Is There a Relationship Among Investor Sentiment Industries? Evidence from the Vietnamese Stock Market

ANH TRAM LUONG, THAI HONG LE, HUONG THI THU PHUNG
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Abstract Investor sentiment and its influence on the stock market dynamics has become a growing concern in recent years especially among emerging economies. While the literature has focused on the sentiment of national stock market, the sentiment related to stock sectors has been largely ignored. Thus motivated, this research aims to examine the dynamic spillover among sentiment of different stock sectors in Vietnam during 2013-2022. To this aim, we use a financial network consisting of the sentiment variable in the TVP-VAR-based spillover framework. Our results show strong independence among sentiment indices in our network, especially from 2015 onwards. Overall, we find that industries heavily affected by government regulation, including Utilities, Finance, Banking, Oil Industry and Consumer Services, are net transmitters of shocks. The other industries, including Technology, Industrials, Consumer Discretionary, Health Care and Basic Materials, are net recipients.

Keywords: • investor sentiment • stock market • TVP-VAR • industries • Vietnam

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1 Introduction

Many researchers have reported the importance of measuring and assessing investor sentiment in stock markets in developed countries (see, among others, Antoniou et al., 2016; Baker et al., 2012; Baker & Wurgler, 2006; Chung et al., 2012; Huang et al., 2015; Smales, 2017; Xu et al., 2022) and emerging and frontier stock markets (Pandey & Sehgal, 2019; Phan et al., 2021 and Xiong et al., 2019). However, most studies in this field have only focused on developed markets. According to Ángeles López-Cabarcos et al. (2019), research on behavioral finance with keywords "emerging markets", "asset pricing", "stock market", and "sentiment" have only appeared from 2014 onwards. The keyword "frontier markets" does not appear as a notable linking phrase. Therefore, investor sentiment in emerging and frontier markets is still a topic that needs further research to add to the behavioral finance knowledge system.

The objective of this study is to explore the dynamic spillovers of investor sentiment among industries in frontier markets with evidence from the Vietnamese stock market during the period 2012-2022. This is an exciting research topic due to two reasons. First, to measure and assess investor sentiment, many previous studies on investor sentiment have recently constructed a sentiment index at country-level (see, for example, Antoniou et al., 2016; Baker et al., 2012; Baker & Wurgler, 2006; Chung et al., 2012; Huang et al., 2015; Smales, 2017; Xu et al., 2022). However, to our knowledge, few authors have drawn on any systematic research into industry-level sentiment index. Indeed, few studies have constructed sentiment indices for one or two specific industries (Peng et al., 2022; G. Wang et al., 2021). This study therefore adds significantly to the existing literature as sentiment indices for 10 industries in the stock market will be established. Second, while many studies have been carried out on investor sentiment, the relationship between industry sentiment indices has been under-studied. This study thus provides an exciting opportunity to advance our knowledge of investor sentiment and behavioural finance.

This paper combines and is related to two strands of literature. First, our topic draws from research investigating the measures of investor sentiment on stock markets. Previous studies have provided three main approaches to construct a sentiment index: market-based, survey-based and text- or media-based (Zhou, 2018). Second, we gain further insight from the literature on the relationship between investor sentiment industries (Kaplanski & Levy, 2010; Tiwari et al., 2022). All these strands of literature have increasingly advocated a time-varying association between investor sentiment industries. In order to allow for such dynamism, we utilize a time-varying parameter vector autoregressive model (TVP-VAR) developed by Antonakakis et al. (2020).

Our study reveals some critical findings using data collected on the Vietnamese stock market. First, we document a strong independence among sentiment indices in our network, especially from 2015 onwards. Second, we find that industries heavily affected

by government regulation, including Utilities, Finance, Banking, Oil Industry and Consumer Services, are net transmitters of shocks. The other sectors, including Technology, Industrials, Consumer Discretionary, Health Care and Basic Materials, are net recipients.
The rest of this paper has been divided into four parts. Section 2 begins by laying out the theoretical dimensions of the research and looks at how to measure investor sentiment. Section 3 introduces the methodology used in this study. Section 4 presents the findings of the research. Section 5 gives a brief summary and critique of the findings.

2 Literature overview

There are two stands of literature relating to this topic.

