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RESEARCH PAPER

Measuring Brazilian Economic Uncertainty

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Abstract
We propose a measure of economic uncertainty, the Brazilian Economic Uncertainty Indicator, based on the news as well as business forecasts. The index expands the variety of newspapers handled by Baker et al. (Q J Econ 131(4):1593–1636, 2016) for Brazil. Our indicator captures Brazilian recent events such as the corruption scandals, the fiscal and economic crisis, the 2016 impeachment, the 2008 financial crisis and the 2002 presidential elections as moments of high uncertainty. An econometric study using a Bayesian Vector Autoregressive approach was carried out and revealed that uncertainty shocks cause an economic downturn in subsequent periods, as emphasized in the relevant literature.

Keywords Uncertainty · Economy · Web-scraping

JEL Classification C32 · E32

1 Introduction

Brazil experienced one of its most severe economic recessions between 2014 and 2016, with an accumulated loss of 8.6% of GDP. Since 2017, the Brazilian economy has been recovering, but slowly. Events such as the corruption scandals, the

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Lava-Jato operation, a serious fiscal crisis, the presidential impeachment, occurred during this period. Despite their diverse differences, they all increased the uncertainty of economic agents in the future. A natural question that therefore emerges is how this uncertainty may have affected the Brazilian economy.

The economic literature investigating uncertainty and its impact on the business cycle has been growing at great speed since the U.S. and the E.U. countries witnessed a slower than expected recovery from the 2008 crisis. Bloom (2014) discusses the main channels through which uncertainty impacts economic activity: (1) real-options effects, (2) risk-premium effects and (3) precautionary-savings effects. In the first, for which the main references are Bernanke (1983), Pindyck (1991) and Dixit and Pindyck (1994), companies become more cautious when decisions are costly to revert, delaying hiring and investments while they wait for more information. Concerning risk-premium effects, an increase in uncertainty raises the probability of default and, consequently, the risk in the financial market (see, for instance, Arellano et al. 2010; Christiano et al. 2014; Gilchrist et al. 2013). Similar to firms, in the last channel, families that are unsure about future income postpone consumption, particularly of durable goods, as a precautionary measure (more details in Romer 1990; Leland 1968; Skinner 1988).

The same theoretical evidence that shows the effects on firms and consumers suggests that monetary policy becomes less effective in environments with a high degree of uncertainty, making larger cuts in interest rates necessary to stimulate the economy (Dow 2004; Aastveit et al. 2017; Caggiano et al. 2017; Vavra 2013).

Numerous studies have attempted to find empirical evidence of these theoretical relationships. Examples include Leahy and Whited (1996), Abel and Eberly (1996) and Guiso and Parigi (1999), who estimated equations involving investment and uncertainty. They confirmed not only that there was a negative relationship between investment and economic uncertainty, but also that responses to uncertainty varied and were greater where investments were more irreversible[1] or for companies with great market power. Another approach involves the use of vector autoregressive models (VARs), which by means of impulse response functions allow, for example, increases in uncertainty to be associated with decreases in equipment purchases and hiring, as well as other macroeconomic variables, as in Bloom (2009) and Basu and Bundick (2017).

Another stylized fact addressed by Bloom (2014) is that developing economies, such as Latin America and South Africa, have higher levels of uncertainty (Bloom 2014). Koren and Tenreyro (2007) and The World Bank (2012) identify three possible explanations: (1) a more concentrated industrial sector, implying that supply shocks have a greater effect on the economy; (2) a dependence on commodities and (3) the severity of the damage caused by, and the difficulty recovering from, natural disasters, epidemics, wars etc. Carrière-Swallow and Céspedes (2013) investigate the differences in the amplitude and persistence of the response of investment and private consumption to uncertainty shocks and conclude that developing economies have a sharper, longer-lasting response than developed countries. In Brazilian

[1] Defined as those in wretainhich the capital invested cannot be recovered or is not worth recovering, a common example being industrial plants.

context, Costa Filho (2014) shows, by considering a set of proxies for uncertainty and macroeconomic variables, that the economy is negatively affected by an increase in uncertainty, with more acute effects on industrial production, GDP, and consumer confidence.

Given the negative consequences of uncertainty shocks on economic activity and the growing body of literature on the subject, an in-depth study of an important developing country like Brazil is relevant. In this article, we propose a measure of the level of Brazilian economic uncertainty,[2] the Economic Uncertainty Indicator for Brazil (IIE-Br[3]), and we present an empirical study on economic consequences of heightened uncertainty.

Because uncertainty is a subjective feeling about the economy, it is not directly observable. Knight (1921) defines uncertainty as an inability to define the probability of events, i.e., a complete lack of knowledge about future events. Based on that, researchers often use a range of proxies that allow measuring this abstract variable. For instance, Baker et al. (2016) developed an indicator based on the frequency of news items in the main U.S. newspapers. The same approach was adopted by Haddow et al. (2013) for England while Alexopoulos et al. (2009) used news articles published in The New York Times.

