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Sectoral volatility spillovers and their determinants in Vietnam

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Abstract
Using the vector autoregression (VAR) connectedness approach, this paper investigates dynamic volatility spillovers across 14 sectors in Vietnam's stock market over the period 2012–2021. The study also explores the differences in sectoral spillovers before and after the outbreak of Covid-19 pandemic. Additionally, the paper also investigates the effects of the current pandemic and macroeconomic fundamentals on intersectoral connectedness in Vietnam. Our findings show that volatility transmission across sectors fluctuates significantly over the research period and spikes during the Covid-19 pandemic. The total spillover index is approximately 64.23 per cent, indicating that volatility spillovers across the Vietnamese sectors are substantial. The risks from the stock market appear to spread quickly and easily across sectors in Vietnam. Among these 14 sectors, food, fisheries, and oil and gas act as net senders of risks while real estate and pharmacy are the greatest receivers of risk. The findings also confirm that the commerce, transportation, manufacturing, and service sectors are more sensitive to the Covid-19 pandemic crisis than other sectors in Vietnam. Furthermore, the empirical results show that an increase in daily Covid-19 infections increases volatility spillover across sectors. Policy implications have emerged based on these findings from this paper for the Vietnamese government and other emerging countries.

Keywords Intersectoral connectedness · Network analysis · Transmission · Vietnamese stock market · Volatility spillover

JEL Classification G01 · G10 · G11 · G18

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1 Introduction

In recent years, financial markets have had exceptionally high volatility, especially since the 2008 global financial crisis and the 2020 global stock market crash following the outbreak of Covid-19 (Zhang et al. 2020). This phenomenon has attracted considerable attention from scholars attempting to estimate systemic risk and analyze risk spillover across markets or sectors within financial markets (Zhang et al. 2020). The systemic financial risk has a negative impact on the functioning of the financial system, which erodes public confidence and jeopardizes the stability of the financial system (Billio et al. 2012).

A rapidly increasing number of studies have found that the coronavirus pandemic has had a negative impact on economies and financial markets worldwide. In Vietnam, various economic activities have been halted due to travel restrictions and lockdowns during the four waves of Covid-19 to date. As a result, the Vietnamese economy has been severely affected by the pandemic (Ho et al. 2021). Although Vietnam still achieved positive economic growth of 2.91% in 2020, this rate was at the lowest during the period 2011–2020 (General Statistics Office 2021). In addition, Vietnam's stock market (VN-Index) experienced substantial price fluctuations over the four waves of Covid-19 (see Fig. 1). Sharp decreases from its peak were seen on the VN-Index, with declines of approximately 33.5% during the first wave (from January to April 2020), 9.7% in the second wave (from July to December 2020) and more than 12% over the third and fourth waves (since January 2021). As illustrated in Fig. 1, significant price volatility has occurred in the sectoral indices throughout the Covid-19 pandemic in Vietnam, specifically during the fourth wave. Most sectors in the Vietnamese financial market have been negatively affected by the pandemic.

With respect to interconnectedness within a financial market, Zhang et al. (2020) show that, after a risk shock arises in one sector, the risk appears to affect other sectors due to strong connectedness and spillover mechanisms, and even leading to spillover to the entire national financial market. Therefore, examining the mechanisms in which systemic risk spills across sectors in a financial market is of great significance for both investors and regulators. Indeed, understanding the sectoral volatility spillover mechanism can help market participants to consider their investment strategies in time to mitigate their exposure to systemic risk. Moreover, analyzing the sectoral spillover effects could help policy makers identify the sources of risk transmission and implement appropriate measures to avoid market failure or its negative impacts on the economy (Wu et al. 2019).

Despite the vital necessity of investigating propagation of sectoral volatility, no previous study examines the contagion mechanism across sectors in the financial market in the context of Vietnam. Thus, this study contributes to the literature in the following ways. First, to the best of our knowledge, this is the first paper to investigate the volatility transmission among sectors in Vietnam's stock market, using the popular approach proposed by Diebold and Yilmaz (2012). This research topic is currently understudied and has not been intensively explored in Vietnam. Second, the study focuses on the period of the Covid-19 pandemic and investigates changes

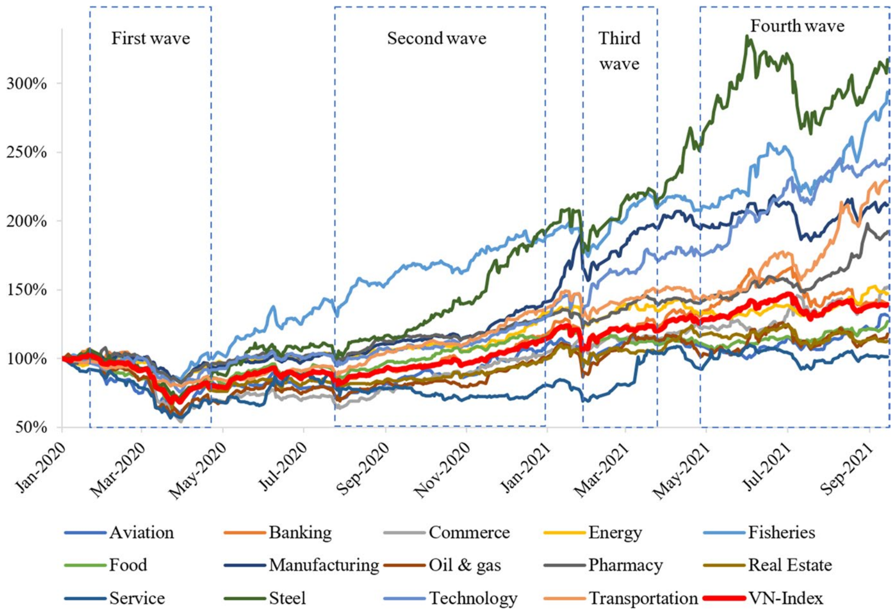

Fig. 1 Vietnam's stock market index (VN-Index) and selected sectoral indices, January 2020-September 2021 (January 2, 2020 = 100%). *Source*: Ho Chi Minh Stock Exchange and Cophieu68.vn

