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Identifying the Frequency and Connectivity Dynamics of the US Economy

Mathias Schneid Tessmann [1,*], Marcelo De Oliveira Passos [2], Omar Barroso Khodr [3], Alexandre Vasconcelos Lima [1] and Pedro Henrique Pontes Fontana [1]

[1] Economics and Management School, Brazilian Institute of Education Development and Research (IDP), Brasília 70750-600, DF, Brazil; alexandre.lima@idp.edu.br (A.V.L.); fontanap@hotmail.com (P.H.P.F.)
[2] Organizations and Markets Graduate Program, Universidade Federal de Pelotas, Pelotas 96010-610, RS, Brazil; molpss@gmail.com
[3] Essex Business School, University of Essex, Colchester C04 3SQ, UK; khodr.omar.business@gmail.com
* Correspondence: mathias.tessmann@idp.edu.br

Abstract: This paper seeks to investigate the connectivity of the US economy through the dynamics of the transmission of volatility in sectoral indices. For this, we use daily asset data and two methodologies. The first creates a spillover index that measures market connectivity and the second partitions this index into different frequency bands that denote periods. We found results that show significant transmissions of volatility among the 64 analyzed assets. Notably, the DJIA, Wilshire 5000, and S&P 500 showed significant volatility and were the main drivers of volatility for the other sectors and indices. Results also indicated that sectors that transferred volatility were influenced by three key factors: periods of economic uncertainty, socioeconomic circumstances resulting from post-crisis events, and the impact of economic and financial news on market sentiment. Additionally, we found that global returns and price changes in market indices sent considerable volatility into commodity assets. Our results are potentially useful for investors, portfolio managers, financial economists, financial advisors, financial market regulators, and policymakers.

Keywords: volatility transmission; spillover index; frequency decomposition; post-crisis volatility

JEL Classification: E30; E44; G01; G10

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1. Introduction

Volatility repercussions, in the view of Chan et al. (1991), can be seen as proxies for assessments of the intensity and quality of economic and financial information flows. In this sense, it is a common practice in financial markets to analyze how information and its consequent volatility transmissions flow from one asset to another, from one sector to another, or even from one market to another. Such analyses are useful for financial market regulators, policymakers, activating circuit-breakers on stock exchanges, analysts and investment managers, investors, hedgers, traders, and commodity producers. Assessing the existing connections in an economy and its intersectoral relationships is an important contribution that empirical economics can bring because, through these identifications, measures to mitigate systemic risks can be taken.

Likewise, one of the most recurrent research topics in the field of financial economics is the verification of the existence of links that may exist between financial and non-financial assets traded in the market. Thus, presenting empirical evidence of how markets interact and how their assets react to changes in expectations and macroeconomic variations makes the measurement of volatility transmissions and interdependencies between sectoral financial assets important.

In this sense, we intend to investigate the patterns and dynamics of the transmission of volatility in a series of sectoral assets of the US economy, including the main indices of the US stock market, the Select Sector SPDR index funds, the Commodity Research Bureau index, and the prices of WTI and Brent oil, as well as US Treasury bond returns. Our study covers a period from 22 December 1998 to 12 July 2021, providing a dataset of 5547 price observations for each asset.

Therefore, we use two econometric methodologies in this paper: the spillover index proposed by Diebold and Yilmaz (2012) and the frequency decompositions method of Baruník and Krehlík (2018). The first method measures interactions and interdependencies based on the decomposition of variances, which allowed us to quantify the extent of volatility transmission and determine overall market connectivity. The second details these interactions and connectivity relationships across different frequency bands, which helped us in the separate analysis of short-term and long-term dynamics.

With the spillover indices, we partitioned their effects into three different frequencies: overnight (1 day), very short term (1 to 4 days), short term (4 to 30 days), and medium/long term (more than 30 days), which provided us with information about frequency band dependent connections. This highlighted the strength of the shocks in these different periods that, without this methodology, could be neglected; that is, more precise evidence that considers the effects over time would be absent.

When we examine the results, we see a pattern that indicates that volatility transmissions were significant across the 64 included assets. Notably, the DJIA, Wilshire 5000, and S&P 500 exhibited high levels of volatility and functioned as significant volatility transmitters for various sectors and market indices. Specifically, the transport, energy, health, industrial, and technology sectors stood out as the most exposed to volatility transmissions. The same happened with the main market indices, such as the S&P 500, Nasdaq, and Wilshire 5000.

Several works dealt with the repercussions of volatility, such as Nazlioglu et al. (2013), who examined volatility transmissions between oil and agricultural commodity returns in pre-crisis and post-crisis periods. The authors found distinct patterns and variations between the two periods. The research by Barunik et al. (2015) investigated the asymmetries in the repercussions between different sectors, finding results for the consumer, telecommunication, and health sectors that presented greater asymmetries in the repercussions when compared to the financial, information technology, and energy sectors. From the perspective of Mensi et al. (2021), there is evidence that the diesel and gas sectors were net transmitters of volatility to other markets since asymmetric repercussions occurred.

Our findings suggest that the sectors that recorded the most intense volatility transmissions were those influenced by three factors. First, circumstances arising from economic instability, uncertainty, and post-crisis factors (global financial crisis, European crisis, and COVID-19 pandemic). Second, financial news affected "market sentiment" and, in effect, increased the repercussions of volatility in the assets and sectors considered. Third, returns and changes in market index prices provoked reactions in raw material assets.

Thus, by making some patterns of connectivity and interdependence explicit, we believe we provide a less distorted view of the dynamics of interactions between assets, indices, and sectors, which, we hope, can be useful for policymakers in the finance and design of policies for financial markets that mitigate systemic risk and promote market stability, for investors and portfolio managers, as well as for the general population benefiting from economic stability.

The paper is structured in four more sections. The second section provides a brief theoretical reference about the sectoral connectivity of the economy, and in Section 3, we define the database, detailing its elaboration process, as well as the methodology used in the empirical analysis. In Section 4, we present and discuss the results, and in Section 5, we make the final considerations.

2. Review of Empirical Literature

Several authors also point out that the circumstances brought about by the post-crisis periods influenced volatility transmissions and connectivity effects (Costa et al. 2022; Umar et al. 2021; Bouri et al. 2017; Vardar et al. 2018). The literature also explored the direct and indirect impacts that financial news had on intra- and cross-sector volatility (Hassan and Malik 2007; Malik and Ewing 2009) across selected sectors and assets and at different frequencies. In this sense, our purpose is, in addition to what has already been mentioned, to contribute to the understanding of some aspects not directly measurable (some of a qualitative nature) that influence the volatility links between and inside assets and sectors.

Ewing et al. (2002) calculated the transmission of volatility between the oil and natural gas markets from a sample of daily returns data. They produced evidence that suggested continued volatility in both markets. Therefore, they found that returns exhibited fluctuations over time in the volatility series. They suggested that *volatility in natural gas returns was more persistent than that in oil returns, stating that this may indicate a greater "window of profit opportunities" for investors in natural gas than in oil*.

Hughes et al. (2006) empirically tested the volatility patterns of American Treasury bonds (Treasury bills or T-bills) between January 1983 and December 2000. They analyzed the daily returns for bonds with different maturities of 13; 26; and 52 weeks, examining trading periods starting from the first half hour of active New York trading, which begins at 8:30 a.m. and proceeds until the close at 4 p.m., as well as the overnight period lasting from 4 p.m. to 9 a.m. (on the next day of negotiations). According to the authors, the night period includes the volatility effect of relevant macroeconomic announcements that take place until 8:30 a.m. The authors investigated variations in standard deviations every 1 h throughout the day. *The results for the different bonds (with and without coupons) suggest that the intraday volatility of 13-week bonds was higher compared to bonds maturing in 26 and 52 weeks*.

For them, in practical terms, there is no daily opening and closing day in trading sessions. This dynamic works according to local (or domestic) trading compared to global trading, which operates 24 h a day. In New York, volatility was concentrated at the beginning and end of Treasury bond trading hours. The literature also suggests similar parameters, presented by Cyree et al. (2014) and Baillie and Bollerslev (1991), who conclude that empirical results in the 24-h foreign exchange markets and the 24-h Eurodollar market confirm that volatility is greatest at the beginning and end of the workday, even in the absence of market closing.

Hassan and Malik (2007) investigated volatility repercussions and shocks among the main sectoral indices in the United States, based on daily data from 1 January 1992 to 6 June 2005. The sectors investigated were financial, industrial, consumer, health, energy, and technology. In a broad sense, both authors achieved results that show *significant occurrences among the second moments of these indices. They concluded that there is a transmission of relevant shocks and volatility between all the mentioned sectors*.

Kumiega et al. (2011) studied the factors that increased the returns on the US stock markets in 2007 and early 2010. This period presented specific trends in the prices of energy and raw materials, in addition to indications that it was affected by the crisis of important institutions' financial and insurance conditions, in addition to high volatility followed by the resumption of activity in the global market. The authors developed an opinion regarding the returns on ETFs in the S&P 500 sector with statistically independent signals and used the independent component analysis method, concluding that there were two sets of overall market betas during the period, combined with a dominant factor for the energy and materials sector.

They also demonstrated that the EGARCH model, which deals with asymmetric responses between returns and volatility, adjusted to significant levels of variance during an international financial crisis. They found that the estimated correlations reduced greatly when raw material prices rose. However, they rose sharply again after the fall of the S&P 500, in the last months of 2008. Finally, the authors found that *the three main factors were a factor of energy and materials, another stock market standard, and a factor dominated by finance*.

Nazlioglu et al. (2013) estimated the volatility connections present between oil prices and the prices of some specific agricultural commodities (wheat, corn, soybeans, and sugar). They used the recently developed causality-in-variance test and computed impulse response functions within a sample with daily observations from 1 January 1986 to 21 March 2011. By identifying the effect of the shock of the crisis on food prices, they separated the observations into two subsamples: the period before the shock (1 January 1986 to 31 December 2005) and the period after (1 January 2006 to 21 March 2011).

