Brazilian stock market: connectivity among financial and non-financial sectors

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Abstract

Objectives - (i) measure the connectivity between the spillovers of returns from the financial and non-financial sectors of the Brazilian stock market; (ii) estimate the spillovers of individual returns for each sector, in order to identify periods of higher and lower profits over a period of around 8 years; (iii) investigate the existence of relationships between these repercussions between pairs of sectoral indices, evaluating how much each specific sector transfers to each other and to the market as a whole. *Methodology* – We researched eight of the most relevant sectoral indices on the São Paulo Stock Exchange (B3) and estimate Diebold-Yilmaz spillover index and frequency decompositions of Barunik-Krehlik. *Results* – there is an overall connection of 66% in the financial and non-financial sectoral indices, with a peak of 83%. The consumer, energy and public services sectors stand out as significant sources of primary spillovers.

Keywords: spillover index; frequency decomposition; emerging markets, sectoral stock indices.

JEL Classification: C22, C51, C58, G11.

1. Introduction

The repercussions of changes in stock prices and interdependencies among financial assets have long been topics of interest among emerging market economists. This occurs for several reasons, one of which is related to possible links between sectoral indices of emerging equity markets. These links are useful proxies of intersectoral connectivity and their measurement can help to accurately verify the possibility of increased uncertainty, as well as identify the effects of shocks that occur in a given sectoral index and are transmitted to others.

In this work, we study the connectivity of the main sectoral indices of the São Paulo Stock Exchange (B3), which is, by a large margin, the most important stock exchange in Brazil. By identifying the patterns and dynamics of transmission of price shocks among a set of indices that include the most traded shares in electricity, raw materials, public services, retail and consumption, financial, housing, real estate and commodities, we believe we are producing a set of relevant information for decision-making by participants in these markets.

For this, we consider daily closing prices of each index in the period from March 3, 2015, to June 21, 2023, totaling 2,059 observations. We use a methodology that combines two well-established approaches: the spillover index proposed by Diebold and Yilmaz (2012) and the frequency decompositions developed by Baruník and Krehlík (2015). The first method aims to measure interactions and interdependencies among indices by decomposing their variances, making it possible to quantify the multiple price shocks to and from the indicesand assess general market connectivity.

The second method details these connectivity interactions across multiple frequency bands that represent different shorter time frames, providing separate analyzes of the dynamics of movements in the short, medium and long terms. This approach helped us discover aspects that would otherwise go unnoticed. Both methods are complementary and their results vary from 0 to 100, and can be interpreted as percentages.

Our results showed that the total connectivity of Brazil's main stock sector indices reached 66%. However, the trajectory of this variable had several peaks of uncertainty, which translated into increases in spillovers from variations in returns on the mentioned sectoral assets. We explain what factors contributed to generating these peaks.

When we divide the spillover index into frequency bands, we empirically demonstrated that as the analysis time frame increases, the total connectivity tends to smooth out, with the effects of a shock suffered by a given sector being dissipated among the others. Although shocks transmitted by closing price changes are not the same thing as volatility spillover, this result is in line with previous studies such as Nazlioglu et al. (2013) who examined volatility spillover relationships between oil and agricultural commodity returns in pre-crisis and post-crisis periods, revealing distinct patterns and variations between the two periods.

Meanwhile, Barunik et al. (2015) investigated the spillover asymmetries among different sectors of the US economy, finding that the consumer, telecommunications, and health sectors exhibited greater asymmetries compared to the financial, information technology, and energy sectors. Likewise, other studies have identified the diesel and gas sectors as net transmitters of volatility to other markets, with results indicating asymmetrical spillovers (Mensi et al., 2020).In addition, several authors have associated post-crisis circumstances with factors that influence the transmission and connectivity of volatility (Costa et al., 2021; Umar et al., 2021; Bouri et al., 2017; Vardar et al., 2018). These studies have shown that financial news significantly impacts volatility, directly or indirectly within or across sectors (Hassan and Malik, 2007; Malik and Ewing, 2009). These findings collectively shed light on the complex dynamics of volatility spillovers and their relationship to market sectors, highlighting the relevance of external factors such as crises and financial news in influencing volatility patterns.

The interest in empirically verifying the dynamics of connectivity among different sectors was the motivation for several studies, such as Elder (2004), Lee et al. (1995), Ratti and Vespignani (2016), Elder and Serletis (2010), Gardebroek et al. (2014), Ahmadi et al. (2016), Hernández et al. (2011), Diebold and Yilmaz (2012), Alsalman (2016), Nazlioglu et al. (2012), Baruník and Krehlík (2015), Ding et al. (2016), Nazlioglu et al. (2015) and Arouri et al. (2011).

Many recent works have also sought to understand the connectivity of economies and the dynamics of transmission of volatility, such as Kang et al. (2023), Choi (2022), Balcilar et al. (2018), Liu et al. (2021), Cheng et al. (2023), Jababli et al. (2022), Arouri et al. (2011), Yin et al. (2020), Chinzara (2011), Fazanya and Akinde (2019), Ajmi et al. (2021), Sarwar et al. (2020), Laborda and Olmo (2021), Si et al. (2021), Li et al. (2021), Mensi et al. (2022) and Malik (2022).

It is with this scientific literature that we seek to contribute by bringing empirical evidence of the connectivity of sectoral stock indices and how the transmission of price shocks behaved in recent periods.

In addition to this introduction, the paper has three more sections. Section two provides a comprehensive definition of the database, detailing its preparation process, as well as the methodology employed in the empirical analysis, section three presents and discusses the results, and, finally, section four makes the final remarks.

2. Methodology

2.1. Data

We use the daily closing prices of sectoral indices of the Brazilian capital market quoted in reais (BRL). The period analyzed is from March 3, 2015 to June 21, 2023, totaling 2,059 price observations for each index. We considered eight different indices from the São Paulo Stock Exchange (B3) that represent important references in the Brazilian economy and financial market.

