Research article

Using uncertainty regional shocks to assess the relationship between the COVID-19 crisis and economic regional cycles in Brazil[♦]

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Abstract

We estimate the effects of COVID-19 on regional economic cycles through uncertainty shocks, using quarterly data (from 2007 to 2022) for 13 Brazilian federative units. The results point to heterogeneity in two ways: persistence of simulated shocks and output recovery speed. Consequently, we found evidence supporting the hypothesis of asymmetric reactions, a feature directly related to resilience over external idiosyncrasies. Therefore, our analysis indicates that the states that react less to external shocks are most likely to recover quickly compared to more susceptible regions.

Keywords

Uncertainty, COVID-19, Cycles.

Usando choques regionais de incerteza para avaliar a relação entre a Crise da COVID-19 e os ciclos econômicos regionais no Brasil

Resumo

Estimamos os efeitos da COVID-19 sobre os ciclos econômicos regionais por meio de choques de incerteza, usando dados trimestrais (de 2007 a 2022) para 13 unidades federativas brasileiras. Os resultados apontam para heterogeneidade em duas formas: persistência dos choques simu-

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lados e velocidade de recuperação do produto. Consequentemente, encontramos evidências que apoiam a hipótese de reações assimétricas, uma característica diretamente relacionada à resiliência sobre idiossincrasias externas. Portanto, nossa análise indica que os estados que reagem menos a choques externos têm maior probabilidade de se recuperar rapidamente em comparação com regiões mais suscetíveis.

Palavras-Chaves
Incerteza, COVID-19, Ciclos.

Classificação JEL
C32, D80, E32.

1. Introduction

Recognizing that economic, political, and social characteristics differ between Brazil's regions, local economic fluctuations can diverge from those observed at the macroeconomic level. Such a deviation would create an asymmetry in decision-making and, consequently, variability in regional cycles (see Haddad et al. (1989)).

The global health crisis (COVID-19) reinforced this hypothesis, as it directly affected local market volatility and the transmission of idiosyncrasies in the decision-making of public agents. Following the Real Business Cycles (RBC) approach, some determinants of output, such as labor dynamics, capital stock, fiscal sustainability, and economic uncertainty, were indicated as possible drivers. Some authors, such as Gomes *et al.* (1986), Guimarães Neto (2011), Cunha and Moreira (2006), and Ellery-Junior and Gomes (2005) were pioneers in this investigation.

However, measuring uncertainty is complex, and several strategies are available in the recent literature. We emphasize three seminal papers on which we will base this study to understand the economic implications of uncertainty shocks[1]: Donadelli (2015) is one of the seminal/precursor works that uses measures of economic uncertainty based on data from public research service (Google). Baker *et al.* (2016) deliver one of the most significant contemporary empirical contributions regarding the effects of uncertainty on economic activity using word frequencies in newspapers. Furthermore, Altig *et al.* (2020) build a robust methodological framework

[1] The indicated studies are based on aggregated data, while here we aim to disaggregate uncertainty shocks into local disturbances.

to identify shocks and empirically analyze the possible effects of the coronavirus crisis on economic activity, using uncertainty indicators from the most diverse sources (Twitter and newspapers).

The established hypothesis is that the Brazilian regional particularities enabled real asymmetric effects on economic cycles through the uncertainty of economic agents. Therefore, the main objective of this paper is to investigate the short-term relationship between uncertainty and real-side economics in 13 Brazilian federative units during the health crisis (COVID-19). The choice of the health crisis (COVID-19) was motivated by identifying an exogenous uncertainty shock, as Altig *et al*. (2020) suggested. Since its occurrence does not depend on endogenous factors (dynamics of economic variables), it differs structurally from crises such as subprime and 2014-2016. Furthermore, we can expect external and internal asymmetry responses for the federative units since they can induce different economic cycles in other states or even respond asymmetrically to negative or positive internal shocks.

However, following the methodology used in the reference papers, the only data source available for the state-level analysis in Brazil (13 federative units between 2007 and 2022) is Google Trends (as in Donadelli (2015)) since most states do not have digital archives of their most prominent newspapers and Twitter does not provide its open database by region. That would be the main difference between the measure we use and aggregated indices such as the Brazilian Economic Uncertainty Indicator by Fundação Getúlio Vargas (FGV) and the Economic Policy Uncertainty Index for Brazil, which predominantly uses the national newspaper. Therefore, since they differ in construction, they are not directly comparable to the regional indices presented in this research based on Google Trends.

To calculate the proxy, first, we standardize the volume of monthly searches related to economic uncertainty and build regional indicators to calculate the proxy. For each state, we identify the magnitude of the uncertainty shock attributed to the pandemic period (in units of standard deviations above the state average). Then, we estimate impulse-response functions through a Global Autoregressive Vectors model, with Bayesian inference, and simulate the disaggregated effects that a regional uncertainty shock exerts on internal and external economic cycles. Finally, we analyze the statistical significance of the impulse-response functions and the expected duration of regional shocks, seeking insights that can help, mainly the economic recovery process of the units.

Our findings have practical implications, allowing the implementation of local recovery strategies that differ from those typically observed at the national level due to the asymmetric effects of regional shocks. In other words, given that state-level economic cycles are not identical (for a deeper understanding, see Val and Ferreira (2001), Mussolini and Teles (2012), Cruz and Colombo (2018), and Souza *et al.* (2022)), we expect that the impulse-response functions (to an uncertainty shock) will be distinct when disaggregating the data. Consequently, policies based on these results will also reflect responses of different magnitudes.

The paper unfolds across five sections. The following Section explains the primary theoretical references and defines the concept of uncertainty and its possible measures. Then, we present the details of the econometric model together with some descriptive statistics from the database. In Section 4, we analyze the estimation results; in Section 5, we discuss some conclusions and their practical implications.

2. Theoretical Background

Knight (1921) introduced the concept of separating risk and uncertainty by distinguishing between measurable and immeasurable probabilities. In decision theory, risky situations are those in which all alternatives are known, and the probabilities of their occurrence can be precisely determined. On the other hand, uncertainty refers to situations in which it is impossible to determine possibilities with precision. According to Bernanke (1983), policymakers and investors should pay attention to the effects of uncertainty. The transmission channel works similarly to an aggregate demand shock, which can lead to higher unemployment and lower prices. Empirical research by Donadelli (2015), Jurado *et al.* (2015), Baker *et al.* (2016), and Altig *et al.* (2020) suggest that uncertainty is negatively related to business cycles and could indirectly impact the duration and intensity of recessions, which would affect economic recovery.

