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Connectedness analysis of price return index among Malaysian economic sectors

Norzalina Ahmad
School of Economics, Finance and Banking, Universiti Utara Malaysia, Sintok, Malaysia

Hazrul Shahiri
Faculty of Economics and Management, Universiti Kebangsaan Malaysia, Bangi, Malaysia

Safwan Mohd Nor
Faculty of Business, Economics and Social Development, University of Malaysia Terengganu, Kuala Nerus, Malaysia and Victoria Institute of Strategic Economic Studies, Victoria University, Melbourne, Australia, and

Mukhriz Izraf Azman Aziz
School of Economics, Finance and Banking, Universiti Utara Malaysia, Sintok, Malaysia

Abstract

Purpose – This study aims to explore the connectedness of price return index spillovers across eight economic sectors in the Malaysian stock market (Bursa Malaysia).

Design/methodology/approach – The analysis uses daily data of sectoral price index from 10 May 2005 to 24 February 2021. The study uses Bayesian time-varying parameter vector autoregressive.

Findings – The degree of price return index spillovers varies over time, reaching unprecedented heights during the COVID-19 pandemic in 2020. The industrial economic sector is the main transmitter of price index return shock, whereas the utilities economic sector is the dominant receiver of index return spillovers.

Originality/value – The findings are critical for investors, market participants, businesses and policymakers in developing action plans for the vulnerable sectors. It further enhances investors' confidence in making investment decisions.

Keywords Connectedness, Business sector, COVID-19, Price index

Paper type Research paper

1. Introduction

The global financial market has shown vigorous fluctuations in recent times. This is especially true since the 2008 crisis that gripped entities worldwide. Previous studies that have examined the relationship of financial markets show that financial strain and crises are directly impacted by the gravity and extent of connectedness among those markets, examples being drawn from previous crises such as the global financial crisis (GFC) and the debt crisis in Europe (Jondeau and Rockinger, 2006; Mokni and Mansouri, 2017). Apart from

JEL classification – G11, G17

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that, financial markets experienced a considerably more rapid and dramatic reaction to the COVID-19 period that started at the end of 2019. This is more evident during the February–May 2020 period, when a large number of big events have exacerbated the misery of turbulent stock markets (Kinateder *et al.*, 2021). In a similar tread, Baker *et al.* (2020) has shown that COVID-19 is far more destructive to the US stock market than previous infectious diseases. In other studies on the US market, Jeris and Nath (2021) indicated that growing COVID-19 cases in the USA have a strong effect on US bank index. Hung (2020) explored the pre- and during COVID-19 spillovers between crude oil prices and five developed stock markets in Europe, concluding that spillovers were more apparent during the COVID-19 period. In term of risk of contagion to other developed or even developing countries, Daly *et al.* (2019) and Yoon *et al.* (2021) suggest that the financial risk experienced during COVID-19 in the Australian stock markets may cause spillover effects to other developed or even developing countries. Aslam *et al.* (2022) concluded that, compared to Asian markets, European markets are more sensitive to asset losses during the pandemic while a study by Al Samman and Akkas (2021) specifically on GSC countries found that COVID-19 severely hit the stock markets in Saudi Arabia, United Arab Emirates and Qatar.

One of the shortcomings of previous studies is the tendency to focus on the overall impacts of a crisis instead of considering the subsets of the business sectors. Albeit leanings towards connectedness have been demonstrated in these studies, the precise orientations and swings of various business sectors within the economy is not shown. The COVID-19 pandemic that swept across the globe had also caused marked impacts on stock markets in Malaysia. For this reason, it is important to conduct a depth analysis of the direction of the risk spillover among business sectors in Malaysia. A better understanding of the connectedness among business sectors can help to avoid potential risk across different business sectors and may provide effective government policy response mechanisms towards major events in financial market. In fact, studies such as Ali *et al.* (2011), Ranjeeni (2014), Yang *et al.* (2016), Lee and Goh (2016) and Wu *et al.* (2019) have all shown how different business sectors and international trade (Duasa, 2009) exhibit varied reactions to market shocks and sectoral heterogeneity. As an example, Lim (2008) made a comparison across eight economic sectors on the Malaysian stock market and found that the 1997 Asian financial crisis had caused impacts to cascade across each of the eight economic sectors, except for the mining and tin sector, respectively.