Ibovespa Index (IBOV): is a widely used indicator of the general performance of the Brazilian stock market and is considered a fundamental barometer of the country's economy. It covers a diverse selection of Brazilian companies from various sectors and industries, making it a benchmark for investors and financial professionals to assess overall market performance. Many financial products, including mutual funds and exchange-traded funds (ETFs), are designed to track or replicate the performance of the Ibovespa. This index comprises the 50 companies with the highest trading volume in the market.

Electric Power Index (IEEX): is a price indicator of the most tradable assets in the electricity sector listed on the São Paulo Stock Exchange. To be included in the index, the asset must have been traded in at least 80% of the trading sessions in the last three months.

Raw Materials Index (IMAT): reflects the average performance of companies in the basic inputs sector, covering sectors such as paper, mining, and steel. Includes shares and units of companies operating in this sector. To be part of the index, assets must be among the 99% most traded on B3 in the three previous portfolios and must be present in at least 95% of trading sessions in the same period.

Utilities Index (UTIL): represents the public services sector, including companies involved in electricity, water, sanitation, and gas. It aims to reflect the average performance of the most traded and representative assets in this sector. This index comprises shares and units of utility companies. For an asset to be included in the index, it must be among the 99% most traded in the last three portfolios and be present in at least 95% of trading sessions in the same period.

Retail and Consumer Index (ICON): includes shares of companies in the consumer cyclical, consumer non-cyclical, and health sectors. To be part of the index portfolio, an asset must have been traded in at least 95% of trading sessions in the last three months. The shares that make up the Consumption Index are unitary, and it is considered a total return indicator, where all revenues, such as interest on equity and dividends, go to the investor, along with the average trading session variation of the assets in the index.

Financial Index (IFNC): covers financial intermediaries, various financial services, pension plans, and insurance sectors. It seeks to represent the average performance of the most traded and representative assets of these sectors. The asset that is the subject of a Public Offering during the term of the last three portfolios may be included in the index, provided that the offering was carried out before the immediately preceding rebalancing. The asset must also have a trading presence of at least 95% since the start of trading.

Real Estate and Housing Index (IMOB): represents the most traded and representative assets of the real estate sector, including real estate exploration and civil construction companies. The index comprises stocks and units. To be included in the IMOB, the asset must be among the 99% most traded in the sector in the three previous portfolios and have at least 95% presence on the trading floor in that period. An asset that is the subject of a Public Offering during the term of the last three portfolios can also be considered for inclusion in the index.

Commodity Index (ICOM): represents the performance of commodities traded in the Brazilian capital market, such as beef, coffee, soy, corn, ethanol, and gold. To assess its performance in the period, a portfolio was created with a naive strategy to obtain its daily closing price. The strategy can be represented as $ICOM = \frac{p_1 + p_2 + \cdots + p_n}{n}$.

In order to understand the factors that influence the connectivity of the Brazilian capital market, we consider the daily series of the following explanatory variables: (i) ten-year future interest rates in the United States (IGlobal) as a global variable; (i) ten-year future interest rates in Brazil (ILocal) as a local variable; and (iii) the Brazilian market's own connectivity series (Conn) as an another local variable. Table 1 lists the descriptive statistics of each index in the period considered.

In Table 1 we see that the average returns of all indices were positive throughout the entire period. IMOB generated the highest standard deviation of its returns, while IEEX generated the lowest. In Table 2, a correlation matrix among sectoral indices.

Table 1. Descriptive statistics

	Closing Prices				Returns			
	Mean	SD	Min	Max	Mean	SD	Min	Max
IBOV	86,848.2400	24,664.5300	37,497	130,766.30	0.0004	0.0161	-0.1599	0.1302
ICON	3,676.5880	903.2608	2,207	5,728.820	0.0001	0.0164	-0.1762	0.1128
IEEX	56,159.6400	20,708.5100	20,873	89,553.360	0.0006	0.0136	-0.1232	0.0861
IFNC	8,997.1780	2,486.1840	3,911	13,612.130	0.0004	0.0187	-0.1425	0.1236
IMAT	3,530.0530	1,794.6710	1,046	7,544.810	0.0007	0.0191	-0.1721	0.1297
IMOB	766.9340	205.1723	417	1,526.200	0.0002	0.0215	-0.1946	0.1438
UTIL	6,089.1950	2,439.9020	2,150	10,226.860	0.0007	0.0154	-0.1460	0.1043
ICOM	449.6134	142.8374	262.14	806.200	0.0003	0.0137	-0.1405	0.1471
IGlobal	2.166	0.809	0.512	4.247	0.0008	0.0332	-0.2768	0.4445
ILocal	10.653	2.434	6.250	16.85	0.0000	0.0182	-0.1080	0.2719
Conn	66.240	3.513	57.333	82.769	0.0001	0.0071	-0.0701	0.0820

Source: Elaborated by authors.

In Table 2 we see that the most correlated sector index pairs are UTIL with IEEX, IBOV with IFNC and IBOV with UTIL. The pairs with the lowest **correlation** are ICOM with IMOB and ICOM with ICON. We highlight that the index with the highest degrees of correlation is the IBOV. The lowest grade is ICOM. After analyzing the data, we adopted a dual but complementary methodological strategy in order to improve the accuracy of the results.

Table 2. Correlation matrix

	IBOV	ICON	IEEX	IFNC	IMAT	IMOB	UTIL	ICOM
IBOV	1.00	0.734	0.956	0.954	0.906	0.716	0.952	0.760
ICON	0.734	1.00	0.662	0.768	0.544	0.868	0.624	0.369
IEEX	0.734	0.662	1.00	0.876	0.897	0.649	0.995	0.818
IFNC	0.954	0.768	0.876	1.00	0.750	0.837	0.880	0.574
IMAT	0.906	0.544	0.897	0.750	1.00	0.406	0.879	0.898
IMOB	0.716	0.868	0.649	0.837	0.406	1.00	0.644	0.231
UTIL	0.952	0.624	0.995	0.880	0.879	0.664	1.00	0.807
ICOM	0.760	0.369	0.818	0.574	0.898	0.231	0.807	1.00

Source: Elaborated by authors.