The variance causality test concluded that the volatility of the oil market extends to agricultural markets—excluding the sugar market—in the post-shock period, even though there was no risk connectivity between oil and agricultural products in the pre-shock period. Regarding the impulse response functions, they also showed that a shock in oil price volatility had repercussions on agricultural markets only in the period after the shock. With this, the authors concluded that there is *a transition in the dynamics of volatility transmission after a food price shock when volatility transmission emerges differently in the risk interconnections between energy and agricultural markets*.

Bouri et al. (2017) examined the effects of commodity volatility on sovereign credit default swap (CDS) spreads in emerging and frontier markets, based on a sample of daily observations from seventeen emerging countries and six frontier countries. They documented a relevant transmission of volatility from commodity markets to sovereign CDS spreads in both emerging and frontier markets. Despite finding a significant effect for most countries in that sample, the authors found that their results vary over time and depending on the country. *They also found evidence of a greater transmission effect of volatility from the energy and precious metals sectors*.

Vardar et al. (2018) used a VAR-BEKK GARCH model to study the shock transmission and volatility spillover (STVS) effects among daily stock market indices from the US, the UK, France, Germany, Japan, Turkey, China, South Korea, South Africa, and India. The five most relevant raw material prices were added to these indices: natural gas, crude oil, platinum, gold, and silver. The period analyzed was from 5 July 2005 to 14 October 2016. Thus, the months before, during, and after the crisis that led to the Great Recession were examined. In the sample period, developed and emerging countries exhibited bidirectional STVS effects between stock and commodity returns.

However, the authors concluded that there were less unilateral effects of the STVS present in commodity returns on stocks, but also clear unilateral effects of the STVS of stock returns on commodity returns, in both developed and emerging countries. They also discovered other instances *of relevant STVS effects across commodity and stock markets across countries during the crisis and post-crisis periods vis-à-vis the pre-crisis period*. The authors stated *that the effects of the STVS are the new normal for stock and commodity markets*, despite the work of monetary authorities in the post-global crisis period. Finally, they stated that resource allocation choices between stocks and commodities could be made while considering analyzing the direction of the effects of STVS in some stock/commodity markets and also throughout the economic cycles of the world economy.

Umar et al. (2021) investigated the *repercussions of volatility in shocks in oil and agricultural commodity prices*. Using a sample starting from January 2002 and proceeding to July 2020, that is, within a period covering the global financial crisis, the European sovereign debt crisis, and the COVID-19 pandemic, the authors ran Granger–Newbold causality tests and computed static and dynamic connection indices, *producing evidence that indicates that oil price shocks were caused, in the Granger–Newbold sense, by changes in the prices of grains, live cattle, and wheat*. The Granger supply shock causes variations in grain prices. The authors also highlighted that livestock was the largest transmitter and lean pork was the largest receiver, whether for price or volatility connectivity and based on a static connection approach. However, considering the dynamic perspective, they concluded that the connection increased during the period of the financial crisis.

Farid et al. (2021) studied the ex ante and ex post periods of the COVID-19 outbreak in the US economy, focusing on critical structural changes and variable patterns of volatility connectivity between stocks and metal and energy commodities such as oil, gold, silver, and natural gas. They investigated 5-min high-frequency trading data from the most traded US ETFs to model a volatility connectivity network, computing intraday volatility estimates using the MCS-GARCH model. After this procedure, they adopted the Diebold and Yilmaz (2012) index methodology to measure volatility transmissions among financial markets. The authors concluded that there was a significant impact of the COVID-19 pandemic on the aforementioned connections among financial markets. Volatility repercussions among different assets reached a peak during the most critical moments of the pandemic.

Mensi et al. (2021) estimated the dynamic connectivity of asymmetric volatility among ten US stock sectors (consumer goods, consumer services, finance, healthcare, materials, oil and gas, technology, telecommunications, real estate investment trusts (REITs), and utilities). They also adopted the indices of Diebold and Yilmaz (2012, 2014) and the realized semivariances introduced by Baruník et al. (2017) for five-minute data. The authors found *variable repercussions over time in the sectors that are part of the US stock markets*. Such repercussions were more intense when significant economic, energy, and geopolitical events occurred.

Furthermore, the repercussions of bad volatility tend to predominate over the repercussions of good volatility. This supports the evidence of asymmetric volatilities. *Financials, materials, oil and gas, REITs, technology, telecommunications, and utilities were net recipients of good volatility (positive semivariance) transmissions*. On the other hand, *oil and gas transmitted bad volatility (negative semivariance*), with the connectivity network among sectors showing asymmetric behavior.

Costa et al. (2022) analyzed volatility transmissions involving 11 sectoral indices in the US. Using daily data from 1 January 2013 to 31 December 2020, the three authors estimated indices from Diebold and Yilmaz (2009, 2012, 2014), noticing changes in the degrees of connections among sectors and finding specifically stylized facts for sectors throughout the COVID-19 pandemic. This work reached several conclusions, including the existence of *a substantial increase in total connectivity, from the initial period of the pandemic until the end of July 2020. Furthermore, there were significant changes in connectivity between pairs of sectors*.

3. Methodology

3.1. Data

We use daily closing prices from major US stock market indices; Select Sector SPDR index funds (in US dollars); the Commodity Research Bureau index; the futures market, in US dollars, of continuous contracts; contracts for WTI and Brent crude oil prices; and, finally, the US Treasury. The period covered is from 22 December 1998 to 12 July 2021, totaling 5547 price observations for each data frame. Table 1 details the assets considered, and Table 2 presents descriptive statistics on closing prices and returns.

Table 1. Assets considered.

Number	Codes	Assets: Indices, Funds and Bonds	Description
1	CRB	Commodity Research Bureau Index	The Commodity Research Bureau (CRB) index is a representative indicator of the global commodity markets.
2	IRX	CBOE 13 Week Treasury Bill Yield Index	Some of the best-known yield-based options follow the yields of the most recently issued 13-week Treasury bills, 5-year Treasury notes, 10-year Treasury notes, and 30-year Treasury bonds.
3	DGS10	Market Yield on US Treasury Securities at 10-Year Constant Maturity	Quoted on an investment basis.
4	DGS2	Market Yield on US Treasury Securities at 2-Year Constant Maturity	Quoted on an investment basis.
5	DGS30	Market Yield on US Treasury Securities at 30-Year Constant Maturity	Quoted on an investment basis.

Table 1. *Cont.*

Number	Codes	Assets: Indices, Funds and Bonds	Description
6	DGS5	Market Yield on US Treasury Securities at 5-Year Constant Maturity	Quoted on an investment basis.
7	XLB	Materials Select Sector SPDR Fund	Composed of companies involved in such industries as chemicals, construction materials, containers and packaging, metals and mining, and paper and forest products.
8	Brent Crude Oil	Crude Oil	Brent blend is a light crude oil (LCO), though not as light as West Texas Intermediate (WTI).
9	WTI Crude Oil	Crude Oil	West Texas Intermediate (WTI) crude oil is a specific grade of crude oil.
10	DJIA	DJIA—Dow Jones Industrial Average	An index of 30 blue-chip stocks of US industrial companies.
11	DJTA	DJTA—Dow Jones Transportation Average	A price-weighted average of 20 transportation stocks traded in the United States. In addition to railroads, the index includes airlines, trucking, marine transportation, delivery services, and logistics companies.
12	DJUA	DJUA—Dow Jones Utility Average	A Dow Jones index group that tracks the performance of several well-established utility companies. DJUA companies must be US-based and incorporated with most of their revenues generated within the US.
13	XLE	Energy Select Sector SPDR Fund	Energy companies in this index primarily develop and produce crude oil and natural gas, and provide drilling and other energy-related services.
14	XLF	S&P Financial Select Sector	A wide array of diversified financial service firms, insurance companies, banks, capital markets, and consumer finance and thrift companies are featured in this index.
15	XLV	S&P Health Care Select Sector	Companies in this sector primarily include healthcare equipment and supplies, healthcare providers and services, and biotechnology, and pharmaceutical industries.
16	XLI	S&P Industrial Select Sector	Industries in this index include aerospace and defense, building products, construction and engineering, electrical equipment, conglomerates, machinery, commercial services and supplies, air freight and logistics, airlines, marine, road and rail, etc.
17	Nasdaq	NDQ—Nasdaq Composite	An index that measures the performance of over 2500 common equities listed on the Nasdaq stock exchange.
18	SPX	SPX—S&P 500 Composite Stock Price Index	A capitalization-weighted index of 500 stocks intended to be a representative sample of leading companies in major sectors of the US economy.
19	XLK	S&P Technology Select Sector	Stocks primarily covering products developed by internet software and service companies, IT consulting services, and semiconductor equipment, computers, and peripherals are included in this index.

Table 1. *Cont.*

Number	Codes	Assets: Indices, Funds and Bonds	Description
20	XLU	S&P Utilities Select Sector	The utilities index primarily provides companies that produce, generate, transmit, or distribute electricity or natural gas.
21	Wilshire 5000	Wilshire 5000 Total Market Index	An index that measures the performance of the entire US stock market.

Source: elaborated by authors.

Table 2. Descriptive statistics of the analyzed indices.