The first stand is measures of investor sentiment. According to Zhou (2018), investor sentiment indicators are classified into 3 categories, based on the data used to measure them, including (1) survey-based sentiment index, (2) text-based index và media-based index, (3) market-based sentiment index. *First*, the survey-based sentiment index is constructed by data from surveys. Some popular surveys worldwide are the American Association of Individual Investors survey, ING Investor Dashboard Sentiment Index, and Investors Intelligence survey. The weaknesses of the survey-based sentiment index include limited scope, limited research time, and that the answer depends a lot on how the questionnaire is designed (Zhou, 2018). Nevertheless, it is an important indicator, especially in the robustness test for sentiment indices constructed by other methods (Shen et al., 2017; Smales, 2017). In Vietnam, there has currently been no organization to survey with a large enough scale and long enough time to build a survey-based sentiment index. *Second*, the text-based index và media-based index is constructed by textual data mining tools. With the development of machine learning, many studies have used text-based and media-based indexes to measure sentiment (Da et al., 2015; García, 2013; Jiang et al., 2019). The strength of this approach is that big data can provide plenty of information, and data can be collected in minutes (Zhou, 2018). *Third*, the market-based sentiment index is constructed by proxy variables related to investor sentiment (secondary data). Several proxies used to construct sentiment indices are closed-end fund discount (Lee et al., 2002; Zweig, 1973), volatility index, put call ratio, option premiums, buy-sell imbalance, and open interest (Bathia & Bredin, 2013; Hachicha & Bouri, 2008; Muhammad, 2022; Pan & Poteshman, 2006; Reis & Pinho, 2020; Yang & Zhou, 2015). The most popular market-based sentiment index is the index proposed by Baker and Wurgler (2006) (Zhou, 2018). This index is constructed from six proxies: closed-end fund discount, market turnover, the number of IPOs, the first-day return of IPOs, the share of equity issues, and dividend premium. Sentiment measurements based on a multifactor approach are better at explaining volatility in stock returns than using each factor alone (Baker & Wurgler, 2006; Huang et al., 2015; Zhou, 2018). In addition, Pandey & Sehgal (2019) mentioned a mixed sentiment index, which is constructed from primary (survey) and secondary (market or text data) data.

The second stand is the relationship of sentiment in different industries. The existing literature on the relationship between sentiment and industry is sparse (Chen et al., 2013). Kaplanski & Levy (2010) found that market sentiment has a more significant effect on less stable industries, such as the Hi-TEC industry, during aviation disasters, whereas utilities are the most negligible influence. Tiwari et al. (2022) also consider indices of Australia's aggregate Consumer Sentiments index and components of the aggregate index, including CSI Rural Australia, CSI-Aged 18–24; CSI – Aged 25 to 44, and CSI–Aged 45 and above for different industries in Australia. The authors report asymmetric and unidirectional causality-in-returns from consumer sentiments to industry stock returns. Gong et al. (2022) said that the relationship between high-frequency stock price volatility and investor sentiment is time-varying. Especially, they found that the connectedness in risk spillover networks between stock volatility and investor sentiment in the long term is considerably lower than that in the short term. However, the above studies only focus on the effect of sentiment on stock returns in various industries. Wang et al. (2022) construct dynamic networks of the investor sentiment of 10 sectors in the Chinese stock market. They figured out that the spillover effect or connectedness on the investor sentiment layer is less than that of stock return, but the connectedness of the investor sentiment increased more rapidly compared to stock returns. The fact that few studies investigate the spillovers among investor sentiment of industries leaves a research gap for this paper.

3 Research methodology

3.1 Principle Analysis Component

This study uses the Principal Component Analysis (PCA) to construct a sentiment index for the Vietnamese stock market. PCA is a method of reducing the dimensionality of the data space. Many variables are correlated while ensuring the maximum possible variance of the data (Jolliffe, 2002). The sentiment index is constructed as follows:

$$SENT = a \times NIPO + b \times RIPO + c \times TURN + d \times S + e \times P^{D-ND} + f \times MFI + g \times INV \tag{1}$$

where: $SENT$ is the investor sentiment, $NIPO$ is the number of IPOs, $RIPO$ is the average first-day return, $TURN$ is the market turnover, S is equity share in new issues, P^{D-ND} is value-weighted dividend premium, MFI is money flow index, and INV is the number of new investors.

3.2 The TVP-VAR-based dynamic connectedness approach

In order to explore the dynamic connectedness in a time-varying manner, we employ the TVP-VAR approach introduced by Antonakakis et al. (2018). The TVP-VAR methodology combines the connectedness approach of Diebold & Yilmaz (2009, 2012, 2014) and Koop & Korobilis (2014). This framework allows the variances to vary over time via a Kalman Filter estimation with forgetting factors. The TVP-VAR(p) model can be expressed as:

$$y_t = \beta_t z_{t-1} + \epsilon_t \qquad \epsilon_t | F_{t-1} \sim N(0, S_t) \tag{2}$$
$$vec(\beta_t) = vec(\beta_{t-1}) + v_t \qquad v_t | F_{t-1} \sim N(0, R_t) \tag{3}$$

where y_t and $z_{t-1} = [y_{t-1}, \dots, y_{t-p}]'$ respectively represent $N \times 1$ and $Np \times 1$ dimensional vectors. β_t is an $N \times Np$ dimensional time-varying coefficient matrix and ϵ_t is an $N \times 1$ dimensional vector of error disturbance with an $N \times N$ time-varying variance-covariance matrix, S_t. $vec(\beta_t), vec(\beta_{t-1})$ and v_t are $N^2p \times 1$ dimensional vectors and R_t is an $N^2p \times N^2p$ dimensional matrix.