However, to better understand the concepts used for constructing our regional uncertainty proxy, in subsection 2.1, we started with some seminal research in decision theory, from expected value to subjective probabilities. Finally, in the 2.2 subsection, we discuss some empirical/applied ways to measure the effects of uncertainty in Brazil. Therefore, our objective with these two subsections is to highlight the origin of the theoretical relationship between uncertainty and economic cycles and to show the most recent applications for Brazilian data.

2.1. Seminal Concepts

Von-Neumann *et al.* (1944) developed a theory for Expected Utility. The derivation occurs through individual preferences under four axioms: consequentialism, rationality, continuity, and independence. In summary, the expected value equals the aggregate of utilities weighted directly by their probabilities of occurrence. In this framework, all agents must know (exclusively) the probability distribution of the existing states.

An early challenge to this concept came from Allais (1953). The author argued that decision-makers would place more importance on events with higher probabilities, contrary to the principle of independence. In other words, decision-makers choose less uncertain options even if they offer the same returns. However, the probabilities are still determined objectively and externally.

To overcome this, Savage (1954) attributed uniqueness to the perceptions and utility of the agent. Even sharing the classic maximizing behavior, subjectivity emerges through different perceptions. Furthermore, the author postulates that people make decisions based on probability distributions formed consciously through personal beliefs. In seven axioms, Savage (1954) proposes extracting the subjective distribution through the revealed preference relations, making the utility function indirectly derivable. Analytically, this still means that the agent has only one subjective probability vector in decision-making. However, now, individual probabilities emerge from preferences. At this point, all risk continues to be identified as uncertainty, coming from subjective experiences, making the seminal concepts proposed by Knight (1921) inseparable from subjective expected utility theory.

Ellsberg (1961) suggests that people prefer options with known probabilities in uncertain environments. However, it violates Savage's (1954) postulate and is related to ambiguity, which represents uncertainty in estimates of relative probabilities, including their quality, type, reliability, and unanimity. In summary, ambiguity occurs when the probabilities of events in the sample space are unclear and the final event is unknown. In this conjecture, uncertainty would be an aggregate state, including risk and ambiguity.

Based on these definitions, some researchers began developing theoretical models that could separate the effects of risk and uncertainty (or accommodate Ellsberg's paradox). In other words, theoretical works such as those of Anscombe and Aumann (1963), Schmeidler (1989), Gilboa and Schmeidler (1989), and Tversky and Kahneman (1992) reinforced the separation between preferences when the probabilities of the sample space are well defined, but individual convictions are not.

The difference between risk and uncertainty is important for empirical applications since the methodology we use to measure uncertainty (see Donadelli (2015)) is not related to the volatility of an asset or financial index. Furthermore, even using an aggregate measure for uncertainty, it is constructed through the perception of a representative agent concerned with the obscurity of possible states of nature. It reinforces the relationship between decision theory and empirical modeling that distinguishes uncertainty from risk. Therefore, as indicated by Donadelli (2015) and Altig et al. (2020), due to the advancement of social media, resources such as online search engines become more suitable for the empirical construction of an uncertainty proxy.

2.2. Empirical Contributions for Brazil

No studies seek to investigate the regional effects of disaggregated uncertainty in Brazil. Therefore, we briefly highlight some papers that, even using aggregated uncertainty measures, contribute to understanding the effects of this variable on the Brazilian economy: Pereira (2001), Silva Filho (2007), Costa Filho (2014), Godeiro and Lima (2017), and Barbosa and Zilberman (2018), Souza *et al.* (2019).

Pereira (2001) uses a model with adjustment costs to analyze the relationship between uncertainty and investments in Brazil. As a proxy for uncertainty, the author considers the mean of conditional variances for interest rate, real exchange rate, and capital goods prices, estimated using a GARCH (1.1). The results reveal that uncertainty negatively affected investment from 1980: Q1 to 1998: Q4. Applying a conditional heteroskedasticity model simplifies the calculation, but using federative units is unfeasible since the selected variables do not have disaggregated versions.

Silva Filho (2007) studies the relationship between inflationary uncertainty and investment in the Brazilian economy from 1974 to 2002. Using forecast errors, the author finds strong evidence of adverse effects on investment, both in the short and long term. In this contribution, inflation uncertainty is a proxy of the economic uncertainty for the period analyzed, in which we can observe high peaks in the price index and sequential monetary strategies. However, there are no spatially disaggregated inflation data for this period, making the methodology unfeasible for our application. Furthermore, after the Plano Real, the volatility of Brazilian inflation is detached from the peaks of economic uncertainty, making the exercise incompatible with our primary objective.

Costa Filho (2014) estimates bivariate vector models to analyze the possible effects of uncertainty on Brazilian economic cycles. The results indicate that positive uncertainty shocks are associated with negative and low persistent effects on the economy's productive dynamics, robust to the inclusion of several macroeconomic controls. The authors advance by using three measures of uncertainty based on frequency in national newspapers, capital market volatility, and growth standard deviation. Nevertheless, from a theoretical perspective, the last two are confused with the concept of risk, and the first (which follows Baker *et al.* (2016)) is not available at the state level.

Godeiro and Lima (2017) follow the methodology that Jurado et al. (2015) proposed in constructing a macroeconomic uncertainty index. Based on the results, they infer that Brazil experiences increased uncertainty before periods of recession, which is negatively related to national industrial production. The methodology provides an interesting exercise in predictability since the authors investigate the correlation between uncertainty (using Jurado et al. (2015) methodology) and expected economic cycles. However, the article does not analyze the disaggregated data for the Brazilian federative units.

In a more recent paper, Barbosa and Zilberman (2018) estimate a sequence of SVAR models, following the approach of Barbosa and Zilberman (2018). The authors diversify the dynamics of uncertainty using multiple available measures and find that the relationship with economic activity, for an average horizon of 6 months, is significant and negative. The most significant advance is the robustness of the negative impact of an uncertainty shock on the output. However, the data is not disaggregated at the state level, even using measures linked to newspapers and online search engines.