	Closing Prices				Returns			
	Mean	**Std. Dev.**	**Minimum**	**Maximum**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
S&P 500	1693.2930	747.5181	676.5300	4384.6300	0.0002	0.0124	−0.1277	0.1042
Nasdaq Composite	3967.5080	2736.3610	1114.1100	14,733.2400	0.0003	0.0160	−0.1315	0.1325
Dow Jones Industrial Average	14,881.2600	6303.3170	6547.0500	34,996.1800	0.0002	0.0118	−0.1384	0.1033
Dow Jones Transportation Average	5843.0840	3051.6690	1942.1900	15,943.3000	0.0003	0.0157	−0.1640	0.0896
Dow Jones Utility Average	487.3838	181.9854	167.5700	960.8900	0.0002	0.0125	−0.1175	0.1277
Wilshire 5000	70.1798	41.6704	24.5800	218.3000	0.0003	0.0125	−0.1306	0.0984
Materials Select Sector	38.1431	14.3355	16.6300	88.6800	0.0002	0.0154	−0.1325	0.1186
Energy Select Sector	54.7083	20.3556	19.8000	101.2900	0.0001	0.0185	−0.2249	0.1537
Financial Select Sector	20.6623	5.9894	5.0203	38.4700	0.0001	0.0190	−0.1807	0.1524
Industrial Select Sector	43.1685	19.6372	15.3600	105.5300	0.0003	0.0137	−0.1204	0.1013
Technology Select Sector	39.6322	26.8948	11.5800	151.3200	0.0003	0.0164	−0.1487	0.1493
Consumer Staples Select Sector	35.9272	14.3787	17.8200	71.5200	0.0001	0.0185	−0.2249	0.1537
Utilities Select Sector	38.0688	11.9984	15.2300	70.9800	0.0002	0.0234	−0.2814	0.1277
Healthcare Select Sector	48.9630	26.4922	21.8800	128.9800	0.0003	0.0329	−0.1038	2.5759
Consumer Discretionary Select Sector	55.7172	36.9693	16.1100	183.7400	0.0005	0.0190	−0.3514	0.1537
30−Year Treasury Bond	4.0043	1.2482	0.9900	6.7500	−0.0001	0.0167	−0.2332	0.2569
10−Year Treasury Note	3.3704	1.4023	0.5200	6.7900	−0.0001	0.0234	−0.3151	0.3417
5−Year Treasury Note	2.7563	1.6036	0.1900	6.8300	−0.0002	0.0329	−0.3567	0.3145
2−Year Treasury Note	2.1419	1.8238	0.0900	6.9300	−0.0004	0.0465	−0.3514	0.3483
13−Week Treasury Bill	1.6575	1.8286	−0.1050	6.2200	−0.0011	0.2473	−4.0073	2.5759
WTI Crude Oil	58.9245	26.7146	−36.9800	145.1600	0.0005	0.0274	−0.2814	0.4258
Brent Crude Oil	61.4961	30.3102	9.1200	143.6800	0.0005	0.0254	−0.2564	0.4120
Commodity Research Bureau Index	240.2832	70.1056	106.2929	473.5200	0.0001	0.0109	−0.0794	0.0742

Source: elaborated by the authors.

3.2. *Diebold–Yilmaz Method*

As presented in Tessmann et al. (2021), the Diebold and Yilmaz (2012) method uses a variance decomposition associated with autoregressive vectors, VAR, estimated using the

Akaike criterion for lag selection. To calculate the total spillover index, the decomposition of the error variance is estimated H steps forward by $\theta_{ij}^{g}(H)$:

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

where Σ is the variance matrix for the error vector ε, each i and j are a different sector of the US economy, σ_{jj} is the standard deviation of the error term for the equation jth, and e_i is the selection vector, with one as the ith element and zeros otherwise. Measure the directional repercussions of volatility received by the US economy sector i from all other sectors j as in Equation (2). The same applies to measuring the directional repercussions of volatility transmitted by sector index i to all other sector indices j by inverting the relationship ij by ji in the numerator.

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \vartheta_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \vartheta_{ij}^{g}(H)} 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \vartheta_{ij}^{g}(H)}{N} 100 \quad (2)$$

3.3. Baruník–Krehlík Refinement

As in Tessmann et al. (2021), the total spillover index that measures the transmission of volatility between the US economy sectors is divided into overnight (1 day), very short-term (1 to 4 days), short-term (4 to 30 days) and medium/long term (more than 30 days) using the method developed by Baruník and Krehlík (2018) that measures connectivity frequency dynamics through the spectral representation of variance decompositions. The measure of connectivity is based on impulse response functions, defined in the time domain, and when defining the generalized decompositions of staggered error variance in the frequency bands $d = (a, b) : a, b \in (-\pi, \pi)a < b$, the frequency connection in frequency band d is then defined as

$$C_{d}^{F} = 100\left(\frac{\sum\left(\theta_{d}^{\sim}\right)_{j,k}}{\sum\left(\theta_{\infty}^{\sim}\right)_{j,k}} - \frac{T_r\{\theta_{d}^{\sim}\}}{\sum\left(\theta_{\infty}^{\sim}\right)_{j,k}}\right) \quad (3)$$

The internal connection in frequency band d is then defined as in Equation (4). The internal connection denotes the connection effect that the frequency connection breaks down the original connection into distinct parts which, in short, provide the original connection measurement C_{∞}.

$$C_{d}^{w} = 100\left(1 - \frac{T_r\{\theta_{d}^{\sim}\}}{\sum(\theta_{d}^{\sim})_{j,k}}\right) \quad (4)$$

4. Results

The Diebold–Yilmaz Spillover Index shows the extent to which volatility is transmitted across reported assets. The index can be interpreted as a percentage varying from zero to one hundred. Its output provides an overview of asset-to-asset, asset-to-market, and market-to-asset volatility, as well as total market connectivity.

Figure 1 depicts the total connectivity of US assets along the years 1998 to 2021. During this period, that is, from 22 December 1998 to 12 July 2021, several significant peaks of volatility occurred in financial markets. Our research began after the Asian financial crisis in 1997. This crisis generated considerable volatility in Asian economies and in other emerging markets. However, this event did not affect the beginning of our study period. In 2000, the bursting of the dot-com bubble resulted in a significant market correction, in addition to a rapid increase in volatility of nearly 80%. The level of uncertainty gradually increased in the years leading up to the Iraq war in 2003. But it stabilized from 2004 to 2006.

Figure 1. US daily connectivity. Source: elaborated by the authors.

However, the global financial crisis (2007–2009) resulted in widespread financial turmoil. These years evidenced sharp declines in global stock markets, bankruptcies of financial institutions, and increased market volatility, reaching a connectivity peak of 95%. Finally, the COVID-19 pandemic in 2020 abruptly slowed down the asset market to a record level. Government interventions and uncertainties arising from the global health crisis contributed significantly to market volatility rising to extraordinary levels, reaching a connectivity peak of 95%.

Connectivity and volatility links among assets can be categorized based on the external factors that influence them. According to Costa et al. (2022), total market connectivity during the COVID-19 pandemic was higher (84.5%) compared to the pre-COVID period (65.9%). Furthermore, Umar et al. (2021) observed that total connectivity tends to peak during episodes of economic instability (such as the global financial crisis, the European sovereign crisis, and the COVID-19 pandemic). These authors argued that behavioral factors, political issues, and aspects related to the pandemic generated externalities in the general market sentiment. This trend is in line with the analysis by Bouri et al. (2017) and Vardar et al. (2018). They also pondered how the spillovers of volatility increased significantly during said ex ante and ex post periods; these peaks of uncertainty were greater compared to normal periods.

In Table 3, we summarize the results that are detailed in five additional tables in Appendix A, which describe the different volatility transmissions among the sample assets in five different temporal horizons: total volatility, overnight (within the same day), 1 to 4 days, 4 to 30 days, and over 30 days.

We analyzed the results, shown in Table 4, having replaced the assets with their respective sectors, in addition to relating these results to others already described in the literature.

Table 3. Volatility transmissions among assets with different time horizons.

N	Assets	Total Spillover (>5.00)	Overnight or Within the Same Day (>2.50)	Very Short-Term or 1 to 4 Days (>2.50)	Short-Term or 4 to 30 Days (>1.25)	Medium- to Long-Term or More than 30 Days (>0.18)
1	CRB	Brent Crude Oil; WTI Crude Oil and XLE	Brent Crude Oil; WTI Crude Oil and XLE	Brent Crude Oil; WTI Crude Oil and XLE	Brent Crude Oil; WTI Crude Oil and XLE	Brent Crude Oil; WTI Crude Oil and XLE
2	IRX	None	None	None	None	None
3	DGS10	DGS2, DGS5, and DGS30	DGS2, DGS5, and DGS30	DGS2, DGS5, and DGS30	DGS2, DGS5, and DGS30	DGS2, DGS5, and DGS30
4	DGS2	DGS5, DGS10, and DGS30	DGS5, DGS10, and DGS30	DGS5, DGS10, and DGS30	DGS5 and DGS10	DGS5 and DGS10
5	DGS30	DGS2, DGS5, and DGS10	DGS2, DGS5, and DGS10	DGS2, DGS5, and DGS10	DGS2, DGS5, and DGS10	DGS5 and DGS10
6	DGS5	DGS2, DGS10, and DGS30	DGS2, DGS10, and DGS30	DGS2, DGS10, and DGS30	DGS2, DGS10, and DGS30	DGS2, DGS10, and DGS30
7	XLB	X.DJI, X.DJT, XLE, XLF, XLI, Nasdaq, X.SPX, Wil 5000	X.DJI, X.DJT, XLI, X.SPX, Wil 5000	X.DJI, X.DJT, <u>XLE</u>, <u>XLF</u>, XLI, X.SPX, Wil 5000	X.DJI, X.DJT, XLE, XLF, XLI, X.SPX, Wil 5000	Brent Crude Oil, X.DJI, X.DJT, XLE, XLF XLI, X.SPX, Wil 5000
8	Brent Crude Oil	CRB, WTI Crude Oil, and XLE	CRB, WTI Crude Oil	CRB, WTI Crude Oil, and <u>XLE</u>	CRB, WTI Crude Oil, and XLE	CRB, WTI Crude Oil, and XLE
9	WTI Crude Oil	CRB, Brent Crude Oil, and XLE	CRB, Brent Crude Oil	CRB, Brent Crude Oil, and <u>XLE</u>	CRB, Brent Crude Oil, and XLE	CRB, Brent Crude Oil, and XLE
10	X.DJI	XLB, X.DJT, XLE, XLF, XLV, XLI, Nasdaq, X.SPX, XLK, and Wil 5000	XLB, X.DJT, XLF, XLV, XLI, Nasdaq, X.SPX, XLK, and Wil 5000	XLB, X.DJT, XLF, XLI, Nasdaq, X.SPX, <u>XLK</u>, and Wil 5000	XLB, X.DJT, XLF, XLI, X.SPX, and Wil 5000	X.DJT, XLF, XLI, X.SPX, and Wil 5000
11	X.DJT	XLB, X.DJI, XLE, XLF, XLV, XLI, Nasdaq, X.SPX, XLK, XLU, and Wil 5000	XLB, X.DJI, XLF, XLI, Nasdaq, X.SPX, and Wil 5000	XLB, X.DJI, XLF, XLI, Nasdaq, X.SPX, and Wil 5000	XLB, X.DJI, XLF, XLI, X.SPX, and Wil 5000	XLB, X.DJI, XLF, XLI, X.SPX, and Wil 5000
12	X.DJU	XLB, X.DJI, XLE, XLI, X.SPX, XLIJ, and Wil 5000	X.DJI, X.SPX, XLK, XLU, and Wil 5000	X.DJI, X.SPX, XLU, and Wil 5000	X.DJI, X.SPX, XLU, and Wil 5000	XLU
13	XLE	CRB, XLB, X.DJI, X.DJT, XLF, XLI, X.SPX, and Wil 5000	XLB, X.DJI, XLI, X.SPX, and Wil 5000	XLB, X.DJI, XLI, X.SPX, and Wil 5000	XLB, X.DJI, XLI, X.SPX, and Wil 5000	XLB, X.DJI, XLI, X.SPX, and Wil 5000
14	XLF	XLB, X.DJI, X.DJT, XLV, XLI, Nasdaq, X.SPX, XLK, and Wil 5000	XLB, X.DJI, X.DJT, XLI, Nasdaq, X.SPX, and Wil 5000	XLB, X.DJI, X.DJT, XLI, X.SPX, and Wil 5000	X.DJI, X.DJT, XLI, X.SPX, and Wil 5000	X.DJI, X.DJT, XLI, X.SPX, and Wil 5000
15	XLV	XLB, X.DJI, X.DJT, XLF, XLI, Nasdaq, X.SPX, XLK, and Wil 5000	X.DJI, XLI, Nasdaq, X.SPX, and Wil 5000	X.DJI, XLI, Nasdaq, X.SPX, XLK, and Wil 5000	X.DJI, XLI, Nasdaq, X.SPX, XLK, and Wil 5000	X.DJI, XLI, Nasdaq, X.SPX, XLK, and Wil 5000
16	XLI	XLB, X.DJI, X.DJT, XLE, XLF, XLV, Nasdaq, X.SPX, XLK, and Wil 5000	XLB, X.DJI, X.DJT, XLF, X.SPX, and Wil 5000	XLB, X.DJI, X.DJT, XLF, Nasdaq, X.SPX, and Wil 5000	XLB, X.DJI, X.DJT, XLF, Nasdaq, X.SPX, and Wil 5000	XLB, X.DJI, X.DJT, XLF, Nasdaq, X.SPX, and Wil 5000