Uncertainty about the economic future is also reflected in an inability to make economic forecasts, as shown by the differences in specialists' expectations about macroeconomic variables. One of the measures of uncertainty described by Haddow et al. (2013) relates to the dispersion of company earnings forecasts and GDP forecasts. Guiso and Parigi (1999), in turn, use information supplied by entrepreneurs about the subjective probability distribution of future demand to measure uncertainty in Italy, while Bachmann et al. (2013) developed another type of uncertainty measure, based on business surveys, that uses microdata from the IFO Business Climate Survey for Germany and the Business Outlook Survey for the United States. Following Bachmann et al. (2013) approach, Morikawa (2016) uses data from Tankan, a representative quarterly business survey in Japan, to construct a measure of uncertainty based on the companies' ex-post forecast errors.

The IIE-Br[4] is built using the frequency of articles about uncertainty in the main Brazilian newspapers and the degree of dispersion among specialists forecasts of variables in the Focus report (see BCB 2018). Section 2 describes the methodology used to develop the indicator; Sect. 3 discusses the choice of the IIE-Br components' weights, presents the IIE-Br time series and points out the main features of its behavior over the years; Sect. 4 presents an econometric study, and Sect. 5 summarizes the findings.

[2] The concept of uncertainty and risk could be interchangeable throughout the text.

[3] IIE-Br is a Portuguese acronym for Brazilian Economic Uncertainty Indicator.

[4] The IIE-Br is available on BETS package in software R.

Table 1 Total number of news items captured

Newspaper	Source	Article
Valor Econômico	Printed	245,910
	Online	424,947
Folha de São Paulo	Printed	178,750
	Online	864,741
Correio Brasiliense	Twitter	33,255
Estadão		225,320
O Globo		409,638
Zero Hora		184,782

2 Analysis of IIE-Br Components

Bloom (2014) and Haddow et al. (2013) argue that there is no single measure for determining uncertainty but, rather, distinct measures that together minimize the errors of each measure in isolation. Following this line of reasoning, the IIE-Br consists of two indicators of uncertainty: (1) IIE-Br Media, which is based on the frequency of articles mentioning economic uncertainty in high-circulation newspapers and (2) IIE-Br Forecasts Disagreement, which uses the dispersion of market experts forecasts (Focus-Market Report).

2.1 IIE-Br Media

Taking the studies by Baker et al. (2016) and Alexopoulos et al. (2009) as a starting point, IIE-Br Media is a proxy that measures economic uncertainty based on the frequency of the news related to the theme.

News from all newspapers are collected on the internet and classified in three different groups: online, from the newspaper's own site; printed, by extracting information from the digitized printed version and, lastly, from newspaper's official account on Twitter, when information could not be obtained in newspapers' website.

Twitter's tremendous popularity, as discussed in Hong and Davison (2010) and Armstrong and Gao (2010), motivates many companies to start advertising their brands on the social network. This includes newspapers, magazines, and news websites. Articles in the printed version tend to be more important than those published in the online version due to the printing costs associated with the printed media. For this reason, we decide to distinguish between online and printed news from the same source (newspaper).

The newspapers were added to the indicator as they became available online, as shown in Fig. 6 ("Appendix A"). In the period between 2000 and 2009, the IIE-Br Media was consisted solely of *Folha de São Paulo* newspaper due to data availability. After 2010, some of the most important Brazilian newspapers started using Twitter and others made their articles available through their websites. Then, in order to reduce possible biases that dependence on a single source can cause, other sources were incorporated into the indicator.

The article database used for the indicator contains over two million articles from the main Brazilian newspapers classified according to three different capture methods (see Table 1). It is worth noting that four newspapers collect data only from Twitter while *Valor Econômico* and *Folha de São Paulo* gather articles from their own websites (online and printed versions).

Articles were classified according to the feeling of economic uncertainty using the index created by Baker et al. (2016), in which terms related to the economy and economic uncertainty were selected and combined. If an article contains a combination of the chosen terms, it is classified as an article about uncertainty. We create two groups of terms for the purposes of classification: one related to the subject "economy", for which the term "economy" was used, and another directly related to uncertainty, which consisted of the terms "uncertainty", "instability" and "crisis". In order to ensure that words related to the selected terms were also included in the search (e.g., "uncertain" as well as "uncertainty"), a type of lemmatization was performed, in which words are reduced to their roots: "ECON" for economy and "INSTAB", "UNCERT" and "CRISIS" for the uncertainty terms. Articles with at least one term from each group were considered to be about economic uncertainty.

The calculation for IIE-Br Media is based on the proportion of articles about economic uncertainty, according to the word-based classification. Define the proportion of economic articles identified by method k (online newspaper, printed newspaper or *Twitter*) in month t as follows:

$$P_{k,t} = \frac{U_{k,t}}{T_{k,t}}, \tag{1}$$

where $U_{k,t}$ is the number of articles published by media k classified as being related to uncertainty and $T_{k,t}$ represents the number of articles published by media k in the month t.