Souza et al. (2019) investigate the dynamics and transition of uncertainty in Brazil, using representations beyond the conditional mean with quantile autoregressions (QAR). Based on monthly data up to 2017, results reveal asymmetric dynamics along different conditional quantiles, corroborated by analysis of dispersion, amplitude, and localized densities. Furthermore, the authors suggest a low probability of direct migration from a condition of high uncertainty to a low level and vice versa (regardless of the type of intervention). The research presents a quantile and extended perspective on the dynamics and states of uncertainty through the Brazilian Economic Uncertainty Indicator by Fundação Getúlio Vargas (FGV) and the Economic Policy Uncertainty Index for Brazil. However, the authors do not offer a disaggregated analysis or investigation of the multivariate effects of uncertainty on aggregate economic cycles.

The results above indicate that uncertainty has significant and recessive effects in aggregate magnitude. However, there is a gap in the literature about this variable's local/microeconomic effects. The following section will discuss the econometric framework and provide more details about the proxy construction.

3. Data and Methodology

The methodological strategy follows:

1) Data Collection: Following Donadelli (2015), we constructed the state uncertainty indicator using the volume of monthly online searches between 2007 and 2022 for 15 keywords related to uncertainty about state government, fiscal policy, and crisis (see Appendix), as suggested by Baker *et al.* (2016). For each state, the 15 series follow a base index of 100. At this stage, we use Google Trends as a tool due to the availability of disaggregated data (temporal and geographic). Our procedure respects

an essential argument by Baker *et al.* (2016): the uncertainty measures constructed through news, research services, and social networks are forward-looking, improving their predictive power. Our uncertainty index will likely include information not captured by other variables. For example, uncertainty movements occur before the official data at the end of the month, making searches a good guide to market expectations. In other words, since our goal is to build a proxy for state uncertainty and relate it to economic cycles, if this variable reflects forward-looking behavior well, we can try to measure the degree of predictability of local economic cycles through regional uncertainty.

2) Identification of shocks: In sequence, from Altig *et al.* (2020), we use the Choleski decomposition in the following order: uncertainty, net state debt, formal jobs, economic activity index, trade openness, and identify, by state, the magnitude of the uncertainty shock attributed to the pandemic. To calculate the magnitude, one must measure the number of standard deviations above the mean of the uncertainty series. Concerning parsimony, we also estimate the effects with an increase/decrease of 0.5 standard deviations about the identified value. Finally, in terms of the identification strategy, instead of including structural breaks, we identified a structural shock for two reasons: First, structural breaks depend directly on unit root tests with low statistical power. Second, the structural break (whether in level or trend) remains for several periods, not just for an isolated peak. Therefore, we focus more on the work of Di-Mauro and Pesaran (2013), in which it is possible to alternate the priors based on the pandemic (see Lenza and Primiceri (2022) and Cascaldi-Garcia (2022)). We tested the following options: Non-conjugate Minnesota prior, Stochastic Search Variable Selection prior, and Normal-Gamma prior, which, for the BGVAR model, generated very similar results. Therefore, we chose Stochastic Search Variable Selection prior, as suggested by Cuaresma *et al.* (2016).

3) Econometric model: Finally, we use a Bayesian Global Autoregressive Vector model, based on Di-Mauro and Pesaran (2013), fed by uncertainty indices developed, by an interstate trade matrix and by state variables (13 UF's available) given the rapid changes in economic activity with the pandemic, collected from the Central Bank of Brazil: net state debt, formal jobs, economic activity index and trade openness. We selected this model because it can generate disaggregated impulse response functions and provide a reasonable inference. Therefore, we estimate how a

local uncertainty shock (for each state) arising from COVID-19 and with the same magnitude calculated in the identification affects the economic cycles of the other states, both in magnitude and temporal persistence.

3.1. Data

We will use quarterly data from the Time Series System of the Brazilian Central Bank, from 2007 to 2022, for 13 federative units: Amazonas (AM), Bahia (BA), Ceará(CE), Espírito Santo (ES), Goiás (GO), Minas Gerais (MG), Pará (PA), Pernambuco (PE), Paraná (PR), Rio de Janeiro (RJ), Rio Grande do Sul (RS), Santa Catarina (SC) and São Paulo (SP).

3.2. Regional Uncertainty Proxy

Google Trends is a tool for real-time search traffic for any word or expression at a given location for a set period. Such a vast source of information can help to analyze the most varied topics and mainly help understand economic uncertainty. The numbers represent the search interest relative to the highest point on the graph for a given region over a period. A value of 100 represents the highest popularity of a term. A value of 50 means that the term was half as popular. A score of 0 means that more data is needed for the term.

In summary, we adopted a scraping procedure covering 15 uncertainty-related terms (as suggested by Baker *et al.* (2016) and Altig *et al.* (2020)): "economic uncertainty"; "tax"; "regional economy"; "fiscal policy"; "public debt"; "public deficit"; "monetary policy"; "inflation"; "public budget"; "congress"; "regulation"; "coronavirus"; "covid19"; "impeachment" and "regional unemployment". Next, we unified the time series available for each region $Iword1$ into a 100-base indicator (2007: Q4 = 100), weighting each observation with the inverse of its volatility (w_1). Algebraically:

$$Uncrtz_{State} = w_1 * I_{\{word1\}} + w_2 * I_{\{word2\}} + \cdots + w_{15} * I_{\{word15\}} \qquad (1)$$

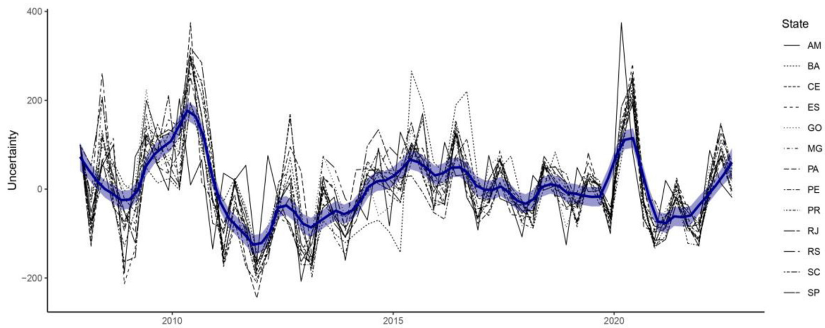

Figure 1 - Uncertainty Series by State
Note: Elaborate by the authors.