Table 3. *Cont.*

N	Assets	Total Spillover (>5.00)	Overnight or Within the Same Day (>2.50)	Very Short-Term or 1 to 4 Days (>2.50)	Short-Term or 4 to 30 Days (>1.25)	Medium- to Long-Term or More than 30 Days (>0.18)
17	Nasdaq	XLB, X.DJI, X.DJT, XLF, XLV, XLI, X.SPX, XLK, and Wil 5000	X.DJI, XLV, XLI, X.SPX, XLK, and Wil 5000	X.DJI, XLV, XLI, X.SPX, XLK, and Wil 5000	X.DJI, X.SPX, XLK, and Wil 5000	X.DJI, XLI, X.SPX, XLK, and Wil 5000
18	X.SPX	XLB, X.DJI, X.DJT, XLF, XLV, XLI, Nasdaq, XLK, and Wil 5000	XLB, X.DJI, X.DJT, XLF, XLV, XLI, Nasdaq XLK, and Wil 5000	XLB, X.DJI, X.DJT, XLF, XLV, XLI, Nasdaq XLK, and Wil 5000	X.DJI, XLF, XLI, Nasdaq XLK, and Wil 5000	X.DJI, XLF, XLI, Nasdaq XLK, and Wil 5000
19	XLK	X.DJI, X.DJT, XLF, XLV, XLI, Nasdaq, X.SPX, and Wil 5000	X.DJI, XLV, XLI, Nasdaq, X.SPX, and Wil 5000	X.DJI, XLI, Nasdaq, X.SPX, and Wil 5000	X.DJI, XLI, Nasdaq, X.SPX, and Wil 5000	X.DJI, XLI, Nasdaq, X.SPX, and Wil 5000
20	XLU	XLB, X.DJI, X.DJU, XLV, XLI, X.SPX, and Wil 5000	X.DJI, X.DJU, X.SPX, and Wil 5000	X.DJI, X.DJU, X.SPX, and Wil 5000	X.DJI, X.DJU, X.SPX, and Wil 5000	X.DJU
21	Wilshire 5000	XLB, X.DJI, X.DJT, XLF, XLV, XLI, Nasdaq, X.SPX, and XLK	XLB, X.DJI, X.DJT, XLF, XLV, XLI, Nasdaq, X.SPX, and XLK	XLB, X.DJI, X.DJT, XLF, XLV, XLI, Nasdaq, X.SPX, and XLK	X.DJI, X.DJT, XLF, XLI, Nasdaq, X.SPX, and XLK	X.DJI, XLF, XLI, Nasdaq, X.SPX, and XLK

Source: elaborated by authors from the results described in the tables of Appendix A. Notes: assets in bold are those that do not appear in the right column; that is, their volatility transmissions do not affect the subsequent period. The underlined assets are those that reappear as transmitters of volatility, after not having sent volatility in the previous period (column).

Table 4. Analysis of volatility transmission results from Table 3 and articles with similar results.

N	Assets	Sectors That Receive Volatility from This Asset	Articles with Similar Results
1	CRB	The volatility of the Commodity Research Bureau (CRB) index, which represents assets in global commodity markets, is sent to crude oil and energy markets.	Passos et al. (2020); Hassan and Malik (2007); Nazlioglu et al. (2013); Vardar et al. (2018); Umar et al. (2021).
2	IRX	None.	None.
3	DGS10	2-year Treasury note; 5-year Treasury note and 30-year Treasury bond.	CIR model (Cox et al. 1985). Hughes et al. (2006) and Bouri et al. (2017).
4	DGS2	5-year Treasury note; 10-year Treasury note and 30-year Treasury bond.	The same as above.
5	DGS30	2-year Treasury note; 5-year Treasury note and 10-year Treasury note.	The same as above.
6	DGS5	2-year Treasury note; 10-year Treasury note and 30-year Treasury bond.	The same as above.
7	XLB	The volatility generated in industries such as chemicals, construction materials, containers and packaging, metals and mining, and paper and forest products (synthesized by XLB) is transmitted, in all periods considered in Table 3, to Brent crude oil; Dow Jones 30 blue chips; transportation; energy; finance; various industrial sectors; 500 leading companies from the largest sectors; technology companies (Nasdaq); stock market as a whole (Wilshire 5000).	Mensi et al. (2021) found that materials and real estate were net recipients of good volatility (positive semivariance) transmissions.

Table 4. *Cont.*

N	Assets	Sectors That Receive Volatility from This Asset	Articles with Similar Results
8	Brent Crude Oil	There are risk spillovers from the Brent crude oil market to the global commodities market (CRB), the WTI crude oil market, and also to the energy market, in all periods considered in Table 3.	Passos et al. (2020); Hassan and Malik (2007); Nazlioglu et al. (2013); Vardar et al. (2018); Umar et al. (2021); and Mensi et al. (2021) found that oil and gas transmitted bad volatility (negative semivariance) to 10 other sectors of the United States economy.
9	WTI Crude Oil	Similarly, there are also risk spillovers from the WTI crude oil market to the global commodities market (CRB), the Brent crude oil market, and again to the energy market, in all periods considered in Table 3.	Passos et al. (2020); Hassan and Malik (2007); Nazlioglu et al. (2013); Vardar et al. (2018); Umar et al. (2021); and Mensi et al. (2021) found that oil and gas transmitted bad volatility (negative semivariance) to 10 other sectors of the United States economy.
10	X.DJI	The volatility effects of the 30 Dow Jones blue chips spread across several industry sectors; the financial sector, transportation, and the stock market as a whole (XSPX and Wilshire 5000).	Hassan and Malik (2007); Kumiega et al. (2011); Farid et al. (2021); and Costa et al. (2022).
11	X.DJT	The volatility of the transportation sector affects several materials industries (XLB) and other industrial segments (XLI). It also impacts the financial sector and the stock market as a whole (X.SPX, Wilshire 5000, X.DJI).	Hassan and Malik (2007); Kumiega et al. (2011); Farid et al. (2021); and Costa et al. (2022).
12	X.DJU	As expected, the volatility produced in US-based utilities (DJUA—Dow Jones Utility Average) affects the S&P Utilities Select Sector, which represents companies that produce, generate, transmit, or distribute electricity or natural gas. The reciprocal reasoning is also valid, as both indices are highly correlated.	Hassan and Malik (2007); Kumiega et al. (2011); Farid et al. (2021); and Costa et al. (2022).
13	XLE	Oscillations in the risk in the energy sector generate spillovers in several industrial sectors (XLB and XLI) and the stock market as a whole (X.DJI, X.SPX, and Wilshire 5000).	Hassan and Malik (2007) highlighted that the energy sector is directly affected by news regarding the dynamics of the sector itself and indirectly affected by news from the industrial sector.
14	XLF	Problems in the financial sector mainly affect, in the medium and long term (above 30 days), industry (XLI), transport, and the stock market (X.DJI, X.SPX, and Wilshire 5000).	Costa et al. (2022) and Mensi et al. (2021) found that financials, materials, oil and gas, REITs, technology, telecommunications, and utilities were net recipients of good volatility (positive semivariance) transmissions.
15	XLV	Factors that cause fluctuations in the shares of healthcare companies generate negative externalities for traditional industry (XLI); the technology industry (Nasdaq and XLK) due to the weight of biotechnology in this index; and also, the entire stock market (X.DJI, X.SPX and Wilshire 5000).	Hassan and Malik (2007) highlighted that the health sector is directly influenced by news from its sector and indirectly influenced by news from the industrial sector. But in the case of the technology sector, we observe a distinct pattern: news from the financial sector generates direct and indirect effects on it. Another aspect that distinguishes this sector from others is that its volatility linkages are directly and indirectly affected by the linkages of all other sectors (including those of assets in its sector).
16	XLI	Volatilities in shares of traditional industries such as aerospace and defense, building products, construction and engineering, electrical equipment, conglomerates, machinery, commercial services and supplies, air freight and logistics, airlines, shipping, road, and rail have an impact, on the medium and long deadlines, on other sectors such as materials (XLB), transport (X. DJT), finance (XLF), technology (Nasdaq), and stock markets (X. DJI, X. SPX and Wilshire 5000).	Hassan and Malik (2007) pointed out that US industry is indirectly affected by news from the energy sector and directly affected by news referring to its sectoral dynamics. Another aspect they highlighted is that volatility in the industrial sector is received by the energy sector (indirectly) and by factors concerning the sector itself (directly).