To calculate the generalised impulse response functions (GIRF) and generalisgeneralized error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran & Shin, 1998), we need to transform the TVP-VAR to a TVP-VMA using the Wold representation theorem:

$$y_t = \sum_{j=0}^{\infty} L' W_t^j L \epsilon_{t-j} \tag{4}$$
$$y_t = \sum_{j=0}^{\infty} A_{it} \epsilon_{t-j} \tag{5}$$

where $L = [I_N, \dots, 0_p]'$ is an $Np \times N$ dimensional matrix, $W = [\beta_t; I_{N(p-1)}, 0_{N(p-1)\times N}]$ is an $Np \times Np$ dimensional matrix. The GIRFs represent the responses of all variables following a shock in variable *i*. We compute the differences between a *J*-step-ahead forecast where once variable *i* is shocked and once where variable *i* is not shocked. The difference can be accounted to the shock in varibale *i*, which is given by:

$$GIRF_t(J, \delta_{j,t}, F_{t-1}) = E(Y_{t+J} | \epsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+J} | F_{t-1}) \tag{6}$$
$$\varphi_{j,t}^g(J) = \frac{A_{J,t} S_t \epsilon_{j,t}}{\sqrt{S_{ij,t}}} \frac{\delta_{j,t}}{\sqrt{S_{ij,t}}} \quad , \quad \delta_{j,t} = \sqrt{S_{ij,t}} \tag{7}$$
$$\varphi_{j,t}^g(J) = S_{jj,t}^{-1/2} A_{J,t} S_t \epsilon_{j,t} \tag{8}$$

where $\varphi_{j,t}^g(J)$ is the GIRFs of variable *j*, *J* represents the forecast horizon, $\delta_{j,t}$ is the selection vector with value of one on the *j*-th position and zero otherwise, and F_{t-1} is the information set until $t-1$. Then, we compute the GFEVD that can be interpreted as the variance share one variable has on others. The calculation is as follows:

$$\tilde{\phi}^{g}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1}\varphi^{2,g}_{ij,t}}{\sum_{j=1}^{N}\sum_{t=1}^{J-1}\varphi^{2,g}_{ij,t}} \tag{9}$$

with $\sum_{j=1}^{N}\tilde{\phi}^{g}_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{N}\tilde{\phi}^{N}_{ij,t}(J) = N$. Based on the GFEVD, we can build the total connectedness index (TCI) as follows:

$$C^{g}_{t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\phi}^{g}_{ij,t}(J)}{\sum_{i,j=1}^{N}\tilde{\phi}^{g}_{ij,t}(J)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\phi}^{g}_{ij,t}(J)}{N} \times 100 \tag{10}$$

The connected approach allows to examine how a shock in one variable spills over to other variables. First, the shock transmitted from variable *i* to all other variables *j*, i.e. the *total directional connectedness TO others* can be defined as:

$$C^{g}_{i\to j,t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\phi}^{g}_{ij,t}(J)}{\sum_{j=1}^{N}\tilde{\phi}^{g}_{ij,t}(J)} \times 100 \tag{11}$$

Second, the shock that variable *i* receives from all other variables *j*, i.e. the *total directional connectedness FROM others* can be defined as:

$$C^{g}_{i\leftarrow j,t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\phi}^{g}_{ij,t}(J)}{\sum_{j=1}^{N}\tilde{\phi}^{g}_{ij,t}(J)} \times 100 \tag{12}$$

Finally, the *net total directional connectedness* can be given by subtracting the total directional connectedness TO others from the total directional connectedness FROM others:

$$C^{g}_{i,t} = C^{g}_{i\to j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \tag{13}$$

This net total directional connectedness can be interpreted as the influence of variable *i* on the analyzed network. If the net total directional connectedness of variable *i* is positive, varibale *i* influences the network more than being influenced by it. This also means that variable *i* is a shock transmitter. On the other hand, if the net total directional connectedness is negative, variable *i* is driven by the network, meaning that it is a shock receiver.

As the net total directional connectedness is an aggregated measure and sometimes masks important underlying dynamics, we want to calculate the net pairwise directional connectedness (NPDC), which informs about the bilateral transmission process between variables I and j:

$$NPDC_{ij}(J) = \tilde{\phi}_{ji,t}(J) - \tilde{\phi}_{ij,t}(J) \tag{14}$$

A positive (negative) value of $NPDC_{ij}(J)$ indicates that variable i is driving (driven by) variable j.