Some singular movements occur in short periods, depending on exogenous factors unrelated to the economy's structural fundamentals. As shown in Figure 1, the regional uncertainty series have a joint movement (macroeconomic), but go through specific cycles (micro/regional noise). To address this issue, we eliminated the shared trend (calculated using a local polynomial regression fitting) and focused on the cycles triggered by structural uncertainty shocks.

However, events such as the Subprime crisis, the 2016 crisis, and the COVID-19 health crisis are visually notable in all regions, corroborating the suitability of the strategy used to build the proxy. Furthermore, Goiás and Santa Catarina have the highest average uncertainty peaks. The asymmetry analysis indicates that all regions (except Minas Gerais) have a left-tail distribution for uncertainty. In other words, it is common to observe situations of low regional uncertainty in Brazil. The summary of this evidence can also be analyzed using Table 1.

Table 1 - Uncertainty Proxy by State

State	Region	Mean	Median	Standard Deviation	Asymmetry
AM	Norte	0.356	0.352	0.171	0.074
PA	Norte	0.395	0.394	0.161	0.023
BA	Nordeste	0.389	0.382	0.229	0.099
CE	Nordeste	0.416	0.389	0.197	0.412
PE	Nordeste	0.421	0.399	0.193	0.337
GO	Centro-Oeste	0.479	0.478	0.171	0.020
ES	Sudeste	0.430	0.427	0.202	0.041
MG	Sudeste	0.383	0.388	0.213	-0.062
RJ	Sudeste	0.375	0.370	0.196	0.071
SP	Sudeste	0.415	0.381	0.197	0.517
PR	Sul	0.358	0.343	0.209	0.204
RS	Sul	0.433	0.411	0.216	0.313
SC	Sul	0.465	0.450	0.253	0.177

Note: Elaborate by the authors. Brazilian Regions: Norte (North); Nordeste (Northeast); Centro-Oeste (Central-West); Sudeste (Southeast); Sul (South).

A second step in descriptive analysis (Figure 2) is calculating the uncertainty evolution in the 13 states of interest. We started in 2008 and used 2-year intervals until 2022. The color distribution follows the following logic: The darker the blue, the higher the level of uncertainty (positive) in the state. The closer the state is to gray, the closer the uncertainty value is to zero. Finally, the closer the state is to dark red, the closer the uncertainty is to negative/damaging.

In the third step, we calculated the correlation between the regional cycles (IBC for each state) and the aggregated uncertainty indexes at the Brazilian level (EPU-Br and IIE-FGV). In this first attempt, the results were ambiguous, ranging from negative to positive correlations. However, the results always indicated a null or negative correlation when we calculated the correlation of the same regional cycles with our regional uncertainty indexes (proposed in this research). This pattern leads us to believe that the disaggregation of uncertainty in state terms presents good advantages for regional analysis. Furthermore, since the result remains even with IBC lags (t-1, t-4, and t-6), there is evidence that models with autoregressive components can meet the initial proposal resolution, understanding the relationship between real cycles and uncertainty for regional data.

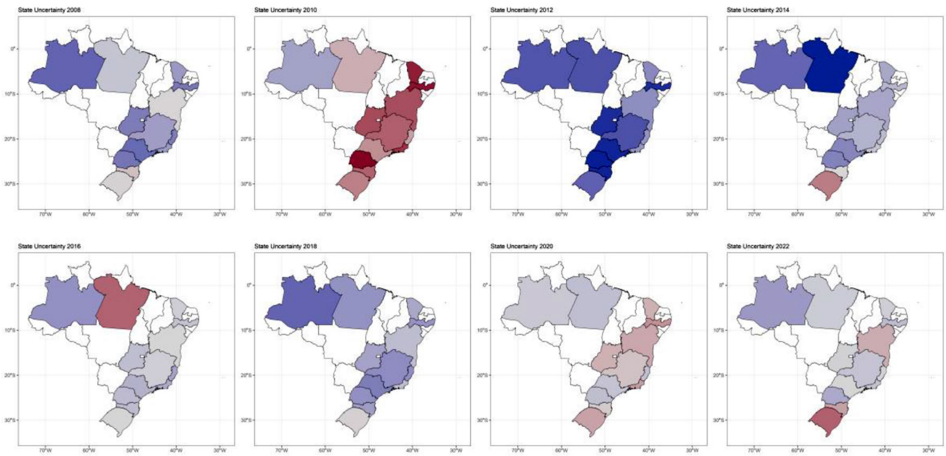

Figure 2 - Geographic Evolution (2007-2022)

Note: Elaborate by the authors. Here, for the sake of illustration, we explore intervals of 2 years. Therefore, we start the maps in 2008 and end in 2022.

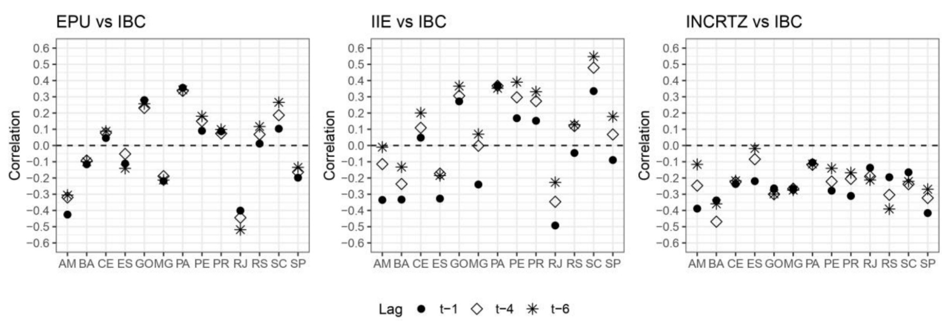

Figure 3 - Correlations Between Uncertainty Measures and IBC

Note: Elaborate by the authors.

Finally, for a deeper investigation of the effectiveness of the regional uncertainty proxy, we calculated the correlation of each with the standard uncertainty measures for Brazil (IIE-FGV and EPU-Br) using the table below:

Table 2 - Uncertainty Proxy by State

Correlation	AM	BA	CE	ES	GO	MG	PA	PE	PR	RJ	RS	SC	SP
$Uncrtz$ x EPU	0.26	0.26	0.38	0.36	0.38	0.35	0.39	0.45	0.33	0.34	0.32	0.37	0.34
$Uncrtz$ x IIE	0.24	0.26	0.31	0.22	0.32	0.34	0.48	0.29	0.35	0.28	0.36	0.37	0.35

Note: Elaborate by the authors.