Then, the next step was to aggregate information from similar sources, i.e, online media, and printed media. As online newspapers and Twitter are both online media, the proportion of articles about uncertainty in this group is given by

$$P_{online,t} = \frac{P_{newspaper,t} + P_{Twitter,t}}{2}. \tag{2}$$

Printed newspapers were grouped together, i.e, the proportion of economic uncertainty articles from printed media was calculated based on economic uncertainty articles present in the printed version of *Folha de São Paulo* and *Valor Econômico*.

Once we calculated both online and printed media proportion, we were able to compute the total media proportion given by

$$P_{media,t} = \frac{P_{printed,t} + P_{online,t}}{2}. \tag{3}$$

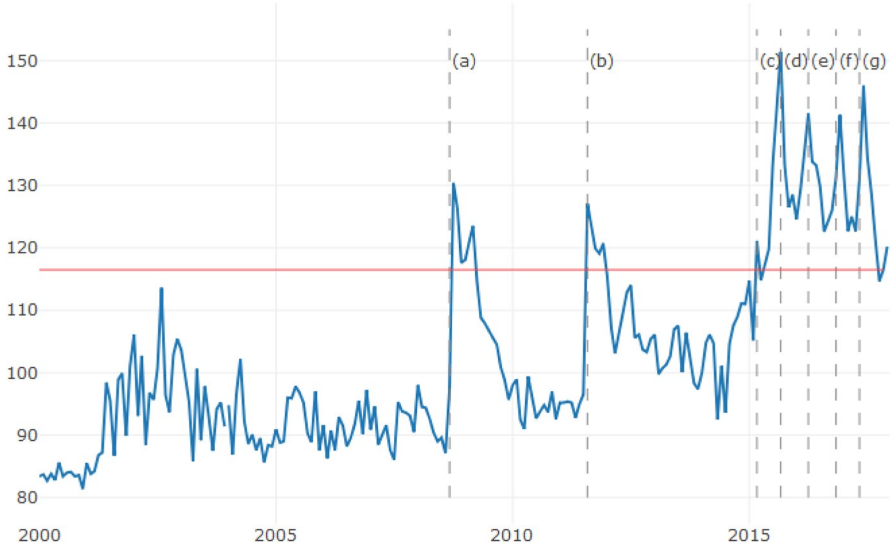

Fig. 1 Media component of IIE-Br. **a** September 2008—collapse of Lehman Brothers; **b** August 2011—US credit-rating downgrade; **c** March 2015—manifestations in Brazil; **d** September 2015—BR credit-rating downgrade; **e** April 2016—impeachment voting; **f** November 2016—government spending ceiling; **g** May 2017—political crisis. The red line indicates a level of 116.5 that represents 1.65 standard deviations above the mean (inside reference window) (colour figure online)

IIE-Br Media is the result of standardizing the time series of P_{media} using the mean and standard deviation in the reference window (January 2005 to December 2014). The standardized time series for the IIE-Br Media components, including Twitter's time series, can be found in "Appendix B" and show that all of them have a similar behavior.

Figure 1 shows that the media indicator is clearly very volatile, with periods of high and low volatility. In addition to showing high overall volatility, three periods stand out. The first period begins with the collapse of Lehman Brothers in September 2008, which would become the beginning of the global financial crisis. After that, another period that stands out is the mid-2011 until mid-2012, with the U.S. credit rating downgrade in August 2011. More recently, we've been observing an increase of IIE-Br Media due to the recurrent corruption scandals and the political and economic crises that have played out in Brazil in recent years.

2.2 IIE-Br Forecasts Disagreement

IIE-Br Forecasts Disagreement is an indicator based on information from the market's expectations series produced by the Central Bank and published in the Focus Report. About 130 financial and non-financial institutions registered with the Brazilian Central Bank publish daily projections for a set of macroeconomic variables such as GDP, Inflation, Interest Rate, etc. for the current period and the next eighteen months. Institutions participating in the Focus survey are not required to update their forecasts on a routine basis. However, since 2006 the Central Bank publishes the Top 5 ranking with the best short-run, medium-run and long-run forecasts of 5 variables: General Price Index-M(IGP-M), General Price Index-DI(IGP-DI), Extended Consumer Price Index (IPCA),[5] short-term interest rate (Selic Rate) and Exchange Rate for the month. One of the requirements for institutions to participate in the Top 5 is to update forecasts before the reference date defined by the Central Bank. To guarantee a sample of forecasts whose data are updated, we will use only Top 5's variables in the construction of the IIE-Br Forecasts Disagreement. We used the IPCA accumulated over the next 12 months as an indicator of inflation, instead of either IGP-M or IGP-DI, because the IPCA is targeted by the Central Bank.

The calculation for IIE-Br Forecasts Disagreement, therefore, considers the coefficient of variation of the 12-month-ahead forecasts for the exchange rate, Selic, and the accumulated IPCA over the next 12 months.