3.3 Data

We selected Vienam to collect data because Vietnam is a frontier market (FTSE Russell, 2022), with more than 95 per cent of investors being domestic individual investors (HOSE, 2022). This group is vulnerable because they are strongly influenced by sentiment rather than fundamental factors (Ackert & Deaves, 2010). Therefore, the Vietnamese stock market can be significantly affected by sentiment. We employ monthly data collected from the FiinPro platform, a financial database in Vietnam, from 2012 to 2022. The choice of these time windows is restricted to the availability of investor sentiment data. We compute investor sentiment indices for industries following the method of Baker and Wurgler (2006). The investor sentiment series for Vietnam is constructed from seven proxies: market turnover, number of IPOs, average first-day return on IPOs, equity share of new issuances, the log difference in book-to-market ratios between dividend payers and dividend non-payers, money flow index and the number of new investors. After using PCA, the sentiment indicators are then transformed into stationary series by taking the growth rate.

Vietnam has two stock exchanges, including Ho Chi Minh City Stock Exchange, which was established in 2005 and Hanoi Stock Exchange, which was established in 2007. Adopting the ICB standard, companies listed on two Vietnamese stock exchanges are classified into 11 industries. Table 1 describes the number of firms in each industry. As the Telecommunications industry has only one company, we need more data to construct a sentiment index for the telecommunications industry. Therefore, we only construct sentiment indices for ten industries except for Telecommunications. As can be seen from Table 1, the selected sample covers all companies listed on the Vietnamese stock market.

Table 1: Number of companies listed in the stock market sectors on the Vietnam stock market

Industry	Number of companies		
	Ho Chi Minh City Stock Exchange	**Hanoi Stock Exchange**	**Total**
Basic Materials	60	43	103
Consumer Discretionary	65	35	100
Industrials	106	159	265
Services	26	34	60
Banking	17	2	19
Finance	94	38	132
Health Care	14	10	24
Utilities	31	18	49
Technology	8	11	19
Oil	2	3	5
Telecommunications	0	1	1
Total	**423**	**354**	**777**

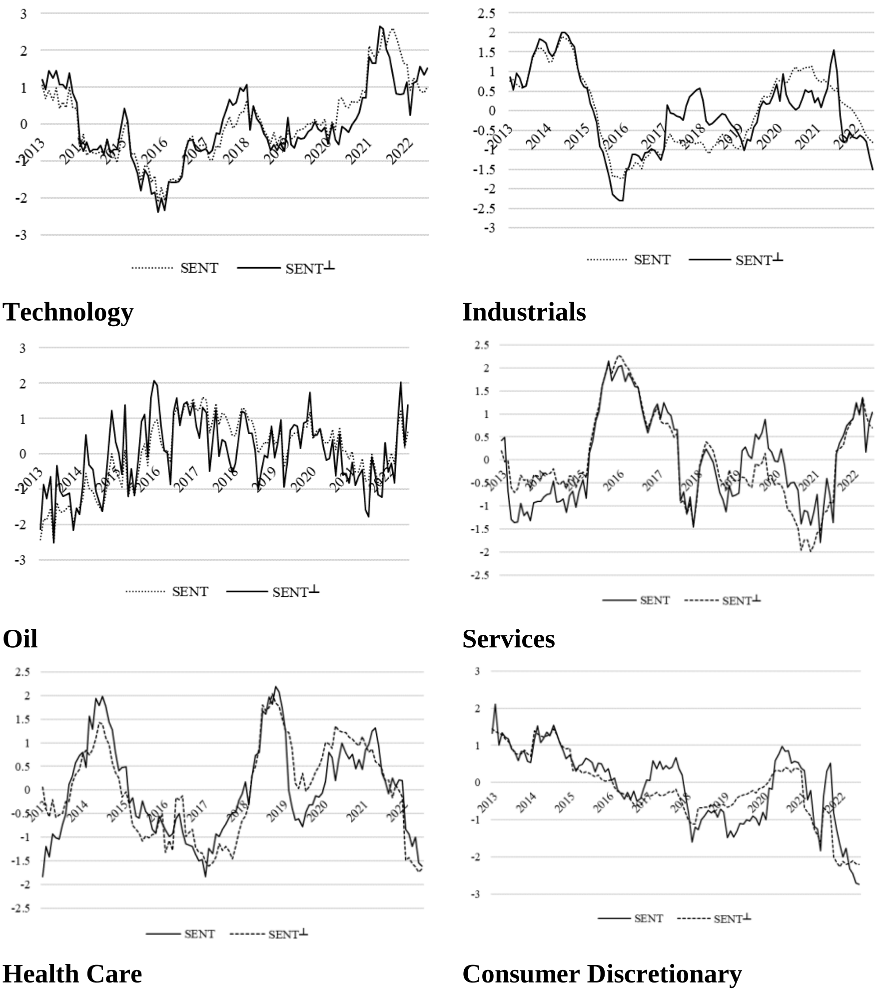
Source: Data collected from FiinPro (2022).