We estimate the spillover index from Diebold and Yilmaz (2012) and the frequency decompositions from Baruník and Krehlík (2015), which appear in subsections 2.2 and 2.4, respectively.

2.2. Diebold-Yilmaz Method

As we can see in Passos et al. (2020), Diebold and Yilmaz (2012) use autoregressive vectors (VAR) to employ a variance decomposition and for that, the Akaike criterion is used for lag selection. The stationary covariance of n variables in VAR (p) is represented by $x_t = \sum_{i=1}^{P} \emptyset_i x_{t-1} + \varepsilon_t$, where $\varepsilon \sim (0, \Sigma)$ represents a vector of independently and identically distributed errors. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-1}$, with the coefficient matrices N × N A_i that follows the recursion $A_i = \emptyset_1 A_{i-1} + \emptyset_2 A_{i-2} + \cdots + \emptyset_p A_{i-p}$. Here, A_0 represents an identity matrix N × N, and $A_i = 0$ for $i < 0$.

The moving average coefficients, including impulse response and variance decomposition functions, are pivotal in understanding system dynamics. Variance decompositions enable the analysis of prediction error variations for each variable, attributing them to various system shocks. They also allow the assessment of the fraction of the error variance H steps forward in the prediction x_i, which is due to shocks to x_j, $\forall j \neq i$, for each i.

To address contemporaneous correlations in VARs, the authors employed Koop, Pesaran, and Potter's (1996) generalized VAR structure and ordering approach. This helps account for non-orthogonalized shocks, as the sum of contributions to the variance of the VAR prediction error. For instance, this installment addresses the sum of row elements in the variance decomposition table) may not necessarily be equal to one.

The defined shared installment of the parts of variance is represented as the fractions of error variations H steps ahead in forecasting x_i that is due to shocks to x_i, for $i = 1, 2, \dots, N$, and cross-variance parts, or spillovers, such as the fractions of the error variations H steps ahead in the forecast x_i that is due to shocks to x_j for $i, j = 1, 2, \dots, N$, such that $i \neq j$. Denoting the prediction error variation decompositions of H steps forward by $\theta_{ij}^{g}(H) \rightarrow H = [1, 2, \dots, n]$, we have

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)} \tag{1}$$

Let Σ be the variance matrix for the error vector ε, where σ_{jj} represents the standard deviation of the error term for the j-th equation, and e_i is the selection vector with a value of one as its ith element and zeros elsewhere. To calculate the spillover index using the variance decomposition matrix information, each entry of the variance decomposition matrix is normalized by dividing it by the sum of the corresponding row, as follows:

$$\vartheta_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{2}$$

By construction, $\sum_{j=1}^{N} \vartheta_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \vartheta_{ij}^{g}(H) = N$.

To address the total spillovers, the volatility contributions of the decomposition of the variable are used, hence, the total volatility reversal index is constructed with the following procedure:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=0 \\ i \neq j}}^{N} \vartheta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \vartheta_{ij}^{g}(H)} 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \vartheta_{ij}^{g}(H)}{N} 100 \tag{3}$$

The total spillover index assesses the extent of volatility shock contributions from four asset classes to the overall forecast error variance. This method helps us comprehend the dispersion of volatility shocks across significant asset classes. The generalized VAR approach further enables us to understand the direction of volatility spillovers within these major asset classes. Since generalized impulse responses and variance decompositions remain unaffected by variable ordering, directional spillovers are calculated using the normalized elements of the generalized variance decomposition matrix. This enables us to quantify directional volatility spillovers received by market *i* from all other markets *j* as:

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \vartheta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \vartheta_{ij}^{g}(H)} 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \vartheta_{ij}^{g}(H)}{N} 100 \tag{4}$$

In this same measure, the directional volatility spillovers transmitted by market i for all other markets *j* is identified below:

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \vartheta_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \vartheta_{ij}^{g}(H)} 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \vartheta_{ji}^{g}(H)}{N} 100 \tag{5}$$

2.3 Ordinary Least Squares

To better understand whether external or internal macroeconomic factors influenced the connectivity of the Brazilian economy, we estimated two ordinary least squares models:

$$\begin{gathered} Y_i = \beta_0 + \beta_1 ILocal_t + \beta_2 ILocal_{t-15} + \beta_3 ILocal_{t-30} \\ + \beta_4 ILocal_{t-45} + \beta_5 ILocal_{t-60} + \varepsilon_i \end{gathered} \tag{6}$$

$$\begin{gathered} Y_i = \beta_0 + \beta_1 IGlobal_t + \beta_2 IGlobal_{t-15} + \beta_3 IGlobal_{t-30} \\ + \beta_4 IGlobal_{t-45} + \beta_5 IGlobal_{t-60} + \varepsilon_i \end{gathered} \tag{7}$$

Where Y_i is the connectivity of the Brazilian economy; $ILocal_t$ is the interest rate of the Brazilian economy at day t; $ILocal_{t-15}$ is the interest rate of the Brazilian economy at day $t - 15$ and so on for the last 30, 45 and 60 days. $IGlobal_t$ is the interest rate of the US economy at day t; $IGlobal_{t-15}$ is the interest rate of the US economy at day $t - 15$ and so on for the last 30, 45, and 60 days. Finally, ε_i is the error term of the models.

2.4 Baruník-Krehlík Refinement

As in Tessmann et al. (2021), based on the construction of the volatility spillover index, it is partitioned into four different timeframes: very short term, short term, medium term, and long term, corresponding to one day, two to four days, four to thirty days and more than thirty days, respectively. This categorization is performed using the method developed by Baruník and Krehlík (2015), who proposed a comprehensive framework to analyze the frequency dynamics of economic variables based on the spectral representation of variance decompositions.

According to the authors, frequency dynamics offer valuable information for the study of variable connectivity since shocks with different frequency responses create frequency-dependent connections of varying strength. These nuances can remain hidden when time-domain measurements are used. Therefore, our primary focus lies in determining the portion of forecast error variance at a given frequency, specifically attributing it to shocks in another variable.