The dates on which these forecasts are collected from the BCB website are based, when possible, on the top 5 regulatory deadlines. The IPCA is collected on the last business day before the IPCA-15[6] announcement, and the exchange rate is collected on the last business day before or on the 15th day of the current month. Selic's reference dates are defined at the COPOM (Monetary Policy Committee) meetings that occur only 8 times a year since 2006, i.e. there is no reference for every month. As a way of getting around this problem, the last business day before or the 15th day of the current month was chosen as the date of collection. The uncertainty captured by market expectations is measured using the coefficients of variation of the Selic, the exchange rate and the 12 months accumulated IPCA standardized in relation to the reference window. This indicator is defined as:

$$U_{exp,t} = \frac{U_{IPCA,t} + U_{exchange\ rate,t} + U_{selic,t}}{3}, \tag{4}$$

where $U_{exp,t}$ is the indicator of economic uncertainty based on market expectations in month t, and $U_{IPCA,t}$, $U_{exchange\ rate,t}$ and $U_{selic,t}$ are coefficients of variation of the 12-month-ahead of expectations for the accumulated IPCA over the next 12 months, exchange rate and Selic, respectively. The IIE-Br Forecasts Disagreement, presented in Fig. 2, consist of the indicator U_{exp} standardized in relation to the reference window (January 2005 to December 2014).

The IIE-Br Forecasts Disagreement, differently from IIE-Br Media, started to be computed in January 2002 due to data availability. Among the several moments of high uncertainty present in the IIE-Br Forecasts Disagreement, one, in particular, stands out: the period around the presidential election of 2002. In October of the said year, the indicator reached its maximum value as consequence of the possibility of a president being elected, with a left-wing agenda, as well as the difficulty in predicting the policies that would be consequently implemented.

[5] IGP-DI, IGP-M and IPCA are Brazilian inflation indicators. The differences among them relate to the collection period and the product basket

[6] IPCA-15 diverges from IPCA just for the period of collection

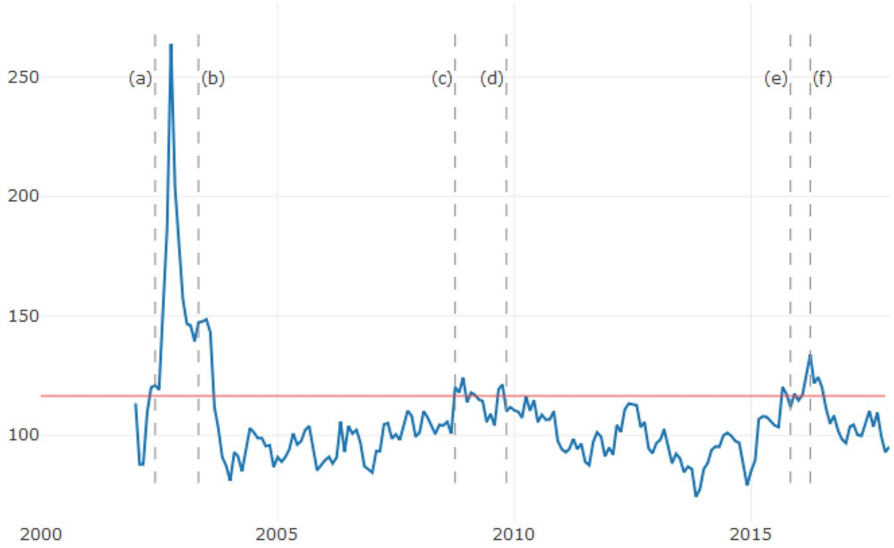

Fig. 2 IIE-Br forecasts disagreement. **a** June 2002—presidential elections; **b** May 2003—uncertainties regarding monetary and exchange rate policies; **c** October 2008—global financial crisis; **d** September 2009—uncertainty regarding monetary policy; **e** September 2015—BR credit downgrade; **f** April 2016—political crisis. The red line indicates a level of 116.5 that represents 1.65 standard deviations above the mean (inside reference window)

3 Weightings Used for the Components of the IIE-Br

The main idea of IIE-Br is to capture if not all, most of the moments of economic uncertainty faced by the Brazilian economy. The components were therefore chosen to provide as much information as possible about economic uncertainty.

Usually, the economic uncertainty indicators presented in the literature are based only on one measure of uncertainty. However, as shown in the previous section, the IIE-Br Media and IIE-Br Expectation can capture different moments in the Brazilian economy when there was an increase in uncertainty. It is clear that the component that best fitted recent oscillations in uncertainty was the media component. Nevertheless, there were times when this component failed to capture increases in uncertainty, but were reflected in oscillations in the IIE-Br Forecasts Disagreement, such as the increase in uncertainty during the 2002 elections. As previously mentioned, the Pearson's correlation between the components is equal to approximately 0.43, indicating that they differ at some points and therefore, don't necessarily capture the same moments of economic uncertainty.