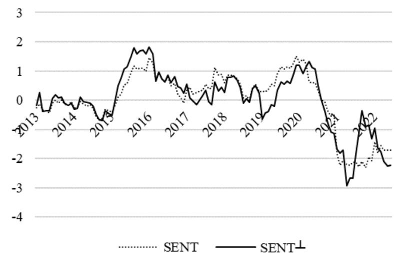
4 Results and Discussion

4.1 Descriptive statistics

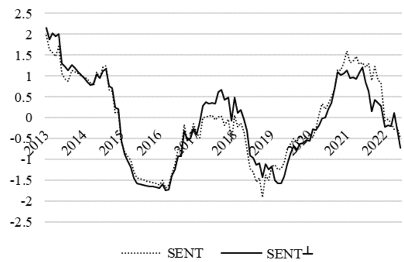
Using the principal component analysis (PCA), this study measures sentiment for ten industries on the Vietnamese stock market (Figure 1). Following Baker & Wurgler (2006), we label SENT ($SENT^{\perp}$) as the sentiment index constructed from the six raw (orthogonalized) measures.

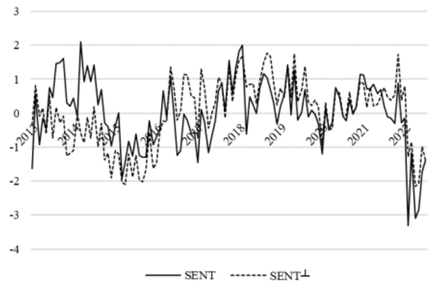
Figure 1: Sentiment indices for 10 industries on the Vietnamese stock market





Banking **Basic Materials**





Finance **Utilities**

Notes: We regress each measure on the growth in industrial production, employment growth, consumption growth and the dummy variable for the business cycle. The dashed (solid) line is the first principal component index of the six raw (orthogonalized) measures, labelled as SENT ($SENT^{\perp}$). Both are standardized to have zero mean and unit variance.

Figure 1 shows market sentiment changes among industries on the stock market. Several features are noticed in Figure 1.

First, in general, the SENT and $SENT^{\perp}$ of ten industries are closely related, and all sentiment indices are influenced by economic and political events. For example, although each sentiment index of each industry changes differently, most of the sentiment indices declined in 2014, 2016, 2018 and 2020. These are the times when several important political and economic events occurred, such as the dispute between Vietnam and China in the East Sea in 2014, the trading interruption of the Chinese stock market in 2016, the US-China trade war in 2018 and the COVID-19 epidemic in early 2020. Second, although most sentiment indices are influenced by economic and political events, sentiment indices vary across industries. While market sentiment in the Oil, Banking, and Utility industries tends to fluctuate continuously, sentiment in the rest tends to fluctuate less continuously. In addition, in some periods, an industry's sentiment index differs from the other industries. For example, the year 2020 saw sentiment for stocks in most industries increase due to the impact of market expectations during the COVID-19 period. However, the sentiment of the Basic Materials and Services industry is still decreasing at a low level. This might be because of the strong damaging impacts from the epidemic.

As another example, Figure 1 shows that sentiment for the Oil industry increased at the beginning of 2022, while sentiment in other sectors did not grow after 2021. This can be explained by the fact that these industries' sentiment depends mainly on each industry's specific characteristics. The sentiment index of Oil stocks is highly dependent on changes in oil prices and government policies (Kassouri et al., 2021; Si et al., 2021) For example, the 2022 Russian invasion of Ukraine led to a sharp increase in oil prices (OECD, 2022), leaving the market to maintain a reasonably positive expectation of the performance of companies in this industry. In addition, government policies affect the Oil, Banking and Utility industries more often than other industries (Si et al., 2021). This is also why the sentiment of these industries fluctuates strongly and does not change cyclically.

After using PCA, the sentiment indicators are then transformed into stationary series by taking the growth rate. Table 2 and Table 3 indicate the summary statistics of the growth rate of investor sentiment industries on the Vietnamese stock market. The variance of sentiment indices indicate that sentiments of Banking and Uitilies are the most volatile, while sentiments of Consumer Discretionary and Finance are the least volatile. Next, skewness and kurtosis measures indicate that all series are leptokurtic and significantly left skewed. All variables except for sentiment indicators are not normally distributed. Moreover, all variable are stationary at 5% significance level. Finally, we find evidence suggesting that series are autocorrelated and exhibit ARCH errors, making it legitimate for the choice of a TVP-VAR model with time-varying covariances.