in intersectoral connections and the risk spillover mechanism before and during the pandemic. This analysis helps to identify the leading sectors (or the risk transmitters among sectors) in Vietnam's stock market before and after the pandemic outbreak. From the perspective of policy makers, discovering the sources of risk is likely to help mitigate systemic risk. At the same time, identifying which sectors are risk transmitters would help investors to determine the proper trading strategy. Third, the effects of the Covid-19 pandemic and macroeconomics fundamentals on the total connectedness among sectors are also investigated. Policy implications are drawn based on these findings for the Vietnamese government to consider and implement appropriate measures to manage volatility transmissions across sectors in the stock market in Vietnam.

Exploring these aspects is even more significant for an emerging country such as Vietnam, especially in light of the country's recent developments. Since its *Doi Moi* (economic renovation) in 1986, Vietnam has achieved sustainable and rapid economic growth (Vo and Ho 2021). Because of the economy's solid foundations, it has remained resilient throughout various crises, including the pandemic. Vietnam is one of the few economies to have achieved a positive growth (2.91%) in its gross domestic product (GDP) in the first year after the outbreak of Covid-19 (2020), and GDP growth in 2022 is expected to rebound to 5.5% (World Bank 2022). In 2021, despite significant declines in most other Asian stock markets, the Vietnamese stock market increased approximately 36% (Reuters 2021). Given that impressive growth, the country was listed among the top seven stock markets, with the strongest increase in the world in 2021 (VnExpress 2022). In Asia, Vietnam's stock market ranked first in terms of growth, outperforming Taiwan (29%) and India (23%) (Vietnam News 2022). In view of these facts, Vietnam and its stock market plays an increasingly significant role in Asia, so it is worthwhile to examine them.

Following this section, the remainder of this paper is structured as follows. Section 2 discusses and synthesizes the existing relevant literature. Section 3 presents the data sample and methodology. The empirical results are presented and discussed in Sect. 4. Finally, key conclusions and policy implications are discussed in Sect. 5.

2 Literature review

2.1 Theoretical background

Engle et al. (1990) proposed two hypotheses regarding volatility spillovers. The "heat wave" hypothesis suggests that volatility in one market will continue only in that market on the following day and will not propagate to other markets. In contrast, the "meteor shower" hypothesis postulates that volatility in one market tends to transmit to another, so a volatile day in one market will be followed by a volatile day in another market. The "meteor shower" hypothesis might be associated with the failures of market efficiency.

Aside from these hypotheses, two other primary theoretical arguments are related to volatility transmission, including the "decoupling" and "contagion" hypotheses. The "contagion" hypothesis suggests that the benefits of portfolio diversification are limited because of the increasing intensity of volatility transmission across markets during a crisis (Hkiri et al. 2017). Alternatively, the "decoupling" hypothesis posits that performance in emerging economies is independent of changes in the developed economies (Wyrobek et al. 2016). The implication of this hypothesis is that the benefits of portfolio diversification are still attainable (Bekiros 2014; Yarovaya and Lau 2016).

2.2 Empirical review

Investigating and modeling systemic risk and risk spillover have attracted massive attention from scholars worldwide (Wu et al. 2019). The methods used to research volatility spillover include Granger causality (Hong 2001; Hong et al. 2009), the generalized autoregressive conditional heteroskedasticity (GARCH) family models (Bouri et al. 2021; Cheung and Ng 1996; Gabauer 2020; Hamao et al. 1990; Hassan and Malik 2007; Malik 2022), and network topology or generalized variance decomposition under a vector autoregression (VAR) framework (Chen et al. 2022; Choi 2022; Diebold and Yilmaz 2009, 2012, 2014; Gabauer and Gupta 2018; Iwanicz-Drozdowska et al. 2021; Laborda and Olmo 2021; Shen et al. 2022; Su and Liu 2021).

In the extant literature, scholars have extensively focused on the spillover effects between financial markets and international assets (Antonakakis et al. 2017; Fassas and Siriopoulos 2019; Jung and Maderitsch 2014; Shahzad et al. 2018). These studies concentrate on the overall trends in spillover between asset classes or financial markets but do not offer insights into dynamic transmission across different sectors within an economy.

Examining the spillover effects among sectors is important because each sector is uniquely connected within the economy (Chatziantoniou et al. 2021). Recently, scholars have extended their studies to the sectoral spillover effects, using the network analysis approach. Yin et al. (2020) employ the spillover index approach to explore interindustry volatility transmission on the Shanghai Stock Exchange from 2009 to 2018. They note that evolution in the process of transmission among industries corresponds to remarkable political and financial events. Meanwhile, Chatziantoniou et al. (2021) investigate sectoral connectedness in the Indian stock market during the period 2006–2019, using the connectedness approach. They find that sectoral connectedness changes over time and became strongest during the 2008 financial crisis, the 2011 stock market crash, the 2014 national elections, and the 2016 demonetization. Shen et al. (2022) analyze volatility spillover effects among 28 different sector indices in China's stock markets from 2000 to 2019. They find that the spillover effects became significantly stronger under extreme conditions, including the global financial crisis, the stock market crash in China and the China-US trade war.