The question that arises is how to combine these indicators since any form of aggregation will invariably lead to some kind of loss of information. Thus, in order to preserve the maximum possible number of uncertainty peaks present in its components, the following procedures were adopted for its construction: first, the peaks of high uncertainty were defined, i.e, the moments in which the value of the component exceeded 1.65 deviations above its mean; then, the number of peaks of each component was counted to give us an idea of the maximum number of the peaks of

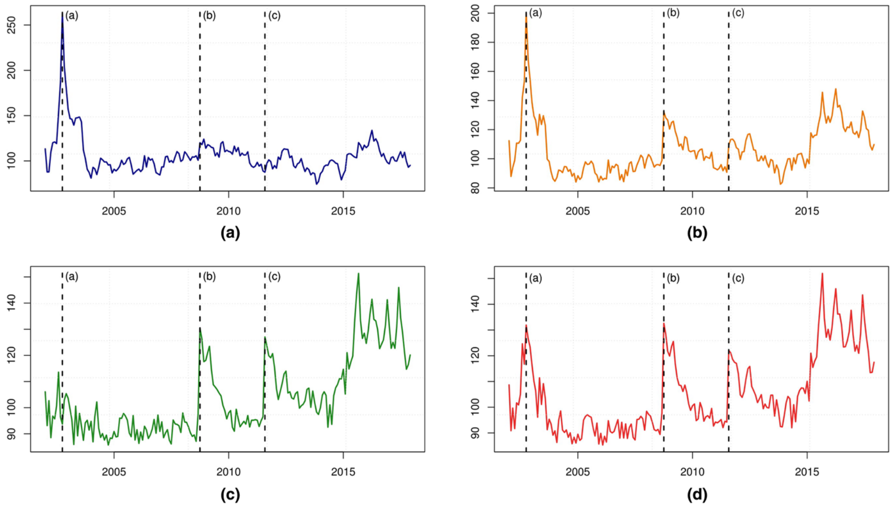

Fig. 3 Different weightings for the IIE-Br Media and IIE-Br Forecasts Disagreement where *a* represents the weight given to IIE-Br Media component and *b* to IIE-Br Forecasts Disagreement. Events **a**–**c** represent the 2002 presidential election, the 2008 global financial crisis and the 2011 U.S credit rating downgrade, respectively

the final indicator; finally, an optimization was made in a way that the main indicator preserves the highest number of uncertainty peaks present in its components between Jan 2008 and Dec 2017. We believe that this 10-year window is ideal because it captures well uncertainty variations, reflecting the peaks.

Suppose a and b are the weights given to IIE-Br Media and IIE-Br Forecasts Disagreement, respectively. Thus,

$$a \times \text{ IIE-Br Media } + b \times \text{ IIE-Br Forecasts Disagreement } = \text{ IIE-Br Candidate}$$

Suppose now that k is the number of peaks of the IIE-Br Candidate (as previously defined), a and b were then chosen so k was maximized. The weights obtained for a and b, were 0.78 and 0.22, respectively. For convenience, we chose to work with only one decimal place. Hence, the final weights are 0.8 for IIE-Br Media and 0.2 for IIE-Br Forecasts Disagreement.

To illustrate this approach, Fig. 3 presents different IIE-Br Candidates based on different weightings for the components. It is possible to verify that if we only use IIE-Br Forecasts Disagreement we would not capture some moments of high uncertainty, for example, the high uncertainty caused by the collapse of Lehman Brothers. IIE-Br Media captures moments of increased economic uncertainty very well, however, it is not able to capture the uncertainty around the presidential elections of 2002. Combinations of the components were tested in order to capture the most moments of uncertainty as possible.

The historical behavior of economic uncertainty in Brazil using the methodology described in this article is presented in Fig. 4. Given the importance of IIE-Br Media in the composition of the final indicator, many of the moments characterized

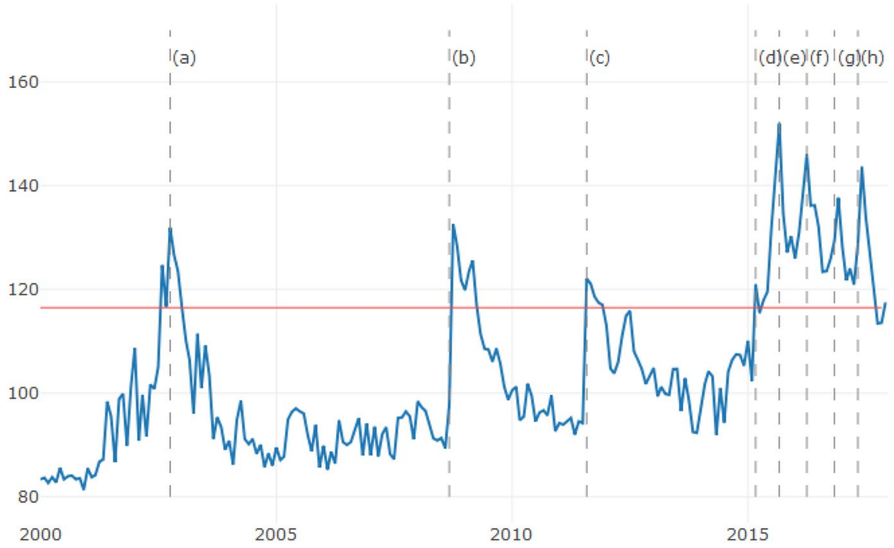

Fig. 4 IIE-BR. **a** October 2002—presidential elections; **b** September 2008—collapse of Lehman Brothers; **c** August 2011—US credit-rating downgrade; **d** March 2015—manifestations in Brazil; **e** September 2015—BR credit-rating downgrade; **f** April 2016—impeachment voting; **g** November 2016—government spending ceiling; **h** May 2017—political crisis. The red line indicates a level of 116.5 that represents 1.65 standard deviations above the mean (inside reference window)