Table 2: Summary statistics

	Mean	Variance	Skewness	Kurtosis	JB	ERS	Q(20)	Q2(20)
Technology	0.517	48.245***	8.655***	86.783***	34766.022***	-4.597***	1.326	1.162
Industrials	0.331*	3.894***	7.265***	66.385***	20087.085***	-2.843***	1.242	0.243
Oil	-1.014**	18.087***	-3.685***	20.045***	1637.946***	-3.976***	18.276**	22.372***
Services	0.182	3.846***	4.097***	38.556***	6323.916***	-5.188***	20.305**	5.418
Health care	0.079	5.394***	6.998***	67.988***	20991.494***	-4.362***	5.685	0.238
Consumer Discretionary	0.001	1.478***	3.036***	28.158***	3181.489***	-3.599***	8.427	1.339
Banking	9.003	7164.231***	10.362***	109.482***	55897.583***	-4.618***	0.080	0.063
Basic Materials	-0.682	41.858***	-7.069***	68.729***	21470.790***	-4.313***	6.877	0.665
Finance	-0.025	1.279***	0.474***	15.877***	791.940***	-4.998***	8.438	10.650
Utilities	-17.224	11346.190***	-6.341***	42.569***	8201.338***	-4.761***	2.553	1.217

Notes: ***, **, and * denote significance at 1%, 5% and 10% significance levels respectively; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Stock *et al.* (1996) unit root test; Q(10) and $Q^2(10)$: Fisher and Gallagher (2012) weighted portmanteau test.

Table 3: Pairwise correlation matrix.

	Technology	Industrials	Oil	Services	Health care	Consumer Discretionary	Banking	Basic Materials	Finance	Utilities
Technology	1									
Industrials	0.029	1								
Oil	0.0208	-0.0103	1							
Services	0.0299	0.0179	-0.0462	1						
Health care	0.0359	0.0575	0.0659	-0.0246	1					
Consumer Discretionary	0.0106	0.0008	-0.0422	-0.0796	-0.0053	1				
Banking	-0.0886	-0.0297	-0.017	-0.005	0.0701	0.0436	1			
Basic Materials	0.0105	-0.0478	0.0048	0.0149	0.0162	-0.0006	0.0166	1		
Finance	0.1249	-0.0393	0.0251	0.1045	0.008	-0.0807	-0.0593	0.004	1	
Utilities	0.0035	0.0587	0.2314	-0.2173	-0.0041	0.038	0.0168	-0.0119	-0.199	1

4.2 The dynamic spillovers among investor sentiment industries on the Vietnamese stock market

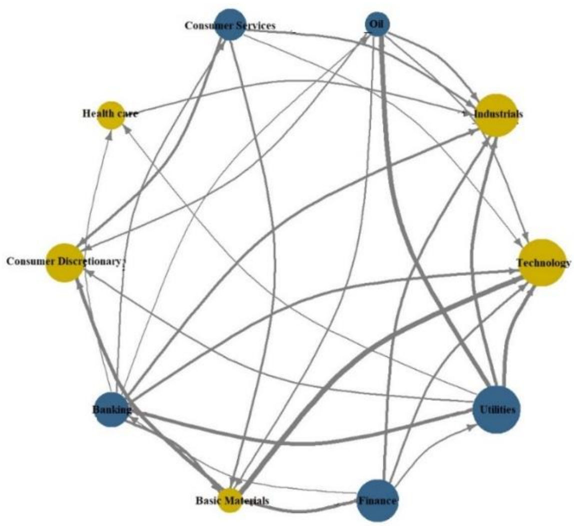
Table 4 reports the results of the average dynamic connectedness analysis. Each row of Table 4 corresponds to the individual contribution of each variable to the forecast error variance of all other variables of our network. In contrast, each column shows the forecast error variance that other variables have contributed to each variable separately. Elements on the main diagonal represent own-variable effects, while the off-diagonal elements show the effect from/to others.

Table 4: Averaged dynamic connectedness table

	Technology	Industrials	Oil	Services	Health care	Consumer Discretionary	Banking	Basic Materials	Finance	Utilities	Contribution FROM others
Technology	16.17	6.14	7.28	7.74	10.95	3.39	9.04	16	11.8	11.49	83.83
Industrials	4.88	15.81	8.42	14.28	8.29	8.66	10.92	6.45	11.17	11.11	84.19
Oil	3.44	3.69	22.19	7.51	6.72	4.81	16.44	3.28	9.41	22.54	77.81
Services	4.77	9.85	7.68	20.84	9.58	9.5	9.82	6.39	13.68	7.88	79.16
Health care	9.84	5.13	6.05	10.51	18.83	7.83	8.98	11.52	13.2	8.11	81.17
Consumer Discretionary	3.12	9.06	7.86	14.74	6.88	17.36	7.62	14.3	11.02	8.05	82.64
Banking	3.86	5.05	13.49	6.84	6.05	5.62	19.97	2.46	13.67	23	80.03
Basic Materials	6.13	5.65	6.34	11.04	9.59	6.71	8.25	25.55	12.61	8.13	74.45
Finance	7.54	5.36	8.35	12.74	11.28	9.36	10.9	6.1	21.49	6.81	78.51
Utilities	3.64	4.43	13.45	5.94	5.21	4.99	15.22	6.25	10.77	30.09	69.91
Contribution TO others	47.22	54.35	78.93	91.33	74.55	60.87	97.19	72.75	107.33	107.16	791.69
Inc. Own	63.4	70.17	101.12	112.17	93.37	78.23	117.16	98.3	128.82	137.26	TCI
NET directional connectedness	-36.6	-29.83	1.12	12.17	-6.63	-21.77	17.16	-1.7	28.82	37.26	87.97/ 79.17
NPDC transmitter	0.00	2.00	5.00	5.00	3.00	2.00	7.00	4.00	9.00	8.00	

