - Newspaper Level

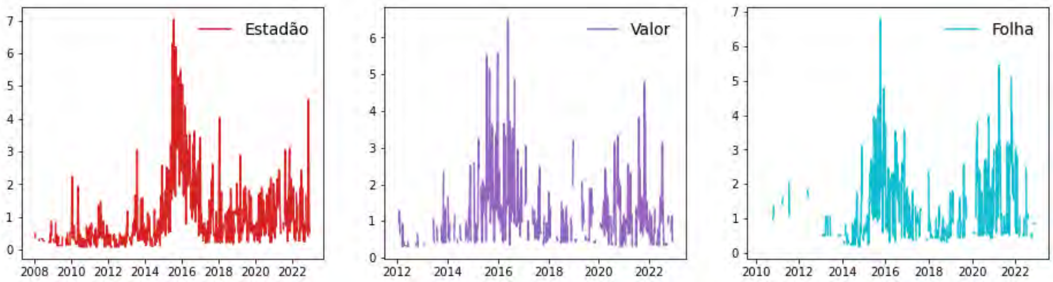


Figure A.6: 5-year Yield and ArCo

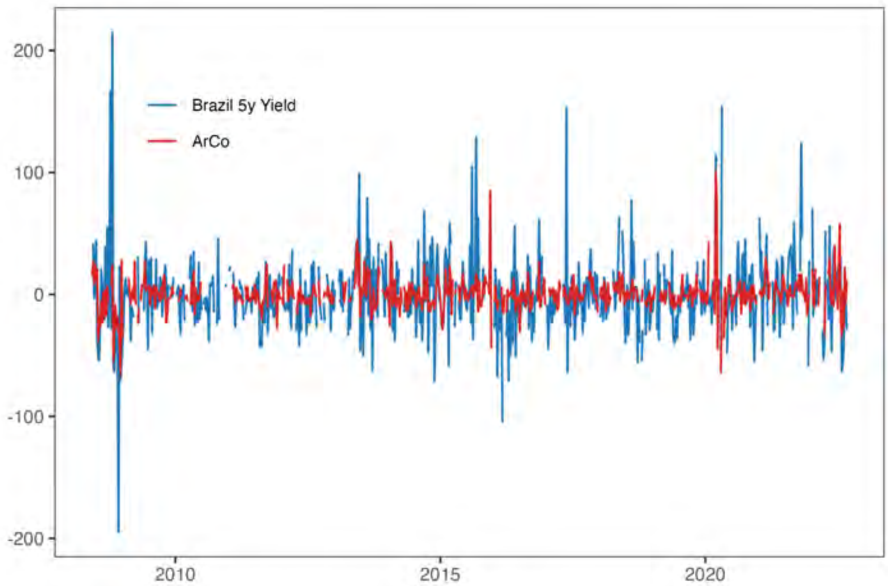


Figure A.7: 10-year Yield and ArCo

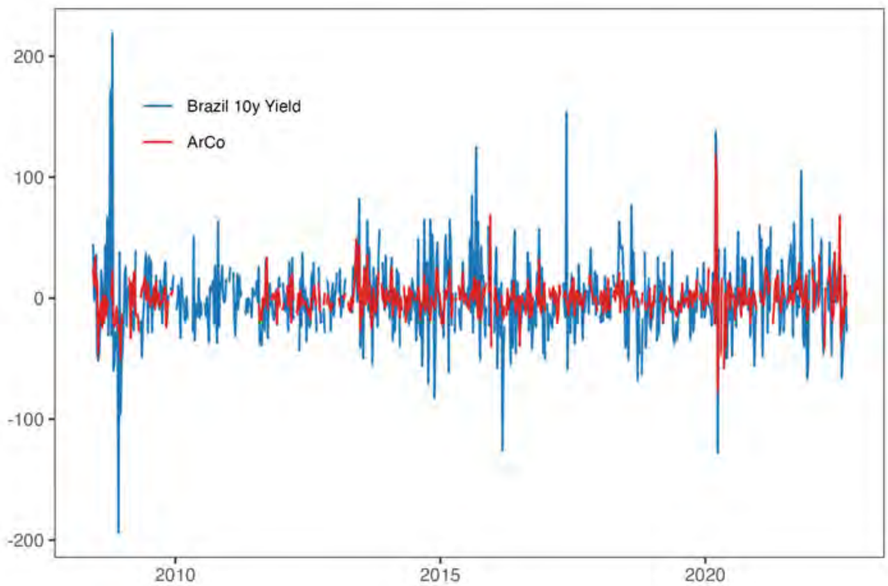


Figure A.8: BRL and ArCo