The table indicates that we have correlations ranging from 0.22 to 0.45. In other words, a particular coincidence exists between the regional and national uncertainty moments, measured by two proxies (IIE-FGV and EPU-Br). However, regional singularities have considerable weight, reinforcing the importance of disaggregated analysis focused on the states' particularities.

3.3. Control Variables

The endogenous control variables, based on the RBC literature, are shown in Table 3. Some adjustments are necessary for comparability between states: i) We seasonally adjust the number of formal jobs generated using the X-13-ARIMA method; ii) We correct the State Net Debt values using the implicit deflator of the Brazilian GDP. iii) We corrected the Import and Export series in dollars, using the US implicit deflator. iv) We work with the relative variations of the series in base 100 (2007: Q4 = 100). Additionally, we remove trends using the same procedure for uncertainty. Then, all series underwent the local polynomial regression fitting procedure. Here, we avoid the use of the HP filter following the work of Hamilton (2018).

Table 3 - Control Variables

Variable	Code	Source	Time
Economic Activity Index	IBC_{sz}	Brazilian Central Bank	2007: Q4 – 2022: Q3
Formal Jobs	JOB	Brazilian Central Bank	2007: Q4 – 2022: Q3
State Net Debt	ND	Brazilian Central Bank	2007: Q4 – 2022: Q3
Trade Openness	TO	Brazilian Central Bank	2007: Q4 – 2022: Q3

Note: Variable descriptions. The export agenda is available on the Ministry of Development, Industry, Trade, and Services.

We chose to adopt the formal employment series, motivated mainly by the scarcity of information on the informal market between 2007 and 2012. Although the informal labor market is more relevant during crises, due to the lack of temporal compatibility (2007-2012), we prefer to explore this effect by decreasing the number of matches in the formal sector, something reported in the search and matching literature (see Andolfatto (1996)). In the following, we did not find any information at the state level or ways to differentiate the regional activity index between real and nominal, which justifies the option for the aggregate deflator. Another point concerns the inflation index (IPCA), which is only available for 10 capitals in the 13 selected states, which would already be a limitation compared to the other control variables that cover the entire state. Furthermore, excluding three states would correspond to a loss of approximately 23% of the sample (27 states), which does not seem to be a good strategy because, in Brazil, the total coverage of the states would fall from 13 (48%) to 10 (37%).

3.4. Global Vector Autoregression Model

GVAR was proposed by Di-Mauro and Pesaran (2013) as an empirical framework for modeling the world economy and the dependence between countries. The model consists of a set of country-by-country $VARX^*(p, p^*)$, which includes the p-lag order of domestic variables (x_{it}) and the $p^* - lag$ order of foreign ones (x_{it}^*). However, in the same way that it applies to countries, the equations below apply to regions, states, or even municipalities:

$$x_{it} = a_{i0} + \sum_{s=1}^{p} \Phi_{is}\, x_{it-s} + \sum_{s=1}^{p} \lambda_{ir}\, x_{it-r}^* + \varepsilon_{it} \tag{2}$$

Where $x_{it}^* = \sum_{j=0}^{N} \omega_{ij} x_{jt}$, with ω_{ij} denoting the trade-weight matrix. Each ω_{ij} element corresponds to a bilateral trade flow between the i and j states, divided by total trade. Thus, for ω_{ij}, we used the interregional trade matrix provided by Haddad *et al.* (2018). We use the average between total international imports and exports for Trade Openness.

Then, we stack the state-specific models to obtain a global representation given by $G\, x_t = a_0 + \sum_{q=1}^{Q} H_q\, x_{t-q} + \varepsilon_t$, G is the matrix of contemporaneous relations between states, a_0 is the constant and H_q is a global coefficient matrix. Finally, ε_t is a global vector error with the variance-covariance matrix equal to $\Sigma_{\varepsilon i}$. Rewriting the model, if $\Pi_i' = \left(1, x_{it-1}', \dots, x_{it-p}', x_{it}^{*'}, \dots, x_{it-p^*}^{*'}\right)$ and $Z_{it-1} = \left(a_{i0}, \Phi_{i1}, \dots, \Phi_{ip}, \Lambda_{i0}, \dots, \Lambda_{ip^*}\right)'$, we have:

$$x_{it} = \Pi_i'\, Z_{it-1} + \varepsilon_{it} \tag{3}$$

Bayesian inference is helpful for global macroeconomic models (see Litterman (1986)) since there are many parameters to estimate (which grow geometrically with model order) and the available time series are limited. Cuaresma *et al.* (2016) propose a

Bayesian inference approach using a set of priors (see George *et al.* (2008)). The Stochastic Search Variable Selection (SSVS) prior is represented by a mix of Normal distributions on each coefficient of the model, and for $\Psi_i = vec(\Pi_i)$ in a hierarchical prior setup:

$$\Psi_{ij}|\delta_{ij} \sim \left(1-\delta_{ij}\right) \mathrm{N}\left(0, \tau_{0,j}^2\right) + \delta_{ij}\ \mathrm{N}\left(0, \tau_{1,j}^2\right) \tag{4}$$

Where δ_{ij} is a binary select variable for the coefficient j in the state i. δ_{ij} follows a Bernoulli distribution with probability (q_{ij}). It equals if the corresponding variable is included in the model, with $\tau_{i,j}^2$ variance and 0 if the respective prior is excluded from the $i-th$ state, with $\tau_{0,j}^2$ close to zero, pushing the coefficient towards zero. The prior mean is around some value $\underline{\Psi}_{ij}$.

Collecting the parameters into a diagonal matrix $D_i = diag(d_{i1}, d_{i2}, \dots d_{i\nu_i})$, the prior in Ψ_i reduces to the following hierarchical prior set-up:

$$\Psi_i|D_i \sim \mathrm{N}\left(0, \underline{R_i}\right) \tag{5}$$

$$\Sigma_{\varepsilon i} \sim \mathrm{IW}\left(\underline{S_i}, \underline{\nu}_i\right) \tag{6}$$

Where $\underline{R_i} = D_i D_i$ and the $\Sigma_{\varepsilon i}$ prior is a standard Inverse Wishart with $\underline{\nu}_i$ degrees of freedom and $\underline{S_i}$ is the scale matrix. Bayesian inference is helpful for global macroeconomic models (see Litterman (1986)) since there are a large number of parameters to estimate (which grow geometrically with model order) and the available time series are limited. Finally, in the structural analysis, we calculated the General Impulse Response Functions (GIRF) median considering 68% confidence intervals and 100,000 repetitions.