Regarding intersectoral volatility spillover during the pandemic, Su and Liu (2021) investigate the transmission structure of financial shock across ten sectors in China from 2004 to 2020 and find that intersectoral connectedness in China's stock market is strong. Additionally, since the outbreak of Covid-19, risk has tended to spread among sectors rapidly, leading to an increase in intersectoral connectivity. Similarly, Shahzad et al. (2021) analyze asymmetric volatility transmission across ten sectors in the Chinese stock market, employing one-minute data from January 2, 2019, to September 30, 2020. Their findings indicate the asymmetric effect of positive and negative volatility, which is intense and time varying during the pandemic. Chen et al. (2022) investigate sectoral returns and volatility spillovers in Shanghai-Shenzhen-Hong Kong Stock Markets from June 2011 to December 2020. The authors note that the spillover effects primarily occur in the short term and that the Shanghai material, energy and industrial sectors act as the risk transmitters while the Hang Seng public utilities, telecommunications and real estate construction sectors play as risk absorbers.

In the context of the US, Laborda and Olmo (2021) used the method by Diebold and Yilmaz (2012) to analyze volatility spillovers among seven economic sectors from July 2003 to December 2020. They find that energy, banking and insurance, and biotechnology transmit risk to the rest of the US economy; banking and insurance was the largest transmitter of risk during the global financial crisis (2007–2009); but during the pandemic, the largest transmitters of risk have been energy and technology. Meanwhile, Malik (2022) uses the bivariate GARCH model to examine the volatility spillover mechanism between six major equity sectors in the US over the period April 2006–March 2021. The author finds different volatility breaks in all sectors which correspond to the Covid-19 pandemic period. The findings show that there are still volatility spillovers from one sector to the other after adjusting for volatility breaks. More recently, Choi (2022) investigates the volatility spillovers across different industries in the US stock market from January 2018 to May 2021. Findings from the paper indicate that the pandemic did increase the volatility spillovers. The author also notes that there were sudden and substantial changes in the dynamic spillovers due to the shock from energy sector on March 9, 2020, which is known as Black Monday.

To the best of our knowledge, no previous papers have studied intersectoral volatility spillovers in Vietnam, especially during the Covid-19 period. This paper fills this gap by examining volatility transmission among sectors on Vietnam's stock market over the period January 2012 to September 2021, which also covers the four waves of Covid-19 in Vietnam.

3 Data and methodology

3.1 Data

This paper uses the daily closing price on sectoral indices in Vietnam's stock market to analyze the sectoral volatility spillover effects.

The study also investigates the effect of the Covid-19 pandemic on intersectoral connectedness in the Vietnamese stock market. Hence, the variables of interest include the daily new Covid-19 infections; the containment and health index, representing the measures enacted by the Vietnamese government to control the pandemic; and the equity market-related economic uncertainty index, which represents the economic policy uncertainty (EPU). In addition to those variables, macroeconomic fundamentals are included in the model, including the exchange rate and the three-month interbank rate.

The data cover the period January 3, 2012, to September 15, 2021, based on data available when this study was conducted. Table 1 presents all variables employed in this study and their data sources.

3.2 Methodology

3.2.1 Sectoral volatility spillover in Vietnam's stock market

In this study, the time series of sectoral indices are transformed into logarithmic returns as shown in Eq. (1):

$$R_t^i = \ln\left(\frac{P_t^i}{P_{t-1}^i}\right) \tag{1}$$

where P_t^i is the closing price of the sectoral index i at time t, and R_t^i is the return on the sectoral index i at time t.

Stationarity tests, including the augmented Dickey-Fuller and Phillips-Perron unit-root test, are performed on the return series. The results of these tests show that all 14 returns series in the sample are stationary at level.

Next, the volatility of each sectoral index's return is estimated using the autoregressive moving average-generalized autoregressive conditional heteroskedasticity

Table 1 List of variables and their respective data sources

Variable	Definition	Symbol	Unit	Source
Sectoral indices	Sectoral indices on Vietnam's stock market	P_t^i	Index	Cophieu68.vn
Variables of interest	Daily new Covid-19 infections	Newcase_t	Cases	*Our world in data* (Dong et al. 2020; Hale et al. 2021; Ritchie et al. 2020)
	Containment and health index	Containment_t	Index	
	Economic policy uncertainty (Equity market-related economic uncertainty index)	EPU_t	Index	FRED economic data (Baker et al. 2022)
Macroeconomic fundamentals	Exchange rate	Exchange_t	Vietnamese dong per US dollar	Investing.com
	Three-month interbank rate	Interbank_t	% per year	State Bank of Vietnam

(ARMA-GARCH) model. The ARMA process is used to model the conditional mean of the time series, while the GARCH process is employed to model the conditional variance of the time series. The ARMA (r, s)-GARCH (p, q) is described in Eqs. (2.1), (2.2) and (3):

$$y_t = \alpha_0 + \sum_{i=1}^{r} \theta_i y_{t-i} + \varepsilon_t + \sum_{j=1}^{s} \varphi_j \varepsilon_{t-j} \tag{2.1}$$

$$\varepsilon_t = \sigma_t u_t \text{ with } u_t \sim WN(0, 1) \tag{2.2}$$

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{3}$$

The study's primary objective is to investigate volatility transmission across different sectors in Vietnam's stock market. So, the next step is to adopt the network analysis approach proposed by Diebold and Yilmaz (2012, 2015) to explore the spillover effects. This approach enables a deeper examination of the association structure. Additionally, the transmission structure's direction and node weight can also be identified simultaneously (Diebold and Yilmaz 2014). The rich information and simplicity of the interpretation provided by this method make it a perfect fit for the study's objectives.