In this context, to effectively define frequency-dependent measures of connectivity, we consider the spectral counterpart of the generalized prediction error variance decompositions. Impulse response functions, defined in the time domain, play a central role in measuring connectivity and aid in quantifying these frequency-dependent relationships.

The connectivity measure is based on impulse response functions, defined by the time frame. It is considered a frequency response function $\Psi\left(e^{-iw}\right) = \sum_h e^{-i\omega h}\Psi_h$ which can simply be obtained from the Fourier transform of the coefficients Ψ, with $i = \sqrt{-1}$. A spectral density of x_t at frequency w can then be conveniently defined as a Fourier transform of Moving Average or MA (∞) filtered series as:

$$S_x(w) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h})e^{-i\omega h} = \Psi(\mathrm{e}^{-\mathrm{i}\omega}) \sum \Psi'(e^{+i\omega}) \tag{8}$$

The power spectrum $S_x(\omega)$ describes how the variation of x_t is distributed by the frequency components ω. Using the spectral representation for covariance. For instance, $E(x_t x'_{t-h}) = \int_{-\pi}^{\pi} S_x(\omega)d\omega$, introduces the counterparts in the variance decomposition frequency domain.

To define the generalized decompositions of staggered error variance in the frequency bands, the method uses, $d = (a, b)\colon a, b \in (-\pi, \pi) a < b$ as:

$$(\theta_{\tilde{d}})_{j,k} = (\theta_d)_{j,k} / \sum_k (\theta_\infty)_{j,k} \tag{9}$$

Next, the frequency connection in frequency band d is then defined as:

$$C_d^F = 100\left(\frac{\sum(\theta_d^{\sim})_{j,k}}{\sum(\theta_\infty^{\sim})_{j,k}} - \frac{T_r\{\theta_d^{\sim}\}}{\sum(\theta_\infty^{\sim})_{j,k}}\right) \tag{10}$$

Lastly, the internal connection in frequency band d is then defined as:

$$C_d^w = 100\left(1 - \frac{T_r\{\theta_d^{\sim}\}}{\sum(\theta_d^{\sim})_{j,k}}\right) \tag{11}$$

In conclusion, the concept of internal connection refers to the connection effect that occurs within a specific frequency range, and its weighting is solely based on the power of the series within that frequency band. On the other hand, frequency connection involves breaking down the original connection into discrete components, which succinctly contribute to the overall original connection measurement, denoted as C_∞.

4. Results

To understand the characteristics of the time series, we estimate the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests. We also ran the Andrews-Zivot test, a unit root test with structural breaks. Table 3 summarizes these tests.

Table 3. Unit root tests

	ADF	KPSS	ZA		ADF	KPSS	ZA
IBOV	0.184	0.010	0.002	ΔIBOV	0.000	0.100	0.007
ICON	0.749	0.010	0.000	ΔICON	0.000	0.100	0.004
IEEX	0.350	0.010	0.000	ΔIEEX	0.000	0.100	0.001
IFNC	0.290	0.010	0.002	ΔIFNC	0.000	0.100	0.028
IMAT	0.553	0.010	0.008	ΔIMAT	0.000	0.100	0.002
IMOB	0.368	0.010	0.001	ΔIMOB	0.000	0.100	0.001
UTIL	0.336	0.010	0.000	ΔUTIL	0.000	0.100	0.016
ICOM	0.363	0.010	0.001	ΔICOM	0.000	0.100	0.012
IGlobal	0.951	0.010	0.004	ΔIGlobal	0.000	0.100	0.000
ILocal	0.010	0.010	0.000	ΔILocal	0.000	0.100	0.010
Conn	0.010	0.013	0.000	ΔConn	0.000	0.100	0.009

Source: Elaborated by authors.

Table 4 shows the general spillover index for Brazilian financial and non-financial sectoral indices. It is possible to note the general connectivity of the market, the extent to which each index transmits and receives spillovers of returns from the market as a whole and the price connectivity between each pair of indices.

Table 4. Spillover index

	IBOV	ICON	IEEX	IFNC	IMAT	IMOB	UTIL	ICOM	FROM
IBOV	19.83	14.82	12.88	16.63	9.69	12.72	13.38	0.05	10.02
ICON	16.55	22.21	13.08	13.12	5.67	15.77	13.56	0.04	9.72
IEEX	14.22	12.90	22.21	12.80	4.43	12.86	20.52	0.04	9.72
IFNC	18.89	13.36	13.10	22.35	5.24	13.51	13.49	0.05	9.71
IMAT	19.14	9.98	8.04	9.15	38.87	6.58	8.21	0.03	7.64
IMOB	14.89	16.48	13.57	13.97	3.91	23.23	13.90	0.04	9.60
UTIL	14.53	13.14	20.14	12.96	4.45	12.94	21.78	0.05	9.78
ICOM	0.20	0.31	0.05	0.05	0.36	0.18	0.05	98.80	0.15
TO	12.30	10.12	10.11	9.84	4.22	9.32	10.39	0.04	66.34

Source: Elaborated by authors.

The spillover index assesses the degree of interdependence among asset prices and can be represented on a scale from 0 to 100, with the results interpreted as percentages. The tables provide a comprehensive representation of the transmissions that each asset's returns send to the market, the amount of feedback each asset receives from the market, and the interconnectedness between pairs of assets. Table 2 lists the total spillover indices, that is, without the frequency bands.

We can observe that the transmission of volatility between assets is high. For example, IEEX (Energy) transmits 20.14 (line 7, column 3) to UTIL (Public Utility), which can be explained by the fact that some companies that are part of the UTIL index act as energy transmitters, waste management, water and sewage services etc. Another example: the IBOV index transmits 12.30 to the entire market (row 9, column 1). ICON (Retail and Consumer) prices affect other sectors by 10.12, due to two of the most important Brazilian retail companies having faced difficulties in the period, due to the drop in sales, the Covid-19 pandemic and the rise the country's basic interest rate. The asset IMAT (Raw Materials) receives 7.64 from price effects from other sectors, due to the fact that this sector is made up of shares highly influenced by the low dynamism of Brazilian industrial GDP in the period studied. Due to this low dynamism, the Brazilian government launched the “Nova Indústria Brasil” Program in January 2024, with the aim of boosting the national industry until 2033.