as being of uncertainty in this component are present in IIE-Br. Examples include the 2008 financial crisis and the downgrade of the U.S. credit rating. However, when we add the IIE-Br Forecasts Disagreement, new periods of uncertainty are added to the final indicator, in particular, the period around the 2002 presidential election.

4 The Impact of Uncertainty on the Real Economy: First Exercises

As briefly discussed above, the literature presents evidence of high uncertainty scenarios undermining economic activity. To illustrate these possible effects, we use data collected from December 2003 to July 2017 in a Bayesian Vector Autoregressive (BVAR) model to extract impulse-response functions for shocks in the IIE-Br.[7]

Following the notation presented in Dieppe et al. (2016), the VAR model with n endogenous variables, m exogenous variables, p lags and sample size T can be written as:

$$Y = XB + \mathscr{E} \tag{5}$$

[7] Since uncertainty was measured only for a short period of time, a Vector Autoregressive (VAR) model is not recommended due to possible overfitting issues caused by the model's dimension. In such cases, Bayesian techniques seem a good alternative, as prior beliefs are used to reduce the number of coefficients, avoiding dimensionality problem.

with:

$$Y=\begin{pmatrix} y_1' \\ y_2' \\ \vdots \\ y_T' \end{pmatrix}, X=\begin{pmatrix} y_0' & y_{-1}' & \cdots & y_{1-p}' & x_1' \\ y_1' & y_{-0}' & \cdots & y_{2-p}' & x_2' \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ y_{T-1}' & y_{T-2}' & \cdots & y_{T-p}' & x_T' \end{pmatrix}, B=\begin{pmatrix} A_1' \\ \vdots \\ A_p' \\ C' \end{pmatrix} \text{ and } \mathscr{E}=\begin{pmatrix} \mathscr{E}_1' \\ \mathscr{E}_2' \\ \vdots \\ \mathscr{E}_T' \end{pmatrix}. \tag{6}$$

where $y_t'=\left(y_{1,t},y_{2,t},\dots,y_{n,t}\right)$ is a $1\times n$ vector of endogenous data, $x_t'=\left(x_{1,t},x_{2,t},\dots,x_{m,t}\right)'$ is a $m\times 1$ vector of exogenous data, $A_1,A_2,\dots,A_p$ are $n\times n$ matrices, C is a $n\times m$ matrix, and $\mathscr{E}_t=\left(\mathscr{E}_{1,t},\mathscr{E}_{2,t},\dots,\mathscr{E}_{n,t}\right)$ is the vector of residuals that follows a multivariate normal distribution with mean zero and covariance matrix Σ.

Equation 5 can be vectorized resulting in:

$$y=\bar{X}\beta+\varepsilon \tag{7}$$

with:

$$y=vec(Y),\bar{X}=I_n\otimes X,\beta=vec(B),\varepsilon=vec(\mathscr{E}) \tag{8}$$

$$\varepsilon\sim N(0,\bar{\Sigma}),\ \text{where } \bar{\Sigma}=\Sigma\otimes I_T. \tag{9}$$

The prior beliefs about BVAR coefficients can be expressed in terms of probability distributions, i.e., we set values for coefficients according to our confidence in them. We decided to work with a normal-Wishart prior as this distribution assumes that both β and Σ are unknown.

After manipulating the likelihood function, it can be found that (see Dieppe et al. 2016 for more details):

$$\beta\sim N(\beta_0,\Sigma\otimes\Phi_0) \tag{10}$$

where β_0 is a $q\times 1$ vector and Φ_0 is a $k\times k$ diagonal matrix being k the number of coefficients to estimate for each equation and q the total coefficients to estimate for the full VAR.

The diagonal elements of the variance matrix Φ_0 were defined as follows (Karlsson 2013):

- For exogenous variables:

$$\sigma_c^2=\left(\lambda_1\lambda_4\right)^2 \tag{11}$$

- Let σ_i^2 be the unknown residual variance for variable i in the BVAR model. For l lags terms of endogenous variables and cross-lags, define the variance as:

$$\sigma_{a_{ij}}^2=\left(\frac{1}{\sigma_j^2}\right)\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2. \tag{12}$$

Table 2 Series used

Series	Source	Order
IIE-Br	FGV|IBRE	1
Exchange rate	BCB	2
PIM-PF	IBGE	3
IBC-Br	BCB	4
Unemployment rate	FGV|IBRE	5
Real SELIC	BCB/authors	6

The prior for Σ is a inverse Wishart characterized by the parameters S_0 and α_0. S_0 is a $n \times n$ matrix, while α_0 represents the prior degrees of freedom.