Similarly, empirical evidence has shown that COVID-19 had also triggered shock waves across sectoral business performances. One such study is Lee *et al.* (2020), who examined the effects of COVID-19 on the performance of 13 sectorial indexes in the Malaysian stock market using daily data from 1 December 2019 to 18 April 2020. The regression analysis demonstrated that the performance of all 13 sectors had been substantially impacted. Outside Malaysia, Zhou *et al.* (2020) have found that in China, the COVID-19 pandemic had a positive and upward impact on the performance of the health sector, but a negative impact on other businesses, such as the transportation, construction and tourism industries. Determining sectoral reactions to market changes and risks arising from inter-sectoral spillovers are important tools for all market participants. Such sectoral indexing supports portfolio performances by reducing risks in an adversely affected market. Because each business sector affects the economy in specific singularities, this becomes a crucial determinant. The perpetual change that occurs in financial markets also means that it will continue to vary in the ways it corresponds with each particular business sector. Therefore, a connectedness analysis across a spectrum of varied business sectors is a highly useful means to support policymakers when deciding policies and measures for necessary sectors based on their growth or decline on its index performance.

Furthermore, the stock market is a complex and dynamic system (Feng *et al.*, 2018). The system can be formed by the various economic sectors in the stock market, as seen through the lens of network theory. These business sectors may interact with one another via information exchange and risk transfer, which is known as the spillover effect (Nazlioglu, 2015). As a result, return in one sector may affect the return of the entire system. Therefore, a thorough understanding of the spillover effect of index return among business sectors is critical because it can influence investment decisions. In addition, Liu and Tse (2012) propose that using network theory in financial analysis is an effective method for determining the interdependence of individual markets. It would also most likely provide quantitative descriptions of some significant systematic financial phenomena.

The main focus of this research is therefore to understand the interrelations of connectedness of the different economic sectors in the Malaysian stock market, and how this has evolved over time. According to World Development Indicator 2020 by The World Bank (2022), Malaysia is the largest stock market among the Association of Southeast Asian Nations-5 in terms of the number of listed companies. The number of public listed companies has risen dramatically from 282 in 1990 to 927 in 2020. The country has grown from 109 in 1990 to 129 in 2020 in terms of market capitalisation ratio. The Malaysian stock market index reached its peak point at 1,866 in 2018. However, COVID-19 pandemic has further worsened the market like other countries. Since the beginning of January 2020, the stock market has been on a downward trend, reaching a low of 1,219.71 points on 19 March 2020. Thereafter, the market was able to sustain a 1,400-point level (Mohamad Jais and Chan, 2020).

Therefore, the understanding of interrelatedness of connectedness across time variants which manifest across a spectrum of economic sectors within the economy will have significant contributions to the robust body of literature on this subject. Moreover, insights will emerge to how such connectedness interplay in the aftermath of economic shocks. While Adnan and Hasan (2021) look into capital market reaction to the emergence of COVID-19, this is the first research of its kind to determine Malaysia's price return index connectedness across several different economic sectors. This is the first research of its kind to determine Malaysia's price return index connectedness across several different economic sectors. It investigates the net value of connectedness across a time period which encompasses significant market shocks, such as the GFC of 2008 by applying high-frequency data, and this investigation runs across multiple economic sectors. Thus, unlike previous research, this study offers higher accuracy and reliability in understanding sectoral interconnectedness which is a useful means for sector-based policymakers. It also enhances precision when determining key sectors which are leading other sectors by providing the underlying elements influencing specific sectors.