This program will use traditional public policy instruments, such as subsidies, loans with reduced interest and expansion of federal investments, in addition to tax incentives and special funds to stimulate some sectors of the industry. Finally, at the bottom edge of the table, we can see the total market-to-market connectivity at 66.34 (row 9, column 9).

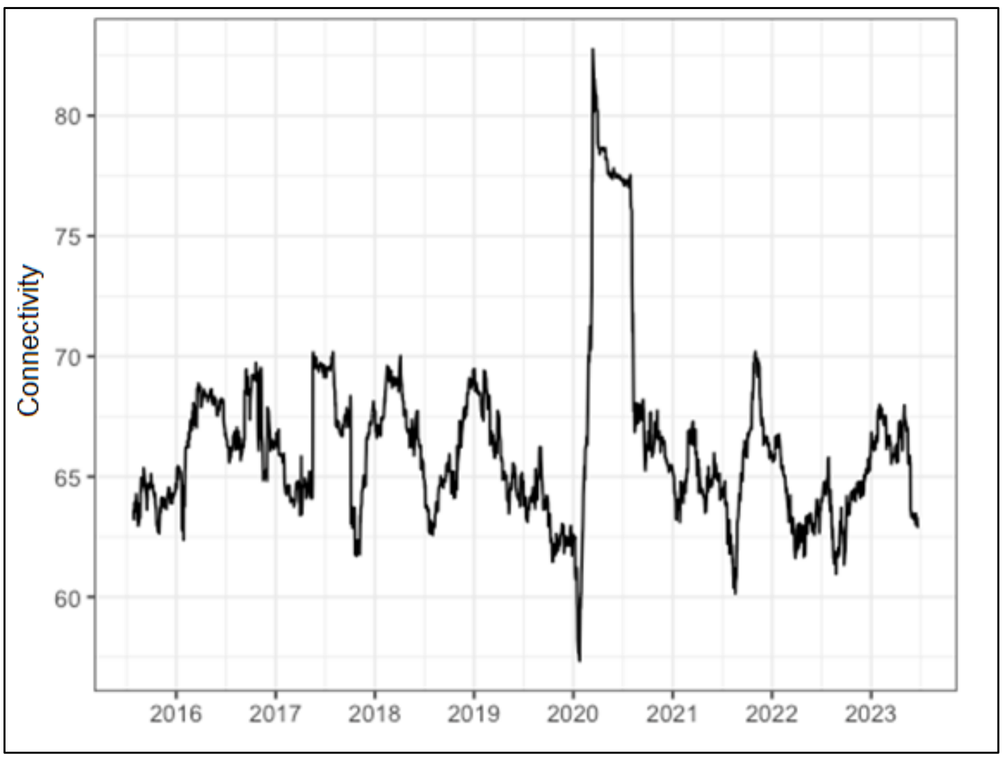
The table without frequency bands shows considerable return spillovers between assets. Notably, we can see how the IBOV index connects considerably to all other indices. In the index-to-index transmission: IEEX (Energy), for reasons already mentioned, impacts UTIL (Public Utility) by 20.14; IFNC (Financial) transmits 16.63 for IBOV (which is a clear sign of high banking concentration, as the 4 largest banks concentrated 59% of the credit supply in 2023); and ICON (Retail and Consumption) transmits 16.48 to IMOB (Real Estate), both sectors being traditionally affected, worldwide, by interest rates. Figure 1 shows the trajectory of inter-indices connectivity in the period constructed using bootstrap.

During the period, the Brazilian stock market recorded several significant peaks of uncertainty. When uncertainty increases, the connectivity or interdependence among stock prices also gets a boost. The first notable event occurred in 2015 with the beginning of the impeachment process against former president Dilma Rousseff, which ended in 2016 with her removal from office. Her government was marked by a rapid increase in the gross debt/GDP ratio, rising real interest rates and unemployment, corruption scandals involving her Workers' Party (Partido dos Trabalhadores) and double-digit inflation. The next government of Micher Temer, who was Dilma Rousseff's vice-president, quickly controlled inflation and reduced the basic interest rate, in 2018, to the lowest level until then reached in its monthly time series. In 2019, then-president-elect Jair Bolsonaro's pro-market agenda may have inspired investor confidence. These factors generated a smoothing in the price connectivity trajectory of the sectoral indices researched for most of 2018. At least until the period of the electoral campaign for the presidency of the republic, when the candidate who won the elections, Jair Bolsonaro, suffers an assassination attempt (September 6, 2018). At this point, we have a new peak of uncertainty/connectivity (figure 1).

We also note that the lowest point of price connectivity in the period studied was at the beginning of 2020 (57% connectivity). At this time, Brazil was experiencing one of the lowest interest rates in its history and the prospect of approval by the national congress of structural reforms that would possibly bring greater productivity and stability to the Brazilian economy.

However, the outbreak of the COVID-19 pandemic, which began in Brazil on February 26, 2020 with the confirmation of the first case in the city of São Paulo, caused a global recession. Government interventions and the exponential increase in uncertainty caused a spike of 83% in connectivity. From figure 1, we observe that the trajectory of connectivity only returns to normal levels when the vaccination process becomes widespread and economic activity begins to react, that is, in the first half of 2021. However, the increase in fuel prices and inflation , in the last quarter of 2021 and the first half of 2022 generates a new peak of unfavorable expectations that only attenuates in the second half of 2022.

Figure 1. Brazilian stock market connectivity trajectory



Source: Elaborated by authors.

We estimate two ordinary least squares models to assess how external and local factors affect the connectivity of the Brazilian capital market. We use ten-year future interest rates in the United States and Brazil as explanatory variables. Taking into account the results of the unit root tests, all the time series were estimated in first difference. Table 5 shows the results of both models.

The effect of 30- and 60-day interest rates on return spillovers is linked to the two sub-periods of contractionary monetary policy with high basic interest rates that the Central Bank of Brazil promoted. The first sub-period was the four-year period from 2015 to 2018, when the average annual basic interest rate (SELIC at the end of the period) was 10.38%. The second was the biennium of 2022 and 2023, when this rate reached 12.75%[1].