Table 4. *Cont.*

N	Assets	Sectors That Receive Volatility from This Asset	Articles with Similar Results
17	Nasdaq	When uncertainty increases in the Nasdaq, the result is a spillover of volatility to other stock exchanges (X. DJI, X.SPX, and Wilshire 5000) and many industrial sectors (XLI and XLK).	See Hassan and Malik (2007) and Costa et al. (2022). Malik and Ewing's (2009) research, in this context, found that the volatility of assets in the technology sector was directly affected by specific news from the technology industry, but indirectly by shocks that impacted the oil sector.
18	X.SPX	X.DJI, XLF, XLI, Nasdaq, XLK, and Wil 5000	Hassan and Malik (2007); Kumiega et al. (2011); Farid et al. (2021); and Costa et al. (2022).
19	XLK	Increasing volatility in internet software and service companies, IT consulting services, semiconductor equipment, computers, and peripherals affect the entire industry (including the traditional companies) and, by extension, negatively impacts the US exchange stock market.	Hassan and Malik (2007) and Costa et al. (2022).
20	XLU	The companies that produce, generate, transmit, or distribute electricity or natural gas generate two types of volatility transmissions: to the stock markets (overnight, very short and short terms) and, as expected, to DJUA—Dow Jones Utility Average (in medium/long term).	Hassan and Malik (2007); Costa et al. (2022); and Mensi et al. (2021) discovered that utilities were net recipients of good volatility (positive semivariance) transmissions.
21	Wilshire 5000	As a proxy for the US stock market, this index impacts all other sectors.	Hassan and Malik (2007) and Costa et al. (2022).

Source: elaborated by authors from the results described in the tables of the Appendix A.

There is also evidence of intra-industry and intra-market volatility links. Bouri et al. (2017) revealed that the returns on commodities such as WTI, Brent oil, gold, and wheat were influenced by S&P 500 returns. Gold was the asset that had the greatest reaction to price changes in the S&P 500, followed by WTI and wheat.

Thus, we can say that the sectors highlighted in Section 4 that were most affected by volatility transfers were directly or indirectly conditioned by three key factors: First, the ex ante and ex post effects in the periods of instability. Second, the financial and economic news played an important role in the general market sentiment and the volatilities transmitted and received by the evaluated assets. Finally, global returns and price changes in market indices were the drivers of reactions in commodity assets.

5. Final Remarks

We examine intra- and inter-volatility transmissions among a set of financial assets. This set includes major US stock market indices, SPDR index funds from select sectors, the Commodity Research Bureau index, WTI and Brent crude oil prices, and US Treasury yields. The database we used covered the period from 22 December 1998 to 12 July 2021, with a total of 5547 price observations for each data frame. The results of transmissions in overnight terms showed that WTI crude transmitted volatility to the CRB; the 30-year Treasury bond transferred considerable volatility to the 10-year notes; the 2-year Treasury note sent volatility to the 2-year Constant Maturity (DGS2). Also, there were volatility connections from DJU to XLU.

However, we assess that there are similar volatility patterns over a slightly longer period, in which significant volatility linkages have occurred: (i) from WTI oil to CRB; (ii) from 30-year Treasuries to 10-year notes; and (iii) from 5-year notes to 10-year notes. Then, in the period of one to four days (i.e., in the very short term) we have lower volatility transfers, with emphasis on the DJIA connections for the entire market and the Wilshire 5000 index for the entire market.

In terms of total market connectivity metrics, the results revealed a distinct pattern, with relevant links among the 64 assets. Once again, indices such as the DJIA, Wilshire

5000, and S&P 500 were identified as the most volatile. They sent volatility to several other sectors and market indices. Indeed, we conclude that the sectors most affected by volatility transmissions were transport, energy, health, industrial, and technology. Market indices such as the S&P 500, Nasdaq, and Wilshire 5000 were also subject to considerable levels of volatility.

When we analyze the results, we see that volatility receiver sectors were influenced by three key factors. First, they were susceptible to externalities resulting from scenarios marked, ex ante and ex post, by the increases in some types of uncertainty (political, economic, financial, health, etc.). Second, the impacts of the news cannot be underestimated, as it influenced general market sentiment, facilitating volatility spillovers inter- and intra-assets. Finally, reactions in commodity assets were influenced by global returns and fluctuations in market indices. Together, these factors contributed to the dynamics of volatility spillovers, as well as their implications for the sectors studied.

Finally, we believe that this paper contributes to future studies that might explore these results in more detail and/or serves to expand the scope of studies on connectivity and volatility spillovers in finance. Our results demonstrate that there was considerable transmission between oil and fixed-income assets (notes and bonds), which may be the subject of further research by financial analysts, regulators, policymakers, investment fund managers, etc. Further exploration of these volatility transfers may require alternative methods that are beyond the scope of this article.

We also consider that the influence of non-economic factors, such as political instabilities and the effect of economic and financial news, raise other research topics. Applying natural language processing (NLP) and machine learning techniques can provide useful insights into how different speech and texting patterns affect volatility spillovers that link assets, sectors, markets, etc. Analysis of the relationship between global returns and price fluctuations in market indices also requires further research. We think, in short, that such questions can be explored by future studies.

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Appendix A. Tables with Detailed Results of Volatility Spillovers

Table A1 presents the results for total spillover indices; Table A2, for the overnight volatility spillovers; Table A3, for the very short term—from one to four days; Table A4, for the short term—from four to 30 days; and, finally, Table A5, for the medium/long term—more than thirty days.

Table A2 highlights volatility transfer patterns that are similar to those presented in Table A1. However, its values are higher. Other transmissions worth mentioning include the WTI oil that impacts the CRB; the 30-year Treasuries, which affect the 10-year notes, and finally the 5-year notes, which send volatility down to the 10-year notes. Table A1 presents the spillover indices for a period of one to four days (very short term). Tables A3 and A4 show smaller transmissions, among which we can highlight the DJIA spillover for the entire market, which reflects the already mentioned importance of this index, and that of the Wilshire 5000 index for the entire market. This last index is a stock market index that tracks the performance of (nearly) the entirety of the publicly traded US equity market.

Table A5 displays the results of medium/long-term impacts (i.e., greater than thirty days). In it, we observe a distinct pattern with significant volatility among the 64 assets involved. The DJIA, Wilshire 5000, and S&P 500 were the assets that transmitted the most volatility for the various sectors and market indices. Overall, the sectors most affected by volatility connections from others were transport, energy, healthcare, industry, and technology. Market indices such as the S&P 500, Nasdaq, and Wilshire 5000 also received considerable levels of volatility.

We also emphasize that the cell at the intersection of the last column and the bottom row of each table represents the total connectivity of the market. In this sense, total connectivity tends to smooth out as time increases. For example, in Table 4, said intersection cell shows a total connectivity of 29.42 in the period of 1 day (overnight). However, when we look at Table A1, where the period considered is 1 to 4 days, we see a small increase to 30.89. However, this trend is reversed in Table A2, which evaluates the period from 4 to 30 days (short term), as connectivity decreases to 14.95. Finally, in the period of 30 days or more (medium/long term), connectivity reaches its lowest point: 2.02.

Table A1. Total spillover indices.