Diebold and Yilmaz (2012, 2015) construct a spillover index based on a forecast error variance decomposition in a VAR model. The method proceeds as follows. First, the VAR model of order p is fitted to the time series of volatility obtained through the ARMA-GARCH process. Second, using the data until time t, the forecast of the volatility series for h periods ahead is estimated, and the error variance decomposition of each forecast is obtained, corresponding to the shocks from the same or other network components at time t. Last, based on the obtained forecast error variance decomposition, the volatility spillover index of each time series and the total spillover index are calculated (see Table 2).

This paper estimates the dynamic volatility spillover effects using a VAR model of order three and the generalized variance decompositions of 12-day-ahead forecast errors with 200-day rolling windows. These parameters are used by Diebold and Yilmaz (2015). The optimal order of three in the VAR model is selected based on the final prediction error (FPE) and Akaike's information criterion (AIC). Furthermore, robustness checks are performed using various VAR lags (from lag 1 to lag 5), forecast horizons (5, 10, 15 days), and rolling windows of various lengths (250, 500, 750 days).

3.2.2 The impact of the Covid-19 pandemic on the volatility transmission across sectors

Together with the analysis of the sectoral spillover effects for the entire research period from January 2012 to September 2021, the effects of the Covid-19 pandemic and macroeconomic fundamentals on intersectoral spillovers in Vietnam's stock

Table 2 An illustration of the spillover across sectors. Source: Diebold and Yilmaz (2015)

	x_1	x_2	...	x_N	From others
x_1	d_{11}	d_{12}	...	d_{1N}	$\sum_{j=1}^{N} d_{1j}, j \neq 1$
x_2	d_{21}	d_{22}	...	d_{2N}	$\sum_{j=1}^{N} d_{2j}, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
x_N	d_{N1}	d_{N2}	...	d_{NN}	$\sum_{j=1}^{N} d_{Nj}, j \neq N$
To others	$\sum_{i=1}^{N} d_{i1}$ $i \neq 1$	$\sum_{i=1}^{N} d_{i2}$ $i \neq 2$	...	$\sum_{i=1}^{N} d_{iN}$ $i \neq N$	$TSI = \frac{1}{N} \sum_{i,j=1}^{N} d_{ij}$ $i \neq j$

$C_{i \leftarrow j} = d_{ij}$ is the pairwise directional spillover from x_j to x_i, indicating the shocks to x_j account for $(d_{ij})\%$ of the h-step-ahead forecast error variance in x_i. The "From Others" column indicates the sum of shocks that one sector (x_i) absorbs from all other sectors $(C_{i \leftarrow} = \sum_{j=1}^{N} d_{ij}, j \neq i)$. The "To Others" row represents the impact of one sector's shocks (x_j) on all other sectors $(C_{\leftarrow j} = \sum_{i=1}^{N} d_{ij}, i \neq j)$. The net total directional spillover of each time series (such as x_i) is $C_i = C_{\leftarrow i} - C_{i \leftarrow}$, representing the net spillover shown by one specific sector. The total spillover index is $TSI = \frac{1}{N} \sum_{i,j=1}^{N} d_{ij}, i \neq j$, showing the intersectoral connectedness within the stock market

market are also estimated. The subsample (ranging from January 2019 to September 2021) is used for this empirical analysis. The regression model is presented in Eq. (4):

$$\mathrm{TSI}_t = \alpha_0 + \beta_1 \mathrm{Newcase}_t + \beta_2 \mathrm{Containment}_t + \beta_3 \mathrm{EPU}_t + \beta_4 \mathrm{Exchange}_t + \beta_5 \mathrm{Interbank}_t + \varepsilon_t \tag{4}$$

where TSI_t represents the total volatility spillover index at time t. $\mathrm{Newcase}_t$ is the number of daily Covid-19 infection cases at time t. $\mathrm{Containment}_t$ is the containment and health index at time t (representing the government's policies in response to the Covid-19 pandemic). EPU_t is the economic policy uncertainty index at time t .$\mathrm{Exchange}_t$ is the change in the exchange rate at time t. $\mathrm{Interbank}_t$ is the change in the three-month interbank interest rate at time t, and ε_t is the residual.[1]

[1] All the variables employed in model (4) are stationary. The regression (4) is estimated using the Ordinary Least Square (OLS). Moreover, the p-values should be corrected for Newey and West (1987) standard errors, which are considered to be robust to autocorrelation and heteroskedasticity (Narayan et al. 2021).