The monthly series of effective federal funds rates, which follow the Fed's target, were low throughout most of the period examined. In April 2015 they were at 0.12%. In March 2019 it reached a peak of 2.41%. In April 2020 it reached a minimum of 0.05%, at the height of the Covid-19 pandemic. In October 2023, it reached a high 5.33%, the highest level since September 2007[2].

Table 5. OLS results

Dependent variable:			
Y_t			
$ILocal_t$	-0.000030	$IGlobal_t$	0.000609
	(0.000104)		(0.004932)
$ILocal_{t-15}$	-0.000009	$IGlobal_{t-15}$	0.004851
	(0.000104)		(0.004930)
$ILocal_{t-30}$	-0.000267**	$IGlobal_{t-30}$	0.002316
	(0.000104)		(0.004926)
$ILocal_{t-45}$	0.000013	$IGlobal_{t-45}$	-0.004522
	(0.000104)		(0.004920)
$ILocal_{t-60}$	-0.000191*	$IGlobal_{t-60}$	0.005560
	(0.000104)		(0.004918)
Intercept	-0.000001	*Intercept*	-0.000004
	(0.000164)		(0.000165)

Source: Elaborated by authors.

However, most Brazilian companies listed on the São Paulo Stock Exchange (B3) do not only lend resources from international financial institutions. In reality, the capital structure of most of them is composed, for the most part, of long-term resources from national banks (development banks, such as BNDES - National Bank for Economic and Social Development, investment and multiple banks with investment portfolio). This is the main

[1] Source: Central Bank of Brazil and IPEADATA (http://www.ipeadata.gov.br).
[2] Federal Reserve Board of Governors via FRED, January 2024 (https://www.bankrate.com/banking/federal-reserve/history-of-federal-funds-rate/).

reason why the analyzed assets have not been affected by US interest rates. Only the largest Brazilian companies have a broad access to resources from international banks that charge interest rates relatively closer to the effective US federal funds rates.

As robustness measures, the *total spillover* index was reestimated by randomly removing two sectoral indices. Table 6 shows the general spillover index without the IFNC and table 7 without the IBOV.

When we randomly removed the IFNC from the sample, the results were not affected as much, because the composition of this index - as well as most of the credit supply in Brazil - is very concentrated in just 7 bank shares. Furthermore, Brazilian banks, due to the high concentration of the sector, are very profitable and their share prices are very little volatile and highly resilient to shocks (table 6).

Table 6. Spillover' index without IFNC

	IBOV	ICON	IFNC	IMAT	IMOB	UTIL	ICOM	From
IBOV	22.76	17.02	19.09	11.11	14.61	15.36	0.05	11.03
ICON	19.84	25.56	15.09	6.52	18.14	15.61	0.04	10.63
IFNC	21.74	15.37	25.72	6.03	15.56	15.53	0.06	10.61
IMAT	20.81	10.85	9.94	42.28	7.15	8.93	0.03	8.25
IMOB	17.23	19.06	16.18	4.53	26.88	16.08	0.05	10.45
UTIL	18.29	16.46	16.24	5.57	16.21	27.27	0.06	10.39
ICOM	0.20	0.31	0.05	0.36	0.18	0.05	98.86	0.16
To	13.89	11.30	10.94	4.87	10.26	10.22	0.04	61.53

Source: Elaborated by authors.

Table 7. Spillover' index without IBOV

	ICON	IEEX	IFNC	IMAT	IMOB	UTIL	ICOM	From
ICON	26.62	15.67	15.72	6.79	18.89	16.25	0.05	10.48
IEEX	15.04	25.91	14.92	5.16	14.99	23.93	0.05	10.58
IFNC	16.47	16.15	27.56	6.46	16.66	16.63	0.07	10.35
IMAT	12.34	9.94	11.32	48.08	8.14	10.15	0.04	7.42
IMOB	19.37	15.94	16.42	4.60	27.31	16.32	0.05	10.38
UTIL	19.38	23.58	15.17	5.20	15.13	25.50	0.06	10.64
ICOM	0.31	0.05	0.05	0.36	0.18	0.05	99.00	0.14
To	11.27	11.62	10.51	4.08	10.57	11.90	0.04	60.00

Source: Elaborated by authors.

When IBOV was removed from the sample, the impact on the results was also small. This occurred because it is a very broad index that reflects the Brazilian stock market as a whole. The very scope of IBOV prevents price fluctuations from being strongly transmitted to other sectoral indices. In fact, the opposite situation would be expected, if we take one of the representative sectoral indices from the sample: this could have a stronger impact on the IBOV closing prices (table 7).

The total spillovers index is then partitioned into different frequency bands that denote periods, making it possible to assess the persistence of the effects of a shock suffered by one sector of Brazilian stock market in others over time. Table 8 presents the transmission of volatility in the very short term, from one day to the next, table 9 presents in the short term, from one to four days, table 10 presents in the medium term, from four to thirty days, and table 11 presents the transmission of long-term volatility, more than thirty days.

Table 8. Overnight

	IBOV	ICON	IEEX	IFNC	IMAT	IMOB	UTIL	ICOM	From
IBOV	7.88	6.15	5.58	6.42	3.87	5.16	5.66	0.01	4.10
ICON	6.60	8.65	5.53	5.03	2.48	6.21	5.71	0.01	3.95
IEEX	4.99	4.71	7.83	4.32	1.55	4.58	7.20	0.02	3.42
IFNC	7.35	5.43	5.47	8.33	2.15	5.29	5.53	0.01	3.90
IMAT	7.53	4.36	3.58	3.75	13.62	2.88	3.66	0.01	3.22
IMOB	5.49	6.01	5.31	4.93	1.66	8.27	5.36	0.01	3.59
UTIL	5.26	4.92	7.31	4.48	1.66	4.67	7.82	0.01	3.54
ICOM	0.04	0.09	0.03	0.01	0.11	0.06	0.02	34.08	0.04
To	4.66	3.96	4.09	3.62	1.68	3.61	4.14	0.01	25.76

Source: Elaborated by authors.