	CRB	IRX	DGS10	DGS2	DGS30	DGS5	XLB	DCOIL BRENTEU	DCOIL WTICO	X.DJI	X.DJT	X.DJU	XLE	XLF	XLV	XLI	NASDAQ COM	X.SPX	XLK	XLU	WIL 5000	FROM
CRB	29.88	0.25	1.51	0.48	1.72	1.13	4.09	11.90	18.69	2.41	1.57	1.38	9.91	1.59	0.92	2.42	1.71	2.83	1.44	1.12	3.03	3.34
IRX	0.51	88.99	0.36	0.77	0.36	0.38	0.55	0.30	0.59	0.71	0.37	0.45	1.20	1.08	0.23	0.47	0.37	0.76	0.33	0.43	0.79	0.52
DGS10	1.12	0.07	22.04	9.26	19.01	18.30	2.47	0.99	0.79	3.06	2.65	0.53	2.59	2.52	1.65	3.01	1.91	2.83	1.80	0.54	2.85	3.71
DGS2	0.54	0.29	13.69	33.06	9.03	19.78	1.66	0.36	0.38	2.52	2.18	0.45	1.63	2.37	1.32	2.39	1.64	2.42	1.51	0.41	2.39	3.19
DGS30	1.44	0.10	21.48	6.88	24.92	15.38	2.58	1.11	1.17	2.94	2.44	0.42	2.87	2.53	1.54	2.88	1.76	2.74	1.60	0.45	2.78	3.58
DGS5	0.90	0.11	19.51	14.24	14.52	23.52	2.11	0.71	0.57	2.84	2.48	0.45	2.18	2.47	1.53	2.79	1.76	2.63	1.61	0.44	2.63	3.64
XLB	1.80	0.08	1.54	0.70	1.41	1.24	13.66	0.63	0.77	8.89	7.76	3.53	6.60	6.47	5.18	9.08	5.32	8.50	4.82	3.51	8.49	4.11
DCOIL BRENTEU	16.79	0.44	1.63	0.40	1.66	1.10	2.08	37.55	17.47	1.56	0.81	0.93	8.37	1.08	0.51	1.39	1.00	1.76	0.89	0.68	1.88	2.97
DCOIL WTICO	22.76	0.25	1.26	0.41	1.69	0.88	2.04	15.07	36.41	1.36	0.63	0.58	8.49	0.76	0.49	1.27	0.97	1.63	0.87	0.43	1.75	3.03
X.DJI	0.84	0.08	1.48	0.83	1.24	1.29	6.93	0.40	0.43	10.67	6.88	3.91	5.07	7.49	6.55	8.76	6.86	9.95	6.70	4.01	9.64	4.25
X.DJT	0.68	0.05	1.65	0.91	1.33	1.45	7.74	0.26	0.25	8.85	13.58	3.02	4.48	7.40	5.39	9.81	6.49	8.85	5.65	3.14	9.02	4.12
X.DJU	0.86	0.07	0.58	0.31	0.41	0.47	5.19	0.47	0.37	7.39	4.42	19.80	5.72	4.98	4.99	5.75	3.62	7.48	3.49	16.53	7.10	3.82
XLE	5.07	0.21	1.79	0.77	1.75	1.43	7.53	2.98	3.61	7.38	5.09	4.50	15.58	5.39	3.96	6.83	3.88	7.48	3.41	3.92	7.46	4.02
XLF	0.72	0.15	1.53	0.96	1.35	1.41	6.44	0.31	0.31	9.53	7.30	3.39	4.74	13.51	5.41	8.31	6.20	9.87	5.39	3.45	9.71	4.12
XLV	0.49	0.03	1.13	0.62	0.93	1.00	5.75	0.21	0.25	9.29	5.95	3.76	3.86	5.99	15.12	7.74	7.59	9.78	6.77	4.14	9.61	4.04
XLI	0.91	0.06	1.58	0.85	1.33	1.38	7.68	0.38	0.42	9.53	8.32	3.35	5.08	7.10	5.93	11.55	6.60	9.23	6.09	3.43	9.20	4.21
NASDAQ COM	0.71	0.05	1.14	0.67	0.92	1.00	5.12	0.29	0.35	8.49	6.24	2.35	3.33	6.05	6.65	7.52	13.09	10.48	11.93	2.63	10.97	4.14
X.SPX	0.95	0.08	1.32	0.76	1.12	1.16	6.37	0.42	0.48	9.56	6.61	3.80	4.94	7.46	6.65	8.16	8.14	10.27	7.65	3.97	10.15	4.27
XLK	0.64	0.05	1.14	0.65	0.89	0.97	4.95	0.29	0.33	8.84	5.78	2.43	3.14	5.61	6.32	7.38	12.70	10.50	13.93	2.86	10.61	4.10
XLU	0.64	0.07	0.54	0.26	0.40	0.42	5.07	0.32	0.27	7.43	4.53	16.33	4.92	4.98	5.43	5.81	3.95	7.65	4.00	19.72	7.26	3.82
WIL 5000INDFC	1.01	0.08	1.33	0.75	1.14	1.16	6.38	0.45	0.51	9.29	6.76	3.62	4.94	7.36	6.54	8.15	8.54	10.17	7.76	3.77	10.27	4.27
TO	2.83	0.12	3.63	1.97	2.96	3.40	4.42	1.80	2.29	5.80	4.23	2.82	4.48	4.32	3.68	5.23	4.33	6.07	3.99	2.85	6.06	77.28

Source: elaborated by the authors.

Table A2. Volatility spillovers in the overnight period (one day only).

	CRB	13-Week Treasury Bill	10-Years Treasury Note	2-Year Treasury Note	30-Year Treasury Bond	5-Year Treasury Note	XLB	Brent Oil	WTI Oil	DJI	DJT	DJU	XLE	XLF	XLV	XLI	NDQ	SPX	XLK	XLU	WILSHIRE 5000	FROM
CRB	10.32	0.02	0.56	0.15	0.56	0.40	0.89	3.99	6.55	0.50	0.28	0.23	2.50	0.31	0.19	0.51	0.31	0.58	0.26	0.15	0.62	0.93
IRX	0.20	38.18	0.23	0.29	0.21	0.20	0.35	0.16	0.19	0.38	0.21	0.30	0.61	0.59	0.15	0.25	0.21	0.43	0.20	0.28	0.44	0.28
DGS10	0.44	0.01	7.74	3.26	6.68	6.47	0.94	0.42	0.36	1.34	1.03	0.28	1.12	1.02	0.78	1.20	0.82	1.23	0.80	0.29	1.23	1.42
DGS2	0.25	0.08	5.45	14.29	3.70	7.81	0.67	0.15	0.18	1.05	0.86	0.20	0.71	1.02	0.56	0.96	0.68	1.02	0.64	0.20	1.01	1.30
DGS30	0.54	0.01	7.35	2.54	8.57	5.54	0.95	0.45	0.49	1.29	0.93	0.21	1.21	1.02	0.72	1.14	0.74	1.17	0.70	0.24	1.18	1.35
DGS5	0.37	0.01	7.26	5.06	5.52	8.79	0.80	0.31	0.24	1.20	0.93	0.23	0.91	0.98	0.69	1.10	0.74	1.11	0.70	0.23	1.11	1.40
XLB	0.72	0.01	0.61	0.27	0.53	0.50	4.97	0.23	0.36	3.25	2.74	1.36	2.41	2.31	1.96	3.25	1.97	3.16	1.80	1.33	3.14	1.52
Brent Crude Oil	2.70	0.06	0.56	0.12	0.45	0.34	0.27	10.94	2.80	0.25	0.12	0.19	1.17	0.12	0.11	0.22	0.12	0.26	0.12	0.11	0.27	0.49

Table A2. *Cont.*

	CRB	13-Week Treasury Bill	10-Years Treasury Note	2-Year Treasury Note	30-Year Treasury Bond	5-Year Treasury Note	XLB	Brent Oil	WTI Oil	DJI	DJT	DJU	XLE	XLF	XLV	XLI	NDQ	SPX	XLK	XLU	WILSHIRE 5000	FROM
WTI Crude Oil	8.07	0.08	0.38	0.11	0.44	0.23	0.51	4.90	13.00	0.38	0.16	0.19	2.36	0.20	0.15	0.34	0.22	0.43	0.21	0.11	0.46	0.95
DJIA	0.41	0.02	0.67	0.35	0.54	0.58	2.76	0.17	0.22	4.34	2.68	1.67	2.15	3.01	2.68	3.45	2.79	4.08	2.73	1.71	3.94	1.74
DJTA	0.31	0.01	0.68	0.36	0.52	0.59	2.85	0.10	0.14	3.43	4.93	1.24	1.78	2.82	2.14	3.62	2.50	3.45	2.20	1.27	3.50	1.60
DJUA	0.41	0.03	0.36	0.17	0.26	0.29	2.22	0.20	0.22	3.31	1.90	7.54	2.36	2.18	2.25	2.42	1.71	3.37	1.67	6.52	3.19	1.67
XLE	1.96	0.04	0.68	0.28	0.61	0.54	2.81	1.10	1.42	2.94	1.87	1.82	5.86	2.11	1.65	2.55	1.55	3.01	1.38	1.58	2.97	1.57
XLF	0.37	0.04	0.63	0.36	0.53	0.57	2.65	0.14	0.18	3.88	2.78	1.48	2.08	5.37	2.28	3.27	2.52	4.03	2.20	1.49	3.96	1.69
XLV	0.26	0.01	0.54	0.27	0.43	0.47	2.25	0.10	0.15	3.52	2.17	1.57	1.63	2.20	5.61	2.91	2.69	3.65	2.46	1.65	3.58	1.55
XLI	0.40	0.01	0.65	0.32	0.54	0.56	2.77	0.14	0.21	3.57	2.94	1.35	1.94	2.54	2.26	4.24	2.44	3.47	2.28	1.36	3.44	1.58
Nasdaq	0.33	0.01	0.52	0.28	0.40	0.45	2.03	0.13	0.17	3.44	2.40	1.05	1.48	2.47	2.70	2.96	4.88	4.15	4.44	1.14	4.31	1.66
SPX	0.46	0.02	0.60	0.32	0.49	0.53	2.57	0.18	0.25	3.91	2.57	1.62	2.12	3.01	2.72	3.23	3.23	4.18	3.04	1.67	4.12	1.75
XLK	0.30	0.01	0.52	0.29	0.39	0.45	2.00	0.12	0.16	3.65	2.25	1.11	1.45	2.34	2.62	2.97	4.81	4.24	5.27	1.27	4.25	1.68
XLU	0.30	0.03	0.32	0.13	0.24	0.25	2.08	0.13	0.16	3.15	1.86	6.28	1.98	2.06	2.33	2.34	1.73	3.25	1.75	7.84	3.08	1.59
Wilshire 5000	0.47	0.02	0.60	0.32	0.49	0.52	2.51	0.19	0.26	3.73	2.57	1.52	2.08	2.92	2.63	3.16	3.29	4.05	3.00	1.56	4.06	1.71
TO	0.92	0.03	1.39	0.73	1.12	1.30	1.66	0.63	0.70	2.29	1.58	1.14	1.62	1.68	1.50	1.99	1.67	2.39	1.55	1.15	2.37	29.42

Source: elaborated by the authors.

Table A3. Volatility spillovers in the very short term: one to four days.