Notes: Values reported are variance decompositions for estimated TVP-VAR(2) model. A lag length of order 2 was selected by the Bayesian information criterion.Variance decompositions are based on 10-step-ahead forecast.

Figure 2: Averaged dynamic connectedness of investor sentiment industries

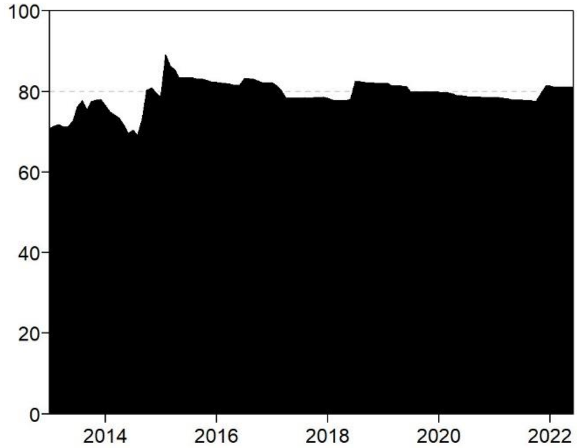


Notes: Blue dots represent net transmitters. Yellow dots represent net recipients. The size of a dot represents the level of effect on investor sentiment of each industry.

As can be seen from Table 4, the total connectedness is 79.17%, suggesting a strong interdependence among the variables in our network. These results indicate that over 20% of the forecast error variance can be attributed to own-variable innovations. On average, we observe from Table 4 and Figure 2 that Oil, Services, Banking, Finance and Utilities are net transmitters of shocks. These industries are heavily affected by government regulation(FTSE Russell, 2022), and as a result, this might be the reason for their impacts on other industries in the network. These findings further support the idea of Hua et al. (2020), who suggest that investor sentiment in the stock market is significantly affected by industry policies promulgated by the government. On the other hand, Technology, Industrials, Health care, Consumer Discretionary, and Basic Materials are net recipients.

Although Table 4 reveals some interesting observations on the interdependence between investor sentiment industries, these results correspond to aggregate measures considering the sample period. Using average figures can mask several economic and geopolitical events during the sample period and may lead to considerable deviations from the average TCI values reported in Table 4. Thus, we will proceed with the dynamic approach. The aim is to identify specific episodes that influenced connectedness across our variables over time.