Table 9. From 1 to 4 days

	IBOV	ICON	IEEX	IFNC	IMAT	IMOB	UTIL	ICOM	From
IBOV	7.94	5.85	5.07	6.72	3.86	5.05	5.28	0.02	3.98
ICON	6.64	8.92	5.19	5.33	2.23	6.33	5.39	0.02	3.89
IEEX	5.83	5.25	9.13	5.30	1.80	5.26	8.43	0.02	3.99
IFNC	7.61	5.30	5.20	9.12	2.08	5.41	5.38	0.02	3.88
IMAT	7.66	3.89	3.12	3.65	15.91	2.56	3.18	0.01	3.01
IMOB	6.11	6.74	5.53	5.79	1.58	9.56	5.67	0.02	3.93
UTIL	5.91	5.31	8.22	5.34	1.78	5.26	8.90	0.02	3.98
ICOM	0.09	0.14	0.02	0.02	0.15	0.08	0.02	40.87	0.07
To	4.98	4.06	4.04	4.02	1.69	3.74	4.17	0.02	25.72

Source: Elaborated by authors.

Table 10. From 4 to 30 days

	IBOV	ICON	IEEX	IFNC	IMAT	IMOB	UTIL	ICOM	From
IBOV	3.55	2.50	2.04	3.07	1.72	2.22	2.16	0.01	1.72
ICON	2.92	4.10	2.09	2.43	0.85	2.85	2.18	0.01	1.67
IEEX	2.99	2.59	4.63	2.80	0.95	2.66	4.31	0.01	2.04
IFNC	3.47	2.32	2.15	4.32	0.89	2.48	2.28	0.01	1.70
IMAT	3.48	1.53	1.19	1.55	8.21	1.01	1.21	0.01	1.25
IMOB	2.90	3.29	2.42	2.87	0.60	4.76	2.53	0.01	1.83
UTIL	2.95	2.57	4.06	2.76	0.88	2.65	4.46	0.01	1.99
ICOM	0.06	0.08	0.00	0.01	0.08	0.04	0.01	21.00	0.04
To	2.35	1.86	1.74	1.94	0.75	1.74	1.84	0.01	12.22

Source: Elaborated by authors.

Table 11. More than 30 days

	IBOV	ICON	IEEX	IFNC	IMAT	IMOB	UTIL	ICOM	From
IBOV	0.47	0.33	0.27	0.41	0.23	0.29	0.28	0.00	0.23
ICON	0.39	0.55	0.27	0.32	0.11	0.38	0.29	0.00	0.22
IEEX	0.41	0.35	0.63	0.38	0.13	0.36	0.59	0.00	0.28
IFNC	0.46	0.31	0.28	0.58	0.12	0.33	0.30	0.00	0.23
IMAT	0.47	0.20	0.15	0.20	1.12	0.13	0.16	0.00	0.16
IMOB	0.39	0.44	0.32	0.39	0.08	0.64	0.34	0.00	0.24
UTIL	0.40	0.35	0.55	0.38	0.12	0.36	0.60	0.00	0.27
ICOM	0.01	0.01	0.00	0.00	0.01	0.01	0.00	2.85	0.00
TO	0.32	0.25	0.23	0.26	0.10	0.23	0.24	0.00	1.63

Source: Elaborated by authors.

The same way of interpreting table 4 can be used to interpret tables 8 to 11. Table 8 illustrates the transmission of market prices for several indices, excluding the commodity index, in the shortest time interval. Notably, considerable price's transmissions can be observed in all indices except the commodities index (column 10). On the other hand, when examining line 10, a contrasting pattern emerges, where the indices show significant transmissions to the market. Specifically, in line 10, the IBOV, IEEX (Energy) and UTIL (Public Utility) indices stand out.

Next, we move on to table 9, where we can see that the IBOV index transmits a lot of price effects to the entire market. In this context, we can notice considerable transmissions of returns from ICON (Consumption) and IEEX (Energy). Vice versa, the entire market also imparts considerable repercussions to all indices excluding commodities (see column 10). In table 10, excluding IMAT (Basic Materials) and ICOM (Commodities), all indices transmit significant price spillovers to the market. On the other hand, the entire market affect all indices, excluding the ICOM (see row 10 and column 10).

In the period of more than 30 days, in table 11, we can observe a pattern like to that of table 5, in which all indices reflect on the market, excluding IMAT and ICOM. In that same context, the market passes price information to all indices, again, excluding IMAT and ICOM.

We note that market price signaling affects most of the indices analyzed, however, Commodities is the index class that presents greater resilience to price-effects. Finally, the IBOV, Energy, and Public Utility are the most affected by volatility. The connectivity and price repercussion among indices can be classified based on the main external factors that influence these phenomena. Umar et al. (2021) found that total connectivity tends to peak during major episodes of economic instability, such as the Covid-19 pandemic. In this context, according to Costa et al. (2021), total market connectivity during the Covid-19 pandemic increased to 84.5%, compared to the pre-Covid period which was 65.9%.

These researchers propose that behavioral factors, political events, and pandemic-specific circumstances all have a significant impact on overall market sentiment. These findings are consistent with previous studies by Bouri et al. (2017) and Vardar et al. (2018), who also suggests that volatility spillovers increase during periods of economic instability, uncertainty, and post-crisis phases compared to pre-crisis periods. Consequently, these findings could explain the gradual increase in volatility in the years leading up to the Covid-19 pandemic, marked by numerous political scandals in Brazil as it reached its highest peak in 2020. In other words, we can say that volatility accumulated over the years before the Covid-19 pandemic until it reached its record high.

Furthermore, financial news plays a substantial role in influencing volatility, either directly or indirectly, depending on the specific case. For example, studies by Hassan and Malik (2007) revealed that the energy sector is directly affected by news from its sector and indirectly influenced by news from the industrial sector. In the Brazilian case, there was a significant role of the press in influencing public opinion and policy formulation. Notable episodes were the car wash operation (series of corruption scandals involving politicians), coverage of the impeachment process of former president Dilma Rousseff and the Covid-19 pandemic.