4. Results

In this section, we will discuss the details of adjustment and diagnosis of the estimated model, the effects of uncertainty on internal economic cycles, and the potential external effects and fragility of economic cycles.

Furthermore, we define the backward effect as the number of states significantly affecting the analysis unit. The forward case occurs by the number of federative units that respond considerably to an uncertainty shock in the domestic state, that is, how strong the local uncertainty shock is in reaching cycles outside the state of origin.

4.1. BGVAR Model Diagnostics

A fundamental ingredient for building the BGVAR model is the weighting matrix ω_{ij}, which summarizes the business flows between the federative units (see DiMauro and Pesaran (2013) for a more in-depth discussion about possible ways of structuring it). Here, we use an interstate trade matrix (provided by NEREUS-USP; see Haddad *et al.* (2018)) representing regional bilateral trade flows. It differs from the control variable, Trade Openness, representing the average between total international imports and exports.

In sequence, we used the AIC, BIC, and HQ criteria to select the lag applied to the system of endogenous variables. All eigenvalues remain within the unit circle and attest to the stability of the estimated model. Nevertheless, some notes regarding the convergence properties of the MCMC chains are necessary, such as the serial autocorrelation in the errors and the mean paired autocorrelation of residues of the crossed units of analysis. It is essential to emphasize the importance of check-ups in the model, as spillover effects directly correlate with all geographic units.

Geweke Statistic follows a typical z-score pattern and reveals that only a tiny fraction (4.07%) of the coefficients did not converge. However, the issue is minimal as the number of burn-ins in the estimated chains increases. Next, for the serial autocorrelation test on errors, we noticed that the highest percentage (69.23%) rejected the null hypothesis of serial autocorrelation, strengthening the previously performed choice of lags. Finally, for the residual unit correlations (later median), we observed reasonably small values, which do not threaten the structural analysis of cross effects (see Dees *et al.* (2007)).

4.2. Internal Shocks Effects

We initially explore the internal effects of an uncertainty shock on the state's economic cycles, a benchmark result for any VAR estimation. Figure 4 reveals some patterns related to the duration of internal shocks. There is a fast reaction for all analyzed federative units (lasting up to 5 quarters after the internal shock). The size and duration of internal disturbances are well controlled at the state level. Next, in Table 4, the cumulative percentage effects for the 1, 4, 6, and 8 quarters provide further evidence.

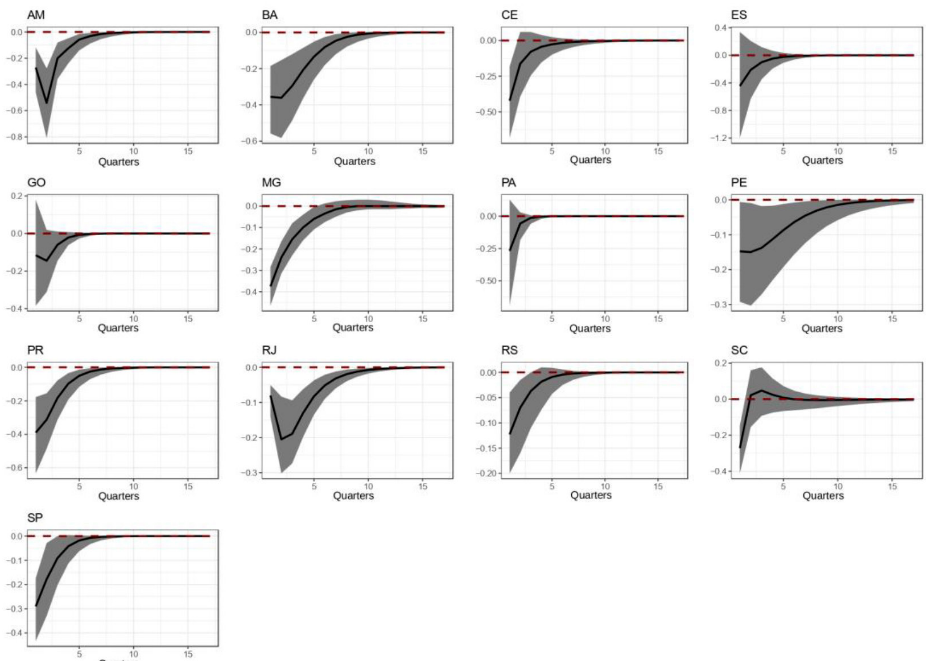

Figure 4 - Internal Impulse Response Functions by State

Note: Elaborate by the authors.

After eight quarters, the states of Amazonas, Bahia, Pernambuco, Rio de Janeiro, and Paraná present a significant retraction, oscillating between 0.25% and 1.50% of economic activity. Furthermore, considering all analyzed horizons, the average accumulated effect is more significant in the Nordeste region. Again, this means that internal disturbances, for the most part, have a short shelf life, and the effects cease in horizons shorter than two years, something close to what is reported by authors such as Barbosa and Zilberman (2018), who analyze the Brazilian aggregate case.

Access to the reasons that led states A or B to recover more quickly or not is complex and may outstrip our arguments in this paper. However, evidence indicates that, on average, states with lower economic diversification are more likely to experience slower internalization of the problem.