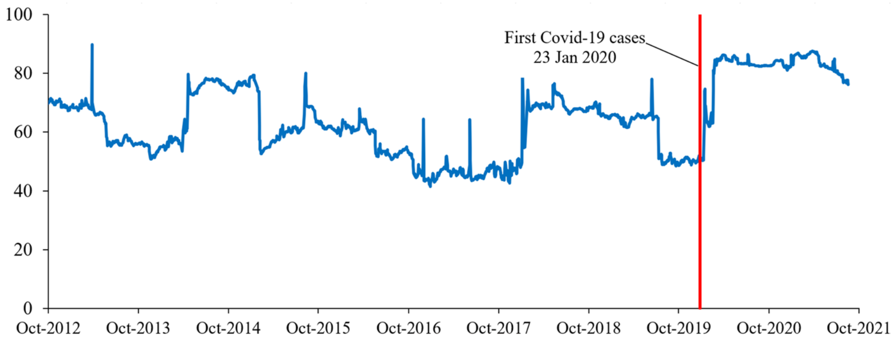

Fig. 2 Total volatility spillover in Vietnam's stock market, January 2012-September 2021 (200-day rolling windows). *Notes*: The red line marks January 23, 2020, when the first two Covid-19 cases in Vietnam were recorded

4 Empirical results

4.1 The sectoral volatility spillover in Vietnam's stock market

Based on the analyses of Diebold and Yilmaz (2012 2015), the total volatility spillover index is estimated (see Fig. 2). The total volatility spillover had soared since the first two Covid-19 cases were recorded in Vietnam on January 23, 2020, and it had remained exceptionally high until September 2021, when this analysis was conducted. In general, the volatility spillover among sectors appears to fluctuate over the study period and particularly spike during the Covid-19 pandemic. This finding is similar to Laborda and Olmo (2021) and Su and Liu (2021).

The details of volatility spillovers across sectors in the sample are presented in Table 3 and illustrated in Fig. 3. As shown in Table 3, the total spillover index is about 64.23%, indicating that the sectoral volatility spillover within Vietnam's stock market is relatively strong. As a result, the stock market risks appear to spread across sectors quickly. Theoretically, this result confirms the "meteor shower" hypothesis or the "contagion" hypothesis (mentioned in Sect. 2.1), which suggest that volatility is likely to spread across sectors.

Table 3 also shows that, over the research period, three sectors, including food, fisheries, and oil and gas, play a role as transmitters of risk because they had the highest "net" values. These sectors are regarded as sources of risk transmission, implying that when significant volatility emerges in these sectors, volatility spreads to other sectors very quickly. As such, policy makers need to identify and consider the characteristics of these sectors when designing appropriate measures to avoid market failure or mitigate negative impacts on the financial market.

The recipients of the highest risk are real estate and pharmacy, with net values of −37.46% and −27.36%, respectively. Because those two sectors receive the most risks from other sectors, they appear to be the market's most vulnerable and fragile sectors. Similarly, Yin et al. (2020) find that these two sectors play a role as risk absorbers in China's stock market. In addition, the remaining sectors also act as net

Table 3 Sectoral volatility spillover for the full sample period (January 2012-September 2021)

	Av	Ba	Co	En	Fi	Fo	Ma	Og	Ph	Re	Se	St	Te	Tr	From others
Aviation	43.13	2.72	2.49	3.26	6.67	10.54	3.97	4.23	4.16	2.91	4.57	2.98	3.47	4.89	56.87
Banking	2.66	26.75	6.32	3.99	8.67	15.07	4.10	7.47	2.72	4.12	4.13	3.84	6.93	3.25	73.25
Commerce	1.84	4.13	35.06	4.39	8.92	10.10	4.62	5.91	3.75	2.23	3.92	4.70	5.38	5.06	64.94
Energy	2.22	4.09	4.83	34.19	8.71	10.13	5.59	7.45	3.23	1.94	3.41	4.51	3.25	6.44	65.81
Fisheries	3.61	3.08	5.05	2.92	49.19	10.73	3.60	3.51	2.39	2.75	3.67	3.01	3.30	3.19	50.81
Food	3.68	4.57	2.88	3.12	8.26	51.25	3.68	3.94	2.92	2.32	3.11	2.82	3.45	4.00	48.75
Manufacturing	2.22	3.75	3.65	4.01	11.93	13.14	29.23	6.21	3.74	2.76	3.52	5.85	4.32	5.64	70.77
Oil and Gas	2.98	3.71	5.20	4.16	10.80	12.71	4.32	31.65	3.58	3.21	3.69	4.85	4.85	4.27	68.35
Pharmacy	3.09	4.21	5.01	3.51	9.47	15.26	4.04	8.04	28.60	3.25	2.59	4.77	4.12	4.03	71.40
Real Estate	2.62	4.99	5.87	5.35	7.47	10.63	6.82	7.30	3.02	25.21	4.37	6.64	4.70	4.99	74.79
Services	2.94	4.39	3.91	3.19	5.93	5.37	3.38	4.94	3.32	2.81	50.47	2.63	3.41	3.30	49.53
Steel	3.52	2.87	5.20	4.58	7.93	10.82	4.51	7.17	4.07	3.05	4.64	33.82	4.40	3.40	66.18
Technology	2.97	3.33	8.02	3.50	7.93	13.92	5.25	7.21	3.66	2.15	3.21	4.54	28.87	5.44	71.13
Transportation	2.87	3.34	5.04	4.32	9.43	10.27	5.13	6.00	3.47	3.80	3.54	4.63	4.86	33.28	66.72
To others	37.23	49.18	63.46	50.32	112.13	148.69	59.01	79.40	44.04	37.32	48.38	55.77	56.46	57.90	**TSI =**
Net	−19.64	−24.07	−1.48	−15.49	61.32	99.95	−11.76	11.04	−27.36	−37.46	−1.15	−10.41	−14.68	−8.82	**64.23**

TSI stands for the total spillover index. The sectors are aviation (Av), banking (Ba), commerce (Co), energy (En), fisheries (Fi), food (Fo), manufacturing (Ma), oil and gas (Og), pharmacy (Ph), real estate (Re), services (Se), steel (St), technology (Te), and transportation (Tr). Each value in the "From others" column indicates the sum of shocks that one sector absorbs from all other sectors. Each value in the "To others" row represents the impact of one sector’s shocks on all other sectors. Each value in the "Net" row is equal to the difference between the "To others" value and "From others" value and represents the net volatility spillover exhibited by one specific sector