In this context, we seek to understand why commodities have shown greater resilience in the face of volatility. According to Nazlioglu et al. (2013), their findings from the pre-crisis period of 2008 indicate that there was no significant spillover of volatility from oil returns to agricultural commodity returns, except for wheat. Likewise, there was no substantial spillover of volatility from agricultural commodity returns to oil returns, except for wheat. These results suggest that commodities tend to operate as volatility transmitters rather than receivers.

It is possible to observe that the repercussion of returns from ICOM to other indices did not show significant levels. However, it is important to emphasize that in our work oil was not included, therefore, we cannot fully determine the impact of oil prices on the other indices studied here. With commodities considered, the volatility of the ICOM appears to be resistant to the price changes of other indices.

Furthermore, Vardar et al. (2018) explain that not all stock markets have volatility links to commodity markets, indicating that there is regional variation in stock market responses to commodity market volatility shocks. Furthermore, evidence indicates that commodities cannot easily be aggregated into a homogeneous asset class, with each commodity being influenced by common macroeconomic developments and market determinants. Given this, the ICOM may not represent an adequate benchmark, as it covers a wide range of commodities with different behaviors and responses to volatility.

The results from the different periods also bring important insights into the dynamic transmissions of volatility. Around 40% of the total volatility is transmitted in the short term, with overnight market connectivity being 25.76% and falling to 25.72% when considering the period of one to four days. With the highest intensity of spillovers occurring on the first day, it is possible to verify the intensity of information flows in the market, as the volatility caused by the shock suffered by an index is transmitted to others quickly.

When analyzing the period that represents the medium term - four to thirty days - the connectivity of the economy drops to 12.22% and reaches 1.63% for the period after thirty days, with the same being verified in the existing relations between each index pair. These results are in line with those of Baruník and Krehlík (2015) and Tessmann et al. (2021), in which they denote that the market assimilates shocks as time passes and their effects dissipate over time, where in the long term the effects tend not to be perceived anymore.

4. Final remarks

We measure the connectivity of the indices of financial and non-financial sectors of the Brazilian stock market in the short, medium and long term. We use the dynamic connectivity method of spillovers from the closing prices of these assets on the São Paulo Stock Exchange (B3). To achieve this, we combine two distinct but complementary econometric methods: the decomposition of variance into Diebold-Yilmaz spillover indices and the partitioning of these indices into frequency bands of the Barunik-Krehlink refinement process that segment such price repercussions into different time frames. . The period studied was from March 3, 2015 to June 21, 2023.

The results we obtained showed a degree of total connectivity between such sectoral indices of 66%, with records of several peaks of uncertainty, in which the repercussions of the price-effects among these assets increased. The first notable event was the impeachment proceedings against former President Dilma Rousseff in 2015, followed by a period of political restructuring and economic reforms, led initially by former president Michel Temer, who, as vice president of Dilma Rousseff, replaced her.

The election of Jair Bolsonaro, who governed from January 2019 to December 2022, signaled the continuity and deepening of the pro-market reforms initiated by Michel Temer (labor reform and the "Spending Ceiling", to control the growth of the deficit and gross debt/GDP, above all). These signals reduced the degree of repercussion of inter-asset price variations to its lowest level: 57%. However, the outbreak of the COVID-19 pandemic in 2020 led to these spillovers peaking. This peak was 83%, aggravated by the ineffective government management of the health crisis and the effects of the global recession. With the economic recovery and advances in the vaccination process, there was a gradual reduction in the systemic effects of these price fluctuations, starting in mid-2021.

We also observed that the results for the different representative periods of short, medium and long term indicated that, over time, the trajectories of inter-index connections tended towards smoothing. This denotes an intense flow of information in the market and shows that the effects of a shock suffered by a certain sector were gradually dissipating.

The peaks of connectivity of price fluctuations in the sectoral indices of the São Paulo Stock Exchange experienced can be attributed, therefore, to three sources of disturbance: (i) economic crisis motivated by fiscal dominance (the years 2015-2016 marked by stagflation Dilma Rousseff's government); (ii) corruption scandals; political crisis and attempted assassination of Jair Bolsonaro in the period 2016-2018, years that preceded the Covid-19 crisis; and (iii) impact of important news on economic agents, mainly investors.

Most sectoral indices, except commodities, were significantly affected by the repercussions of price changes in the market as a whole. The resilience of commodity indices to price shocks can be explained by the fact that they generally act as transmitters of these shocks rather than as receivers. Especially when we look at individual classes of commodities, like oil, rather than looking at an index. Therefore, the commodity index may not be fully reliable as an active agent of shocks capable of affecting a broader spectrum of this asset class.

We diagnosed the presence of a reasonable level of serial autocorrelation in the model. Unfortunately, it is not that rare to have this problem in samples with high frequency data. Engle (1996) assert that the transition towards higher frequency econometrics is predominantly a consequence of the heightened availability of data featuring finer temporal resolutions. This affords researchers more frequent measurements of economic phenomena. Although an intuitive expectation may exist for an ongoing progression towards even higher observation frequencies, a cursory reflection reveals the impracticality of such an anticipation. In many instances, the ultimate constraint is encountered when meticulously recording all transactions, particularly within the domain of financial market data. The identification of economic variables amenable to measurement at arbitrarily high frequencies presents a significant challenge for researchers and econometricians.

In a somewhat similar way to what happened with Schorfheide et al. (2018), they conducted a study employing a Long Run Risks (LRR) model with high-frequency data on cash flows. This model incorporates measurement errors and three volatility processes to enhance its fit. The authors also introduce an additional process for variation in the time rate of preference, generating risk-free rate variation independent of cash flows, resulting in an improved fit for the risk-free rate. Notably, his LRR model demonstrates a pronounced autocorrelation in the persistent cash-flow component.

Finally, we believe in the informative potential of this article and its usefulness for policy makers, investors, investment portfolio managers, investment consultants and researchers interested in the connectivity between emerging market stock indices.

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