	CRB	13-Week Treasury Bill	10-Year Treasury Note	2-Year Treasury Note	30-Year Treasury Bond	5-Year Treasury Note	XLB	Brent Oil	WTI Oil	DJI	DJT	DJU	XLE	XLF	XLV	XLI	NDQ	SPX	XLK	XLU	WILSHIRE 5000	FROM
CRB	12.31	0.12	0.63	0.21	0.73	0.48	1.85	4.94	7.65	1.10	0.72	0.65	4.36	0.74	0.43	1.09	0.79	1.30	0.66	0.54	1.39	1.45
IRX	0.21	34.40	0.12	0.33	0.12	0.14	0.17	0.10	0.25	0.24	0.12	0.13	0.43	0.37	0.06	0.16	0.12	0.25	0.11	0.13	0.26	0.18
DGS10	0.45	0.04	9.02	3.79	7.80	7.48	1.00	0.39	0.31	1.18	1.06	0.19	1.01	0.99	0.62	1.20	0.75	1.10	0.70	0.19	1.11	1.49
DGS2	0.20	0.13	5.44	12.52	3.56	7.85	0.66	0.14	0.14	0.99	0.87	0.17	0.63	0.91	0.52	0.95	0.65	0.95	0.59	0.16	0.94	1.26
DGS30	0.59	0.05	8.81	2.77	10.23	6.21	1.05	0.45	0.47	1.14	0.98	0.15	1.13	1.00	0.59	1.15	0.70	1.07	0.63	0.16	1.09	1.44
DGS5	0.36	0.06	7.89	5.86	5.84	9.48	0.86	0.28	0.23	1.11	1.01	0.17	0.86	0.99	0.59	1.12	0.70	1.03	0.63	0.16	1.04	1.47
XLB	0.69	0.04	0.61	0.28	0.56	0.49	5.55	0.25	0.28	3.60	3.18	1.42	2.67	2.65	2.09	3.71	2.15	3.44	1.95	1.42	3.44	1.66
Brent Crude Oil	7.96	0.21	0.66	0.17	0.69	0.46	0.95	16.09	8.28	0.70	0.36	0.42	3.89	0.52	0.22	0.61	0.45	0.80	0.39	0.31	0.85	1.38
WTI Crude Oil	9.18	0.09	0.52	0.18	0.73	0.39	0.89	6.27	14.70	0.59	0.27	0.25	3.63	0.33	0.21	0.55	0.43	0.71	0.38	0.19	0.76	1.26
DJIA	0.29	0.03	0.56	0.32	0.47	0.49	2.72	0.15	0.14	4.17	2.73	1.51	1.94	2.94	2.56	3.47	2.68	3.88	2.62	1.55	3.76	1.66
DJTA	0.24	0.02	0.64	0.37	0.52	0.57	3.12	0.10	0.08	3.52	5.52	1.18	1.75	2.96	2.14	3.97	2.59	3.51	2.25	1.24	3.59	1.64
DJUA	0.29	0.02	0.19	0.11	0.13	0.15	1.97	0.17	0.11	2.76	1.67	7.89	2.18	1.88	1.87	2.20	1.32	2.80	1.28	6.52	2.65	1.44
XLE	1.98	0.09	0.70	0.31	0.71	0.57	2.98	1.19	1.40	2.87	2.03	1.76	6.21	2.12	1.53	2.71	1.50	2.91	1.32	1.54	2.91	1.58
XLF	0.24	0.07	0.60	0.40	0.54	0.56	2.52	0.12	0.10	3.75	2.93	1.30	1.81	5.36	2.10	3.31	2.45	3.88	2.12	1.33	3.82	1.62
XLV	0.17	0.01	0.43	0.25	0.35	0.38	2.32	0.08	0.07	3.75	2.44	1.49	1.51	2.45	6.15	3.15	3.13	3.97	2.75	1.66	3.91	1.63
XLI	0.33	0.02	0.62	0.35	0.52	0.54	3.12	0.15	0.14	3.83	3.40	1.32	2.02	2.90	2.38	4.68	2.66	3.71	2.45	1.36	3.70	1.69

Table A3. *Cont.*

	CRB	13-Week Treasury Bill	10-Year Treasury Note	2-Year Treasury Note	30-Year Treasury Bond	5-Year Treasury Note	XLB	Brent Oil	WTI Oil	DJI	DJT	DJU	XLE	XLF	XLV	XLI	NDQ	SPX	XLK	XLU	WILSHIRE 5000	FROM
Nasdaq	0.25	0.02	0.43	0.26	0.35	0.38	2.02	0.11	0.12	3.33	2.49	0.89	1.26	2.37	2.61	2.98	5.25	4.13	4.79	1.01	4.34	1.63
SPX	0.34	0.03	0.50	0.30	0.43	0.44	2.50	0.16	0.16	3.73	2.63	1.47	1.89	2.93	2.60	3.23	3.21	4.01	3.02	1.54	3.97	1.67
XLK	0.23	0.02	0.43	0.26	0.34	0.37	1.94	0.11	0.11	3.45	2.30	0.91	1.17	2.18	2.47	2.91	5.10	4.12	5.58	1.08	4.18	1.60
XLU	0.22	0.02	0.18	0.10	0.13	0.14	1.96	0.12	0.08	2.84	1.75	6.50	1.90	1.92	2.08	2.26	1.49	2.93	1.52	7.78	2.78	1.47
Wilshire 5000	0.36	0.03	0.50	0.30	0.44	0.44	2.52	0.17	0.17	3.64	2.70	1.40	1.90	2.91	2.57	3.24	3.39	4.00	3.08	1.47	4.05	1.68
TO	1.17	0.05	1.45	0.80	1.19	1.36	1.77	0.73	0.97	2.29	1.70	1.11	1.81	1.72	1.44	2.09	1.73	2.40	1.58	1.12	2.40	30.89

Source: elaborated by the authors.

Table A4. Spillovers in the short term: four to thirty days.

	CRB	13-Week Treasury Bill	10-Year Treasury Note	2-Year Treasury Note	30-Year Treasury Bond	5-Year Treasury Note	XLB	Brent Oil	WTI Oil	DJI	DJT	DJU	XLE	XLF	XLV	XLI	NDQ	SPX	XLK	XLU	WILSHIRE 5000	FROM
CRB	6.39	0.09	0.29	0.10	0.38	0.21	1.19	2.61	3.94	0.71	0.50	0.44	2.68	0.48	0.27	0.72	0.54	0.84	0.45	0.37	0.90	0.84
IRX	0.08	14.49	0.02	0.14	0.02	0.04	0.03	0.03	0.13	0.08	0.03	0.02	0.14	0.11	0.01	0.05	0.03	0.07	0.03	0.02	0.08	0.05
DGS10	0.20	0.02	4.65	1.94	3.99	3.83	0.48	0.16	0.11	0.48	0.50	0.06	0.41	0.45	0.22	0.54	0.30	0.45	0.27	0.05	0.45	0.71
DGS2	0.08	0.07	2.48	5.51	1.56	3.63	0.29	0.06	0.06	0.42	0.39	0.06	0.26	0.39	0.21	0.42	0.27	0.39	0.24	0.05	0.39	0.56
DGS30	0.27	0.03	4.68	1.38	5.38	3.20	0.51	0.18	0.18	0.45	0.47	0.05	0.47	0.45	0.21	0.52	0.28	0.44	0.24	0.05	0.45	0.69
DGS5	0.15	0.04	3.84	2.92	2.78	4.62	0.40	0.11	0.09	0.47	0.48	0.05	0.36	0.44	0.22	0.51	0.28	0.43	0.25	0.04	0.43	0.68
XLB	0.34	0.03	0.28	0.13	0.28	0.22	2.76	0.13	0.13	1.79	1.63	0.67	1.35	1.33	1.00	1.87	1.06	1.68	0.94	0.67	1.68	0.82
Brent Crude Oil	5.38	0.15	0.36	0.10	0.46	0.26	0.76	9.24	5.61	0.53	0.30	0.29	2.91	0.39	0.15	0.48	0.38	0.61	0.33	0.23	0.67	0.97
WTI Crude Oil	4.84	0.07	0.31	0.11	0.47	0.23	0.56	3.43	7.67	0.35	0.17	0.12	2.20	0.20	0.11	0.34	0.28	0.43	0.25	0.11	0.47	0.72
DJIA	0.13	0.02	0.22	0.13	0.20	0.20	1.27	0.07	0.06	1.91	1.30	0.64	0.87	1.36	1.16	1.62	1.23	1.76	1.19	0.67	1.71	0.75
DJTA	0.11	0.02	0.29	0.17	0.25	0.26	1.56	0.05	0.03	1.68	2.75	0.53	0.84	1.43	0.99	1.96	1.23	1.66	1.06	0.55	1.7	0.78
DJUA	0.14	0.01	0.03	0.02	0.02	0.02	0.88	0.08	0.04	1.16	0.75	3.84	1.05	0.81	0.77	0.99	0.52	1.16	0.48	3.07	1.11	0.63
XLE	0.99	0.06	0.35	0.15	0.38	0.28	1.52	0.60	0.69	1.38	1.05	0.81	3.09	1.03	0.69	1.37	0.73	1.38	0.63	0.70	1.40	0.77
XLF	0.99	0.04	0.27	0.18	0.25	0.25	1.12	0.05	0.03	1.68	1.39	0.53	0.76	2.45	0.91	1.52	1.09	1.73	0.94	0.55	1.71	0.72
XLV	0.05	0.01	0.15	0.09	0.13	0.13	1.05	0.03	0.02	1.77	1.018	0.62	0.64	1.18	2.96	1.48	1.56	1.90	1.36	0.74	1.87	0.76
XLI	0.16	0.02	0.27	0.16	0.24	0.24	1.58	0.08	0.06	1.88	1.74	0.59	0.99	1.46	1.13	2.32	1.32	1.81	1.20	0.62	1.81	0.83
Nasdaq	0.11	0.01	0.17	0.11	0.15	0.14	0.95	0.05	0.05	1.53	1.19	0.37	0.53	1.07	1.19	1.39	2.60	1.93	2.38	0.43	2.05	0.75
SPX	0.14	0.02	0.19	0.12	0.18	0.17	1.15	0.07	0.07	1.69	1.24	0.63	0.82	1.34	1.17	1.50	1.50	1.83	1.41	0.67	1.82	0.76
XLK	0.10	0.01	0.17	0.10	0.14	0.14	0.89	0.05	0.05	1.54	1.08	0.36	0.47	0.95	1.09	1.32	2.47	1.89	2.71	0.44	1.92	0.72
XLU	0.11	0.01	0.03	0.02	0.03	0.02	0.91	0.06	0.03	1.27	0.81	3.13	0.92	0.88	0.90	1.06	0.64	1.30	0.65	3.62	1.24	0.67
Wilshire 5000	0.16	0.02	0.20	0.12	0.18	0.17	1.19	0.08	0.07	1.69	1.31	0.61	0.85	1.36	1.18	1.54	1.64	1.87	1.48	0.65	1.90	0.78
TO	0.65	0.04	0.70	0.39	0.58	0.65	0.87	0.38	0.54	1.07	0.83	0.50	0.93	0.81	0.65	1.01	0.83	1.13	0.75	0.51	1.14	14.95

Source: elaborated by the authors.

Table A5. Spillovers in the medium/long term: more than thirty days.