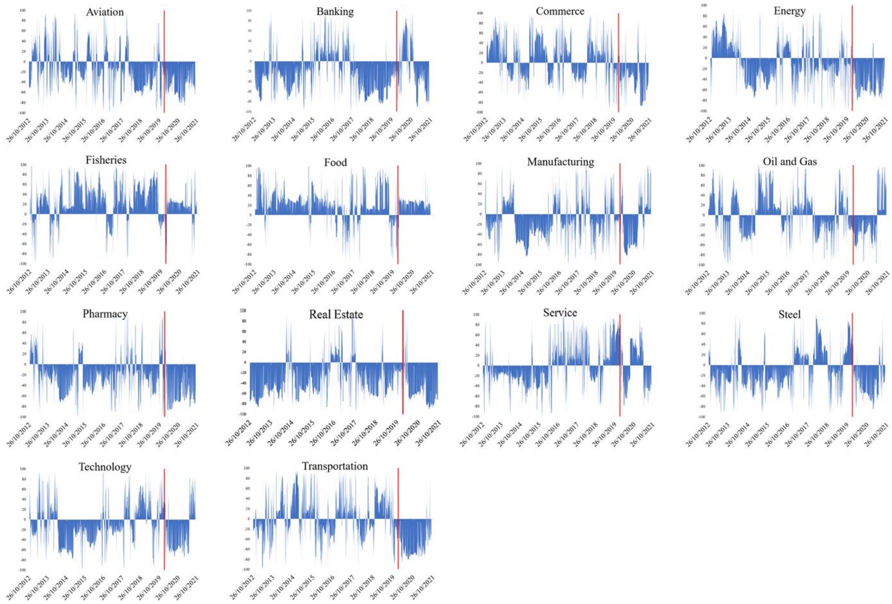

Fig. 3 Sectoral volatility net spillover in Vietnam's stock market, January 2012-September 2021 (200-day rolling windows). *Note*: The red line marks January 23, 2020, when the first two Covid-19 cases in Vietnam were recorded

recipients of risk, in particular including technology, which is also found to be a net receiver by Yin et al. (2020), Chatziantoniou et al. (2021), Laborda and Olmo (2021) and Su and Liu (2021).

Figure 3 illustrates each sector's "net" values from January 2012 to September 2021 with 200-day rolling windows. Food and fisheries almost acted as risk transmitters, especially during the Covid-19 pandemic. Among the risk absorbers, aviation, commerce, energy, pharmacy, real estate, steel, and transportation received the most risks from other sectors during the Covid-19 period, meaning that investing in those sectors might have high risk for investors during the pandemic. Additionally, manufacturing, oil and gas, and technology appeared to be risk absorbers in 2020 whereas they became risk transmitters in 2021. Meanwhile, banking and services turned from risk-transmitting sectors into risk-absorbing sectors in 2021, when the Covid-19 outbreaks became more devastating, with a complete lockdown of Ho Chi Minh City, the largest local economy in Vietnam, for more than five months.

Next, to explore the change in sectoral volatility transmission before and during the current pandemic, spillover effects are estimated for two subsamples: the periods before the pandemic (January 3, 2012, to January 22, 2020) and during the pandemic (January 23, 2020, to September 15, 2021).

The results in Table 4 indicate that volatility transmission is significantly more robust during the Covid-19 period than before the pandemic outbreak. The total spillover index is significantly higher during the pandemic than before it (83.25% compared with 60.28%). Figure 4 illustrates the pairwise spillover of pairs of sectors

Table 4 Sectoral volatility spillover comparison between the periods before and during the Covid-19 pandemic

	Aviation	Banking	Commerce	En	Fi	Fo	Ma	Og	Ph	Re	Se	St	Te	Tr	TSI
Pre-Covid	−12.20	−25.26	6.63	−6.15	40.16	66.40	−14.06	14.02	−19.26	−32.88	−4.02	−4.00	−11.76	2.39	60.28
During Covid	−53.86	−48.79	−51.35	−57.19	99.58	227.19	49.09	31.71	−56.72	−67.97	23.60	−36.53	−6.91	−51.84	83.25
Full sample	−19.64	−24.07	−1.48	−15.49	61.32	99.95	−11.76	11.04	−27.36	−37.46	−1.15	−10.41	−14.68	−8.82	64.23

TSI stands for the total spillover index. Pre-Covid stands for the period January 3, 2012, to January 22, 2020. During Covid stands for the period January 23, 2020, to September 15, 2021. The sectors were aviation (Av), banking (Ba), commerce (Co), energy (En), fisheries (Fi), food (Fo), manufacturing (Ma), oil and gas (Og), pharmacy (Ph), real estate (Re), services (Se), steel (St), technology (Te), and transportation (Tr)