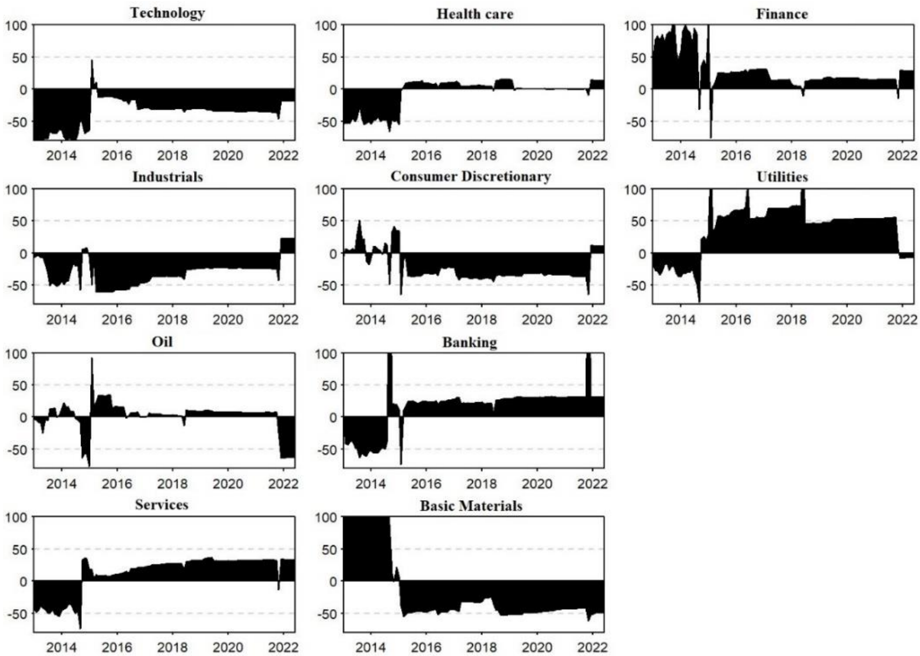
Figure 3: Dynamic total connectedness



The time-varying connectedness measures are shown in Figure 3. It is clear that the total connectedness measure changes considerably over time and behaves heterogeneously across industries. The range for the total connectedness spans from 64% to 84%. Thus, the interrelationship between investor sentiment industries is indeed time-dependent. A closer look at Figure 4 reveals that the connectedness is less pronounced during periods of economic turbulence or bear periods. These episodes include, for example, rumours of prosecuting Mr Tran Bac Ha, Chairman of the Board of Directors of the Bank for Investment and Development of Vietnam and the adoption of policies closer to international standards in calculating non-performing loans (2013), the event that China placed an oil rig in the East Sea (which is called as South China Sea by China) (May 2014), the global oil price plummet (December 2014), US-China trade tensions in 2018 and the onset of the COVID-19 pandemic (March 2020). Thus, it is evident that time-specific developments and events entirely drive the relationship among variables in our networks. However, the fact that the connectedness index fluctuates around 80% shows that the magnitude of the spillover effects has remained strong over the studying time.

Next, we compute the time-varying net directional connectedness to disentangle the linkage between investor sentiment industries further. By concentrating on net directional connectedness, we can deduce whether one of the variables is either a net transmitter or a net receiver of shocks within a particular country. Initially, we concentrate on the nature (net transmitter or net recipient of shocks) of each one of the variables of interest in contrast with all other variables. The variable of interest is considered a net transmitter of shocks when the line lies within the positive upper part of each panel. Results are plotted in Figure 4.

Figure 4: Net directional connectedness



Most variables are persistent about the role they assume throughout the sample period. Regarding transmitters, for example, the oil industry appears to be a persistent transmitter of shocks except for the second half of 2014 with the event that China placed an oil rig in the East Sea and the year 2022 with the Russia–Ukraine war, though the magnitude is relatively small. These results match those observed in earlier studies about the oil industry's importance. Le & Luong (2022) demonstrate the influence of oil prices on the sentiment index and stock return on the Vietnamese market from 2010 to 2020. In which, oil price plays the role of a transmitter of shock and has greatly influenced the other two variables in the oil price crisis period from 2014 to 2018 and the COVID-19 period from 2019 to 2020. We also can observe that the Banking, Utilities and Services industries were always net receivers of shock prior to 2014; yet, their role has been switching between net transmitters for the rest of the remaining time. Regarding the Finance industry, its sentiment was a significant net transmitter of shocks in most of the study period. This finding corroborates with Swamy & Dharani (2019), who conclude the critical role of finance in the economy and its effects on other industries.

Turning to net recipients, Technology and Industrials were persistent receivers of shocks for most of the examination period. Basic materials and Consumer Discretionary were net transmitters of shock in the early period of our study, especially from 2012 to 2015, with the net directional connectedness measure of Basic materials peaking up at over 100%. The fear of the flash crash is hence clearly felt. Since 2015, the sentiment of Basic materials and Consumer Discretionary has switched its role and turned into a net receiver of shocks.

5 Conclusions

This paper aims to examine the dynamic spillovers between investor sentiment of Vietnam's industries during 2012-2022. In doing so, we consider a financial network consisting of 10 sentiment indices in a time-varying parameter vector autoregression (TVP-VAR)-based spillover framework. Following Baker and Wurgler (2006) method, we construct a sentiment indicator from seven proxies by PCA. These proxies include market turnover, number of IPOs, average first-day return on IPOs, equity share of new issuances, the log difference in book-to-market ratios between dividend payers and dividend non-payers, money flow index and the number of new investors.

Our results show a strong interdependence among the variables in our networks. Further, the relationship among investor sentiment industries is driven by time-specific developments and events. Overall, we find that industries heavily affected by government regulation, including Utilities, Finance, Banking, Oil Industry and Consumer Services, are net transmitters of shocks. The other industries, including Technology, Industrials, Consumer Discretionary, Health Care and Basic Materials, are net recipients.

These findings have important policy implications. Firstly, this study has confirmed that government regulations are one of the decisive factors in the performance of financial markets in Vietnam. The sentiment of industries heavily affected by government regulations will influence the sentiment of other industries. Secondly, because the relationship between sentiment indices of industries is time-varying and entirely driven by time-specific developments and events, policymakers should have a monitoring system in all the above areas to react promptly. Our results suggest that a change in Utilities, Finance, Banking, Oil Industry and Consumer Services likely impacts the others, thus posing spillover risks to the financial system.

Our study, however, is not without limitations. Due to the different characteristics of mature and emerging countries (Chang et al., 2000; Corredor et al., 2013), it is possible to lead to different results as developed markets are examined. Future studies should shed further light on this by considering sentiment of industries in developed countries.

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