Table 4 - Cumulative Percentage Effects

State	Region	T+1	Signif.	T+4	Signif.	T+6	Signif.	T+8	Signif.
AM	Norte	-0.271	Yes	-1.137	Yes	-1.277	Yes	-1.251	Yes
PA	Norte	-0.268	No	-0.341	No	-0.341	No	-0.340	No
BA	Nordeste	-0.355	Yes	-1.219	Yes	-1.434	Yes	-1.495	Yes
CE	Nordeste	-0.422	Yes	-0.707	No	-0.749	No	-0.765	No
PE	Nordeste	-0.147	Yes	-0.548	Yes	-0.699	Yes	-0.776	Yes
GO	Centro-Oeste	-0.115	No	-0.341	No	-0.350	No	-0.351	No
ES	Sudeste	-0.446	No	-0.806	No	-0.841	No	-0.850	No
MG	Sudeste	-0.375	Yes	-0.870	Yes	-0.965	No	-0.985	No
RJ	Sudeste	-0.080	Yes	-0.604	Yes	-0.738	Yes	-0.789	Yes
SP	Sudeste	-0.290	Yes	-0.601	No	-0.626	No	-0.630	No
PR	Sul	-0.390	Yes	-0.982	Yes	-1.057	Yes	-1.076	Yes
RS	Sul	-0.123	Yes	-0.248	No	-0.261	No	-0.265	No
SC	Sul	-0.272	Yes	-0.178	No	-0.171	No	-0.181	No

Note: Elaborate by the authors.

4.3. External Shocks Effects

Finally, we present the cross effects (forward and backward) of a regional uncertainty shock, which is one of the main contributions of this paper. In other words, looking at trade openness with Table 5 and Figure 5 help us understand which states propagate domestic uncertainty. First, we can find the deviation of the susceptibility backward behavior for some states, reaching more than five times the value of other regions (Sul and Nordeste or Centro-Oeste). Moreover, even with low variability in forward movements, there are significant deviations in receptivity to external shocks.

However, data on interregional transactions (see Haddad et al. (2018)) point in the opposite direction. It occurs because, for example, states with high international trade (Rio de Janeiro and São Paulo linked to oil and minerals, and Minas Gerais linked to iron ore) may obtain exchange rate advantages and prefer to trade more with external players than with the domestic market. A good trade openness index does not mean this state will be among the best domestic market players. In contrast, they tend to be much more balanced in the domestic market, with stability between backward and forward shocks. On the other hand, we have the Sul states, which are lower in the international trade table (with Paraná and Rio Grande do Sul associated with soybeans and Santa Catarina with poultry meat), and they pass on many of the external shocks without internalizing almost any of these shocks from the other states. Once again, international trade and the exchange rate are essential, as goods have a lower value than exports from the Sul region; the domestic market can be much more attractive, being less exposed to fluctuations in the exchange rate and concentrating its activities on interregional transactions. The number of associations indicates that the response to external disturbances occurs in 9 of the 13 states, except for Amazonas, Espírito Santo, Rio Grande do Sul, and Santa Catarina. In addition, on average, the Sul region concentrates on the states that most affect other locations but suffer less from external disturbances.

The evidence for the cross effects indicates considerable interdependence between the Brazilian federative units. Ceará is one of the largest propagators of uncertainty, and Espírito Santo is almost unaffected by external disturbances. Once more, Espírito Santo is more involved in trade openness than Ceará.

Our focus in this paper is not to investigate the structural nature of these associations, which can be related to historical competitive advantages and local long-term dynamics. However, some results can elucidate reasonable interpretative hypotheses when considering Trade Openness and the interregional matrix. For example, observing the productive profile, São Paulo's economy is focused on industry, while Paraná and Goiás are intensive in agricultural activities. Thus, goods and services are exchanged between different states to meet the specific demands of each region. Given these local specificities, interstate trade seems fundamental for understanding the propagation and receptivity of the evaluated shocks. In Figure 6, external disturbances would not significantly affect the more developed states (self-sufficient).