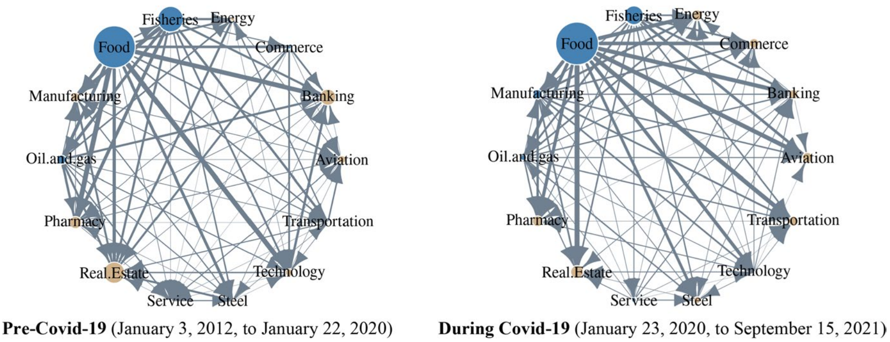

Fig. 4 Sectoral volatility spillover comparison between the periods before and during the Covid-19 pandemic. *Notes*: Blue (yellow) nodes illustrate the net transmitter (receiver) of shocks. Vertices are weighted by the averaged net pairwise directional connectedness measures. The size of nodes represents the weighted average net total directional connectedness

in the network, indicating clearly that volatility spread across sectors in both periods, before and during the Covid-19 pandemic.

Furthermore, as presented in Table 4 and Fig. 4, after the Covid-19 outbreak, commerce and transportation changed from risk transmitters to risk absorbers. Meanwhile, after the pandemic, manufacturing and services changed from risk recipients to risk senders. These findings imply that those four sectors were more sensitive to the Covid-19 pandemic crisis than other sectors in the stock market. As in the results for the full sample, food and fisheries consistently play a role as the leading risk senders, whereas real estate is consistently the largest risk absorber before and during the pandemic.

4.2 The impact of the Covid-19 pandemic on volatility transmission across sectors

The ordinary least squares (OLS) regression with Newey and West (1987) standard errors is employed to investigate the effects of the pandemic (proxied by new cases of infection with Covid-19, *Newcase,* and the containment and health index, *Containment*), economic policy uncertainty (*EPU*), and macroeconomic fundamentals (proxied by the exchange rate, *Exchange,* and the interbank rate, *Interbank*), on sectoral volatility spillover (proxied by the total spillover index, *TSI*) (see Table 5).

The findings indicate that the daily increase in new infections increase intersectoral connectivity, implying that sectoral volatility spillovers became stronger during the pandemic. As a result, market risk easily spreads across sectors in this period. Meanwhile, mitigating economic policy uncertainty appears to help reduce intersectoral connectedness within Vietnam's stock market. This shows that the more the government managed to deal with market-related economic uncertainty, the more it could curb the risk transmission across the sectors. Additionally, reducing the interest rate might increase total volatility spillover. The interest rate reduction appears to signal to the market that the economy needs support from the central bank/

Table 5 The effect of the Covid-19 pandemic on total volatility spillover

	Coefficient	Newey-West standard error	*t*-statistic
Newcase	0.03636***	0.01066	3.41
Containment	0.02309	0.05971	0.39
EPU	0.06793*	0.03550	1.91
Exchange	− 0.00127	0.00154	− 0.83
Interbank	− 0.33673**	0.16029	− 2.10
Constant	33.58871***	0.16814	199.77

*, **, and *** significant at 10%, 5%, and 1%, respectively. The *p*-values are corrected for Newey and West (1987) standard errors, which are considered robust to autocorrelation and heteroskedasticity (Narayan et al. 2021)

government. This signal increases volatility spillover across sectors in Vietnam's stock market.

4.3 Robustness test

The empirical results presented in Sect. 4.1 are based on the VAR model of order three, 12-day-ahead forecast errors, and 200-day rolling windows. In this section, the sensitivity analysis is performed using different VAR lag orders (from lag 1 to lag 5),[2] forecast horizons (5, 10, 15 days),[3] and rolling windows (250, 500, 750 days)[4] to confirm the robustness of the empirical results (see Fig. 5).

Figure 5 shows that total spillovers tend to become smoother when the window is longer, during which detailed information might be lost. Additionally, when the forecast horizon is longer, the total spillover index appears to be more significant. Similarly, higher VAR orders appear to be associated with stronger spillover effects. However, the variations in VAR lag lengths, forecast horizons, and rolling windows appear to have minor impacts on the total spillover index. The trends in the total spillover index under various conditions remain the same. Therefore, the sensitivity analysis confirms that the total spillover effects are very robust across possible combinations of alternative model specifications.

[2] The accuracy of the VAR forecasts changes significantly among different lag lengths. The VAR models with relatively short lags appear to produce more accurate forecasts than the models with longer lags (Hafer and Sheehan 1989). As such, a VAR order from 1 to 5 is chosen.

[3] The forecasting horizons (5, 10, 15 days) are used in the sensitivity analysis, as done by Greenwood-Nimmo et al. (2019), who find their estimation results robust to changes in the forecast horizon of 5, 10, and 15 days.

[4] A rolling-window analysis can extract the time-varying characteristics of the spillover effects across different sectors. It appears more accurate to use this method for identifying the crucial sectors in the network (Su and Liu 2021). However, the selection of the window length could be a trade-off between smooth data (with long windows) and noisy data (with short windows) (Ji and Fan 2016). As such, different window lengths, ranging from short to long, are employed in the robustness tests (i.e., 250, 500, 750 days).