Following Karlsson (2013):

$$S_0 = (\alpha_0 - n - 1)\begin{pmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \dots & \sigma_n^2 \end{pmatrix} \text{ and } \alpha_0 = n + 2 \tag{13}$$

Working with these priors will result in a normal-Wishart posterior. To get the estimates of the coefficients, the Gibbs sampling algorithm can be used. Following these specifications, the model was tested using our data. The hyperparameters λ_1, λ_3 and λ_4 were defined as 0.1, 1 and 100, respectively. Also, since uncertainty is usually considered to be a cyclical and not a long-run phenomenon, the BVAR was estimated in levels as in Jurado et al. (2015); Bachmann et al. (2013).

Table 2 summarizes the series used and their ordering. BCB corresponds to the Central Bank of Brazil, IBC-Br represents the Index of Economic Activity of the Central Bank of Brazil and PIM-PF is the Monthly Survey of Industry-Physical Production. We collected data from December 2003 to July 2017 and consider as monthly unemployment the Continuous National Household Sample Survey (PNAD) backward extrapolation done by the Department of Applied Economics at the FGV–IBRE. The Commodities index from BM&F entered the model as an exogenous variable. The data were seasonally adjusted when needed. To determine the number of lags needed, we used the Bayesian Information Criteria (BIC) and the number of lags suggested was 2. The analysis presented here was done by using the MATLAB-based "BEAR Toolbox" developed by the European Central Bank.[8] Notice that the impulse response functions are derived from a structural vector autoregressive (SVAR) model estimated with Bayesian techniques. The recursive identification strategy was used here.

Figure 5b shows the response of the PIM-PF, which, within the 95% credible intervals (shown as dotted red lines), the response of the PIM-PF reacts between

[8] The toolbox is freely available and can be obtained from https://www.ecb.europa.eu/pub/research/working-papers/html/bear-toolbox.en.html.

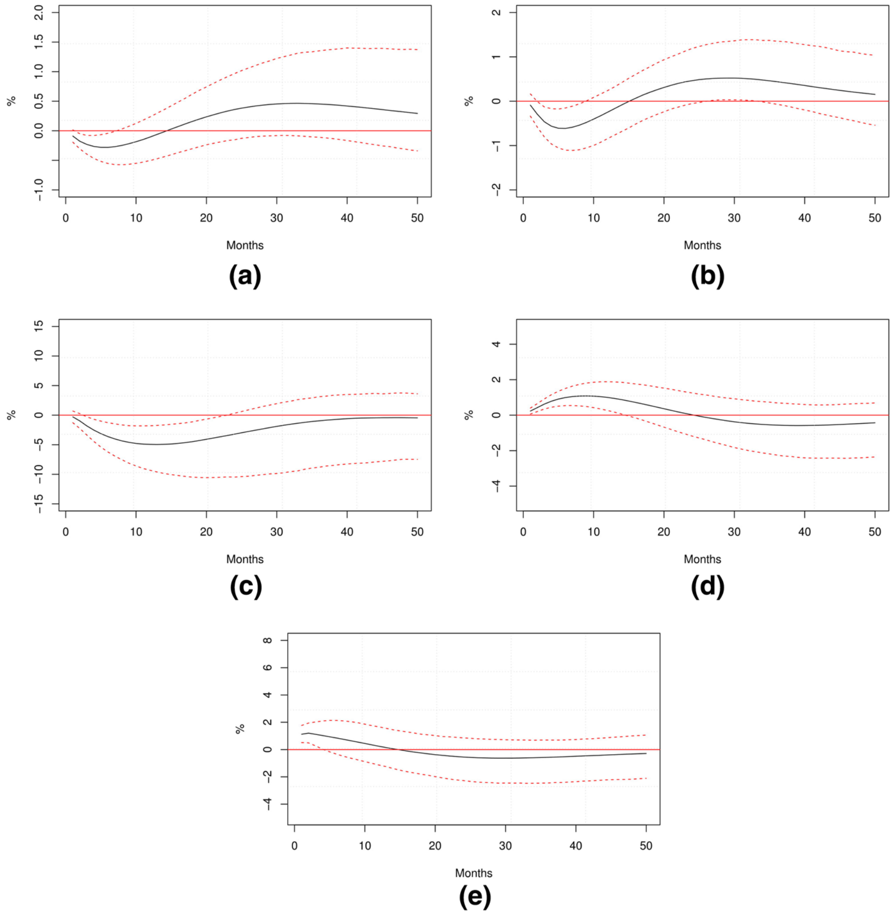

Fig. 5 Responses to shocks in the IIE-Br (median impulse response). **a** IBC-Br, **b** PIM-PF, **c** real selic, **d** unemployment rate **e** exchange rate

the second and the third month after one standard deviation shock. The response reaches a maximum in the fifth month, then the curve starts to return to zero. The negative effect of the shock, therefore, lasts about seven months. For the IBC-Br, in Fig. 5a, the response also reaches its maximum in the fifth month and the effects of the shock last about six months. These results are consistently reproduced for various orderings. This indicates that they are robust.