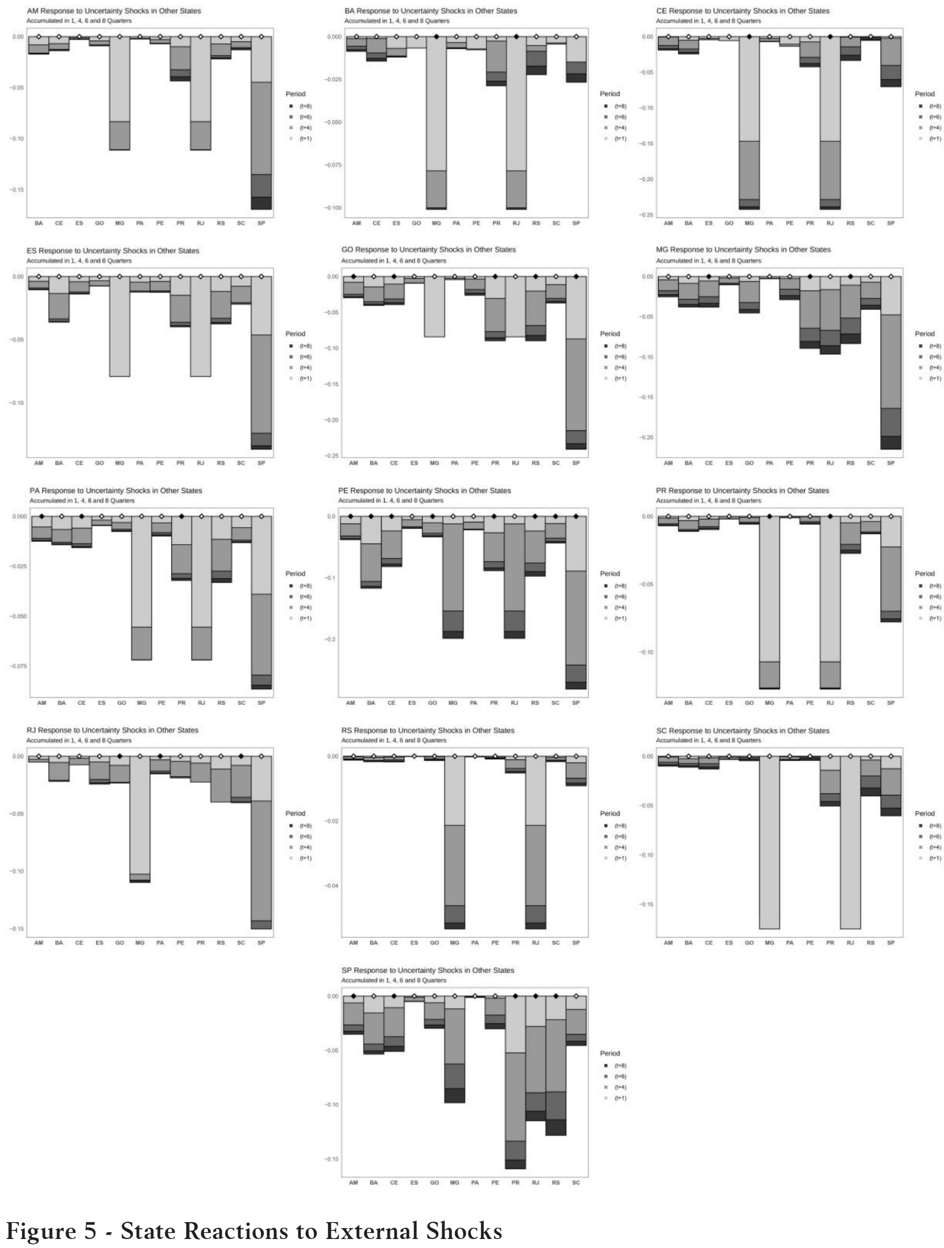

Figure 5 - State Reactions to External Shocks

Note: The dots indicate significance. Black means significance, and blank we expect the average effect to be null.

Table 5 - Forward and Backward Behavior

State	Forward	Backward	Region	Forward Mean	Backward Mean
AM	4	0	Norte	2.5	1.5
PA	1	3	Norte	2.5	1.5
BA	1	2	Nordeste	2	4
CE	5	2	Nordeste	2	4
PE	0	8	Nordeste	2	4
GO	2	5	Centro-Oeste	2	5
ES	0	0	Sudeste	2.25	2.75
MG	3	3	Sudeste	2.25	2.75
RJ	4	3	Sudeste	2.25	2.75
SP	2	5	Sudeste	2.25	2.75
PR	5	2	Sul	3.65	0.67
RS	4	0	Sul	3.65	0.67
SC	2	0	Sul	3.65	0.67

Note: Elaborate by the authors.

To complement this perception, we advanced in constructing correlation measures between the internalization of shocks and fluctuations in the state Economic Activity Index. The relationship between the economy's ability to pass through idiosyncratic shocks and internalize them, as seen in Figure 6, points to an effect close to -0.35.

Again, spillovers are less common than expected and, in many cases, sharing physical boundaries does not imply intense transmission of shocks between neighbors. On the other hand, the presence of "shielded" states (which do not suffer significant effects) seems to be negatively related (around -0.27) to the rate of recovery of the IBC after the first quarter of 2022 (point of beginning of the gradual return to activities, due to Covid-19 vaccination).

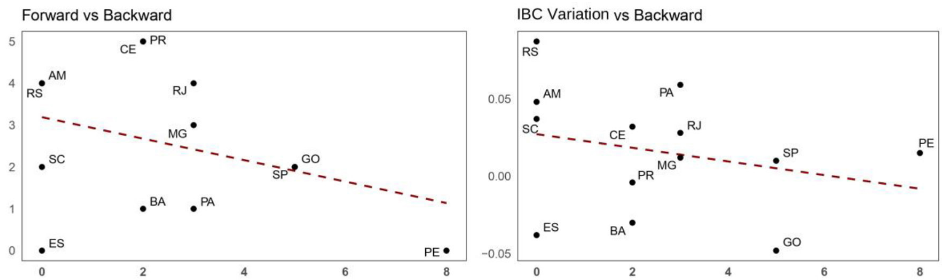

Figure 6 - Responses and Cycles

Note: Elaborate by the authors.

The pattern shown in the last two figures and the values observed in Table 5 corroborate the initial hypothesis: There is an asymmetry in the economic reaction of the federative units. Nevertheless, these results reinforce that economic recovery's power is associated with the ability not to absorb economic volatility generated by third parties, that is, economic resilience to the point of smoothing local uncertainties.

Conclusively, regions that participate in the economic game can benefit from strategies aimed at internal strengthening. These are some of the main points related to the recovery of economic activity at the beginning of 2022. This argument indicates that noise reduction improves domestic cycles' predictability (formation of expectations) since the coordination of agents involved is explicit. This evidence dialogues directly with the considerations made by Leduc and Liu (2016): increased uncertainty resembles a negative aggregate demand shock, increasing unemployment and reducing inflation.

5. Conclusion

This research investigated the short-term relationship between uncertainty and economic cycles in the Brazilian federative units. The working hypothesis is that Brazilian regional particularities enabled the global pandemic to impact economic cycles through a wave of local economic uncertainty, which oscillated around a central tendency (equivalent to the macroeconomic/aggregate case) and generated retraction movements in the production of the federative units (micro disturbances).

Following Baker et al. (2016) and Altig et al. (2020), the calculation of indicators involves computing relative frequencies in the search (geographically disaggregated) for several terms on Google Trends between 2007 and 2022. This paper's main contribution is to disaggregate the effects of uncertainty, identifying the possible consequences to neighbors.

Our results provide favorable evidence for the working hypothesis, indicating plurality in the internal and external effects of uncertainty, which determine the recovery speed of the units. Furthermore, as local variability occurs without a pre-established pattern, divergence occurs in several spheres related to shocks' duration, peak, and persistence. On the other spectrum, we identified that part of these recoveries is directly related to the ability to "not react" to external uncertainty shocks.

Finally, even considering controls related to the labor market, external cycles, and fiscal situation, our research has some limitations, such as the number of states with available data, the absence of determinants commonly related to economic growth (capital stock, technological asymmetries and design institutional) and even the difficulty in controlling heterogeneous historical moments, such as the popularization of the internet. In this sense, future works can extend the performed analysis and cover gaps in the theoretical direction.

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Appendix

KEYWORDS LIST – PORTUGUÊS

incerteza econômica, taxação, economia regional, política fiscal, dívida pública, déficit público, política monetária, inflação, orçamento público, congresso, regulação, coronavírus, covid19, impeachment, desemprego regional.

KEYWORDS LIST – ENGLISH

economic uncertainty, tax, regional economy, fiscal policy, public debt, public deficit, monetary policy, inflation, public budget, congress, regulation, coronavirus, covid19, impeachment, regional unemployment.

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JA: Análise formal, Investigação, Validação, Visualização, Escrita - rascunho original e Escrita - revisão e edição.

OD: Análise formal, Investigação, Validação, Visualização, Escrita - rascunho original e Escrita - revisão e edição.

CONFLITO DE INTERESSE

Os autores declaram não terem quaisquer conflitos de interesse.

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