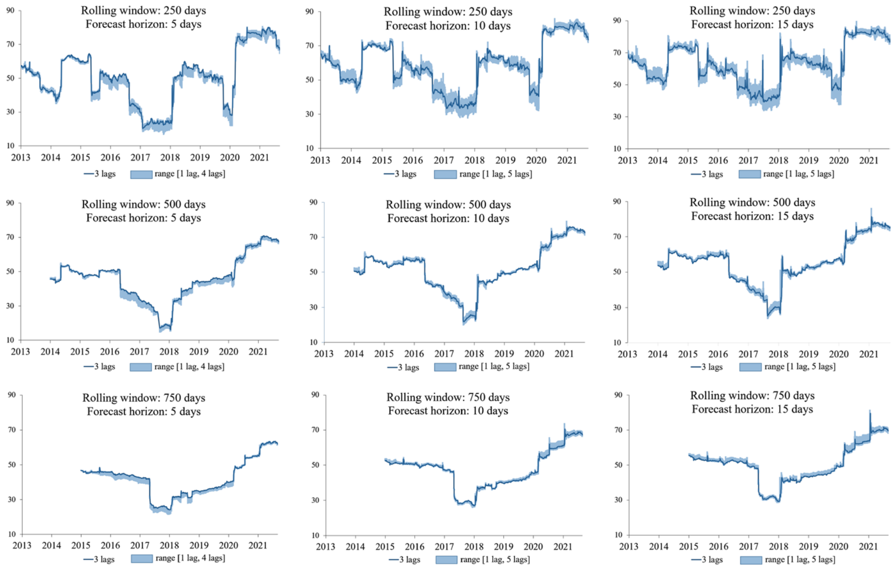

Fig. 5 The robustness test of the total volatility spillover index of Vietnam's stock market. *Notes:* In each figure, the blue band corresponds to the total spillover index using the VAR order from 1 to 5 days. The solid dark blue line represents the total spillover index using the VAR order of three, the lag length employed for analysis in Sect. 4.1

5 Conclusions and policy implications

This study examines volatility transmission across sectors in Vietnam's stock market from January 2012 to September 2021 using the network analysis method proposed by Diebold and Yilmaz (2012). They developed a spillover index based on a forecast error variance decomposition of the VAR model. Additionally, the effects of the coronavirus pandemic and macroeconomic fundamentals on intersectoral connectedness in the stock market are also investigated. Each of the findings from this analysis and the respective policy implications are summarized and discussed in turn below.

First, sectoral volatility transmission oscillates throughout the research period and spikes during the Covid-19 pandemic in 2020–2021. The total spillover index is approximately 64.23 per cent, implying that sectoral connectedness is relatively strong. The risks appear to spill over quickly across sectors in Vietnam's stock market. Additionally, the robustness test confirms that the total spillover effects are robust to variations in the VAR order, forecast horizons, and rolling windows.

Second, food, fisheries, and oil and gas are found to play a role as risk transmitters or risk transmission sources over the research period. After a significant shock occurs, these sectors need to be stabilized first to mitigate the spread of the risk, as they are likely to transmit risks rapidly and intensely to other sectors. For food and fisheries sectors, the government should create a trade environment with open, predictable and transparent supplies, ensuring a reliable food network. For oil and gas sector, comprehensive legal reforms are required because Vietnam's Law on Petroleum, enacted in 1993, show several limitations and the overlapping regulations appear to cause difficulties for gas projects to be implemented smoothly. Meanwhile, real estate and pharmacy are found to act as the greatest risk receivers during the research period. Based on this finding, the government should also pay more attention to these sectors as they appear to absorb the most risks and become the most vulnerable and fragile sectors in the market. The Vietnamese government's supports might include: (i) setting the legal framework to control real estate trading activities, ensuring sustainable development of the property market and avoiding real estate bubble (for real estate sector); and (ii) developing a modern, standardized and professional medicine distribution system (for pharmacy sector). From the investors' perspective, identifying sectors acting as risk transmitters and risk absorbers could help them design appropriate investment portfolios for risk minimization. More specifically, investors should avoid investment portfolios with highly related sectors or stocks, such as a portfolio including stocks from real estate and pharmacy sectors.

Third, commerce, transportation, manufacturing, and services appear to be more sensitive to the Covid-19 pandemic crisis than other sectors in the stock market. Their roles have changed from risk recipients (risk transmitters) to risk transmitters (recipients) after the pandemic outbreak. Therefore, the Vietnamese government should implement policies to stabilize those sectors when they start experiencing shocks due to crises. These supportive policies should include, but not be limited to, offering low-cost loans and providing tax breaks and exemptions for companies in those sectors.

Fourth, our empirical results show that the increase in new Covid-19 infections tend to raise connectivity among sectors, meaning that the pandemic probably amplifies volatility transmission and that market risks could be transmitted easily across sectors during the pandemic. As such, the Vietnamese government should consider adopting comprehensive Covid-19 control measures proposed by the World Health Organization to halt the spread of the virus. Especially, the government should accelerate vaccination against Covid-19 to reduce the number of new infections, which in turn could help mitigate sectoral volatility transmission within the stock market.

Last, mitigating economic policy uncertainty appears to help reduce sectoral spillovers in the Vietnamese stock market. Policymakers should monitor the EPU index to assess the changes in sectoral spillovers. Then, they can implement timely and focused responses, such as stabilizing the sectors playing as the greatest risk transmitters/receivers and adjusting determinants of sectoral spillovers to reduce the spillovers.

Although the original VAR connectedness approach of Diebold and Yilmaz (2012) is widely employed in existing studies, the standard VAR model can be used only to examine mean connectedness dynamics but not time-varying spillovers in different volatility regimes (i.e., normal versus extreme conditions). This creates a limitation in this study. Therefore, future studies should adopt the quantile VAR (QVAR) model, which enables investigation of time-varying connectedness among different quantiles. This approach could help reveal the differences between high- and low-volatility regimes, which could offer significant insights for both policy makers and portfolio managers.

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Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by TH-ND, NTN and DHV. All authors read and approved the final manuscript.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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