5 Conclusion

Similar to what happened internationally during the 2008 crisis, Brazil is experiencing difficulties that emerged from the last recession (2014–2016). A series of events in recent years, such as the fiscal crisis, the corruption scandals, and the political instability, indicate that there has been an increase in economic uncertainty during this period.

In light of this, measuring uncertainty in Brazil is clearly important. Nicholas Bloom presents an indicator of Brazilian economic policy uncertainty[9] based on the article by Baker et al. (2016). However, besides having a more restricted sense of uncertainty, this indicator is based on only one newspaper. Moreover, it was not able to capture a moment of great uncertainty in the Brazilian economy that occurred during the presidential election of 2002.

In an attempt to correct any bias introduced by analyzing just one national newspaper, the IIE-Br also analyzes the contents of five other national newspapers. It includes information about the forecasts disagreement of market analysts too. Hence, it consists of two components: IIE-Br Media and IIE-Br Forecasts Disagreement, available at different times as shown in "Appendix A". A technologically innovative aspect of the indicator is that it captures all the data automatically by web-scraping.

An econometric study was carried out to investigate the effects of uncertainty shocks on the Brazilian economy. Statistically significant decreases in economic activity variables were observed in the months following the uncertainty shock. which indicates that the increase in uncertainty in recent years made the recovery of the Brazilian economy slower.

A Availability of IIE-Br Components

See Fig. 6.

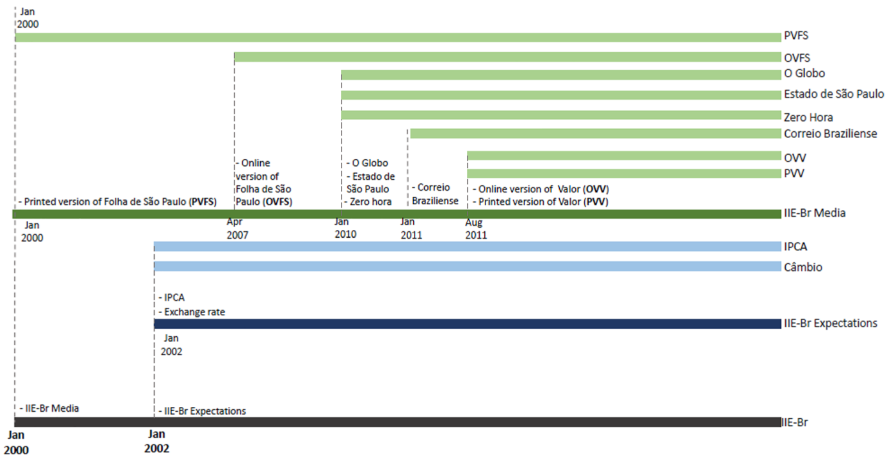

Fig. 6 Construction of the historical series

[9] http://www.policyuncertainty.com/brazil_monthly.html.

B Time Series for Online and Printed Media

See Fig. 7.

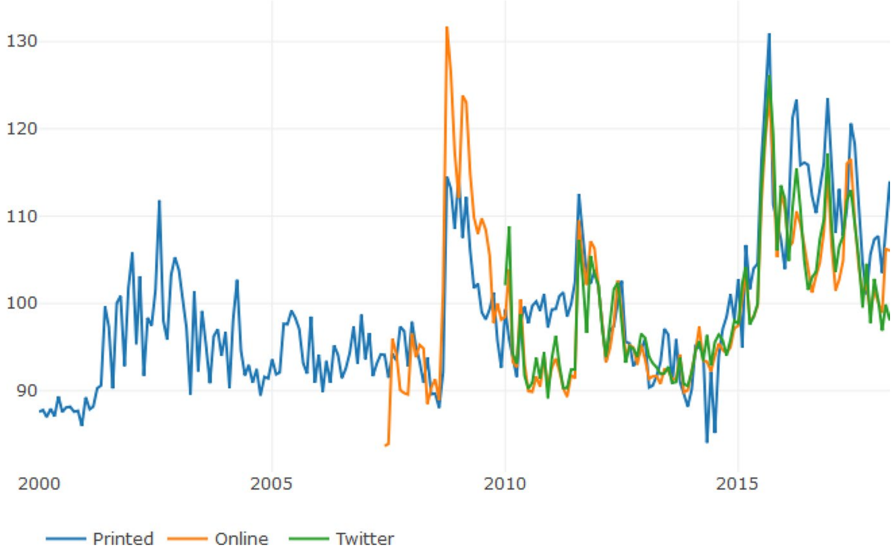

Fig. 7 Time series of IIE-Br Media components

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