	CRB	13-Week Treasury Bill	10-Year Treasury Note	2-Year Treasury Note	30-Year Treasury Bond	5-Year Treasury Note	XLB	Brent Oil	WTI Oil	DJI	DJT	DJU	XLE	XLF	XLV	XLI	NDQ	SPX	XLK	XLU	WILSHIRE 5000	FROM
CRB	0.87	0.01	0.04	0.01	0.05	0.03	0.17	0.36	0.54	0.10	0.07	0.06	0.37	0.07	0.04	0.10	0.08	0.12	0.06	0.05	0.13	0.12
IRX	0.01	1.92	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.02	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.01
DGS10	0.03	0.00	0.63	0.26	0.54	0.52	0.06	0.02	0.01	0.06	0.07	0.01	0.05	0.06	0.03	0.07	0.04	0.06	0.03	0.01	0.06	0.10
DGS2	0.01	0.01	0.33	0.74	0.21	0.49	0.04	0.01	0.01	0.06	0.05	0.01	0.03	0.05	0.03	0.06	0.04	0.05	0.03	0.01	0.05	0.07
DGS30	0.04	0.00	0.64	0.19	0.74	0.44	0.07	0.02	0.02	0.06	0.06	0.01	0.06	0.06	0.03	0.07	0.04	0.06	0.03	0.01	0.06	0.09
DGS5	0.02	0.00	0.52	0.40	0.38	0.62	0.05	0.01	0.01	0.06	0.06	0.01	0.05	0.06	0.03	0.07	0.04	0.06	0.03	0.01	0.06	0.09
XLB	0.05	0.00	0.04	0.02	0.02	0.04	0.03	0.38	0.02	0.24	0.22	0.09	0.18	0.18	0.13	0.25	0.14	0.23	0.13	0.09	0.23	0.11
Brent Crude Oil	0.75	0.02	0.05	0.01	0.06	0.04	0.11	1.28	0.79	0..08	0.04	0.04	0.41	0.05	0.02	0.07	0.05	0.09	0.05	0.03	0.10	0.14
WTI Crude Oil	0.66	0.01	0.04	0.01	0.07	0.03	0.08	0.47	1.05	0.05	0.02	0.02	0.31	0.03	0.02	0.05	0.04	0.06	0.04	0.01	0.07	0.10
DJIA	0.02	0.00	0.03	0.02	0.03	0.03	0.17	0.01	0.01	0.26	0.18	0.09	0.12	0.18	0.15	0.22	0.17	0.24	0.16	0.09	0.23	0.10
DJTA	0.01	0.00	0.04	0.02	0.03	0.03	0.21	0.01	0.00	0.23	0.37	0.07	0.11	0.19	0.13	0.27	0.17	0.22	0.14	0.07	0.23	0.11
DJUA	0.02	0.00	0.00	0.00	0.00	0.00	0.12	0.01	0.00	0.15	0.10	0.52	0.14	0.11	0.10	0.13	0.07	0.15	0.06	0.41	0.15	0.08
XLE	0.14	0.01	0.5	0.02	0.05	0.04	0.21	0.08	0.09	0.19	0.14	0.11	0.42	0.14	0.09	0.19	0.10	1.19	0.09	0.09	0.19	0.10
XLF	0.01	0.00	0.04	0.02	0.03	0.03	0.15	0.01	0.00	0.22	0.19	0.07	0.10	0.33	0.12	0.20	0.15	0.23	0.13	0.07	0.23	0.10
XLV	0.01	0.00	0.02	0.01	0.02	0.02	0.14	0.00	0.00	0.24	0.16	0.08	0.08	0.16	0.40	0.20	0.21	0.26	0.18	0.10	0.25	0.10
XLI	0.02	0.00	0.04	0.02	0.03	0.03	0.21	0.01	0.01	0.26	0.24	0.08	0.13	0.20	0.15	0.31	0.18	0.24	0.16	0.08	0.25	0.11
Nasdaq	0.02	0.00	0.02	0.01	0.02	0.02	0.13	0.01	0.01	0.20	0.16	0.05	0.07	0.14	0.16	0.19	0.35	0.26	0.32	0.06	0.28	0.10
SPX	0.02	0.00	0.03	0.02	0.02	0.02	0.15	0.01	0.01	0.23	0.17	0.08	0.11	0.18	0.16	0.20	0.20	0.25	0.19	0.09	0.24	0.10
XLK	0.01	0.00	0.02	0.01	0.02	0.02	0.12	0.01	0.01	0.21	0.14	0.05	0.06	0.13	0.15	0.18	0.33	0.25	0.37	0.06	0.26	0.10
XLU	0.01	0.00	0.00	0.00	0.00	0.00	0.12	0.01	0.00	0.17	0.11	0.42	0.13	0.12	0.12	0.14	0.09	0.17	0.09	0.49	0.17	0.09
Wilshire 5000	0.02	0.00	0.03	0.02	0.02	0.02	0.16	0.01	0.01	0.23	0.18	0.08	0.11	0.18	0.16	0.21	0.22	0.25	0.20	0.09	0.26	0.11
TO	0.09	0.01	0.09	0.05	0.08	0.09	0.12	0.05	0.08	0.14	0.11	0.07	0.13	0.11	0.09	0.14	0.11	0.15	0.10	0.07	0.15	2.02

Source: elaborated by the authors.

References

Baillie, Richard T., and Tim Bollerslev. 1991. Intra-day and inter-market volatility in foreign exchange rates. *Review of Economic Studies* 58: 565–85. [CrossRef]

Baruník, Jozef, and Tomáš Krehlík. 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Economics* 16: 271–96. [CrossRef]

Barunik, Jozef, Evzen Kocenda, and Lukas Vacha. 2015. Volatility Spillovers Across Petroleum Markets. *William Davidson Institute Working Paper* 1093. Available online: https://ssrn.com/abstract=2600204 (accessed on 12 March 2024).

Baruník, Jozef, Evžen Kočenda, and Lukáš Vácha. 2017. Asymmetric Volatility Connectedness on the Forex Market. *Journal of International Money and Finance* 77: 39–56. [CrossRef]

Bouri, Elie, Maria E. De Boyrie, and Ivelina Pavlova. 2017. Volatility transmission from commodity markets to sovereign CDS spreads in emerging and frontier countries. *International Review of Financial Analysis* 49: 155–65. [CrossRef]

Chan, Louis K. C., Yasushi Hamao, and Josef Lakonishok. 1991. Fundamentals and Stock Returns in Japan. *Journal of Finance* 46: 1739–64. [CrossRef]

Costa, Antonio, Paulo Matos, and Cristiano da Silva. 2022. Sectoral Connectedness: New Evidence from US Stock Market during COVID-19 Pandemics. *Finance Research Letters* 45: 102124. [CrossRef] [PubMed]

Cox, John C., Jonathan E. Ingersoll, and Stephen A. Ross. 1985. A Theory of the Term Structure of Interest Rates. *Econometrica* 53: 385–407. [CrossRef]

Cyree, Ken B., Mark D. Griffiths, and Drew B. Winters. 2014. An Empirical Examination of the Intraday Volatility in Euro–Dollar Rates. *The Quarterly Review of Economics and Finance* 44: 44–57. [CrossRef]

Diebold, Francis X., and Kamil Yilmaz. 2009. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal* 119: 158–71. [CrossRef]

Diebold, Francis X., and Kamil Yilmaz. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28: 57–66. [CrossRef]

Diebold, Francis X., and Kamil Yilmaz. 2014. On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms. *Journal of Econometrics* 182: 119–34. [CrossRef]

Ewing, Bradley T., Farooq Malik, and Ozkan Ozfidan. 2002. Volatility transmission in the oil and natural gas markets. *Energy Economics* 24: 525–38.

Farid, Saqib, Ghulam Mujtaba Kayani, Muhammad Abubakr Naeem, and Syed Jawad Hussain Shahzad. 2021. Intraday volatility transmission among precious metals, energy, and stocks during the COVID-19 pandemic. *Resources Policy* 72: 102101. [CrossRef]

Hassan, Syed Aun, and Farooq Malik. 2007. Multivariate GARCH modeling of sector volatility transmission. *The Quarterly Review of Economics and Finance* 47: 470–80. [CrossRef]

Hughes, Michael P., Stanley D. Smith, and Drew B. Winters. 2006. An empirical examination of intraday volatility in on-the-run US Treasury bills. *Journal of Economics and Business* 59: 487–99. [CrossRef]

Kumiega, Andrew, Thaddeus Neururer, and Ben Van Vliet. 2011. Independent component analysis for realized volatility: Analysis of the stock market crash of 2008. *The Quarterly Review of Economics and Finance* 51: 292–302. [CrossRef]

Malik, Farooq, and Bradley T. Ewing. 2009. Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis* 3: 95–100. [CrossRef]

Mensi, Walid, Ramzi Nekhili, Xuan Vinh Vo, Tahir Suleman, and Sang Hoon Kang. 2021. Asymmetric volatility connectedness among US stock sectors. *The North American Journal of Economics and Finance* 56: 101327. [CrossRef]

Nazlioglu, Saban, Cumhur Erdem, and Ugur Soytas. 2013. Volatility spillover between oil and agricultural commodity markets. *Energy Economics* 36: 658–65. [CrossRef]

Passos, Marcelo de Oliviera, Mathias Schneid Tessmann, Régis Augusto Ely, Daniel Uhr, and Marcio Taceli Taveira. 2020. Effects of volatility among commodities in the long term: Analysis of a complex network. *Annals of Financial Economics* 15: 2050014. [CrossRef]

Tessmann, Mathias Schneid, Régis Augusto Ely, and Mario Durante Canever. 2021. Volatility transmissions between commodity futures contracts in the short, medium and long term. *International Journal of Financial Markets and Derivatives* 8: 79–99. [CrossRef]

Umar, Zaghum, Mariya Gubareva, Muhammad Naeem, and Ayesha Akhter. 2021. Return and volatility transmission between oil price shocks and agricultural commodities. *PLoS ONE* 16: e0246886. [CrossRef] [PubMed]

Vardar, Gülin, Yener Coşkun, and Tezer Yelkenci. 2018. Shock transmission and volatility spillover in stock and commodity markets: Evidence from advanced and emerging markets. *Eurasian Economic Review* 8: 231–88. [CrossRef]