In fact, to the best of our knowledge, this is the first ever attempt made to use the time-varying parameter vector autoregressive (TVP-VAR) connectedness methodology to measure and compare price return index spillovers across multiple business sectors. By adopting the TVP-VAR model introduced by Koop and Korobilis (2014) and integrating it with the dynamic connectedness schema of Diebold and Yılmaz (2012, 2014) to analyse the observables during the time period, we are able to determine whether price return index spillovers are greater or less across multiple economic sectors during the periods of economic shocks, when compared with normal times. This methodology enables more flexible and robust capturing of potential changes in the underlying structure of the data (Antonakakis *et al.*, 2020). Indeed, Diebold and Yılmaz (2012, 2014) connectedness measures are closely related to network theory and modern measures of systematic risk. This novel approach has piqued the interest of academics, and studies have estimated network connectivity among various market segments (refer to Maghyereh *et al.*, 2016; Mensi *et al.*, 2018; Antonakakis *et al.*, 2020; Polat, 2021).

Our empirical analysis shows that the transmission of price return index spillovers among economic sectors is a significant source of sectoral price index fluctuations. We also find that the magnitude of price return index spillovers varies over time, reaching unprecedented highs during the COVID-19 pandemic in 2020. From the network of various economic sectors analysed, we find that the industrial sector is the dominant transmitter of price return index shock, whereas the utilities sector is the dominant receiver of price return index spillovers. As such, this study has important implications for investors, portfolio managers and policymakers.

The rest of the research paper is organized accordingly. The methodology is presented in Section 2. Section 3 presents the data and the descriptive statistics. In Section 4, we discuss the empirical results and outline the robustness test. Finally, Section 5 concludes and highlights several significant implications.

2. Methodology

To investigate the transmission mechanism of the economic sectoral price return index over time, Koop and Korobilis's (2014) methodology of TVP-VAR is integrated with the model developed by Diebold and Yılmaz (2014) in measuring connectedness. Relying on this schema and the Kalman Filter estimation of decay factors enables the change of variation over a period of time. Of course, the course of time that present from the observables means that there are no obvious outliers here that will skew the readings. Hence, there is no necessity to set up a rolling window nor is there any loss of observations when calculating the dynamic measures (refer to Antonakakis *et al.*, 2018; Korobilis and Yilmaz, 2018; Gabauer and Gupta, 2018). Moreover, this form of schema is able to encapsulate the representation of connectedness of the price return index changes using the TVP-VAR(1) model endorsed by the Bayesian Information Criterion depicted as follows:

$$\Delta x_t = \beta_t \Delta x_{t-1} + \epsilon_t \quad \epsilon_t \sim N(0, \Sigma_t) \tag{1}$$

$$\text{vec}(\beta_t) = \text{vec}(\beta_{t-1}) + v_t \quad v_t \sim N(0, R_t) \tag{2}$$

where $\Delta x_t, \Delta x_{t-1}$ and ϵ_t are $N \times 1$ dimensional vector, β_t and Σ_t are $N \times N$ dimensional matrices. The parameters $\text{vec}(\beta_t)$ and ν_t are $N^2 \times 1$ dimensional vectors, whereas $\boldsymbol{R}_t$ is an $N^2 \times N^2$ dimensional matrix.

The transformation of the TVP-VAR to a TVP-VMA is done by applying the Wold representation theorem, $\Delta x_t = \sum_{i=1}^{p} \beta_{it} \Delta x_{t-i} + \epsilon_t = \sum_{j=1}^{\infty} \Lambda_{jt} \epsilon_{t-j} + \epsilon_t$. This, of course, takes place after the estimation of time-varying parameters. The subsequent step involves the extraction of the TVP-VMA coefficients to enable the calculation of the generalized forecast error variance decomposition (GFEVD) (Koop *et al.*, 1996; Pesaran and Shin, 1998). From this, the schema of dynamic connectedness is developed.

The (unscaled) GFEVD, $\phi^g_{ij,r}(J)$– characterising the paired directional connectedness from j to i and exemplifying the influence which variable j has on variable i with respect to its share of forecast error variance – is defined below:

$$\phi^g_{ij,t}(J) = \frac{\Sigma_{i,t}^{-1} \sum_{t=1}^{J-1} \left(\iota_i' \Lambda_t \Sigma_t t_j\right)^2}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \left(t_i \Lambda_t \Sigma_t \Lambda_t' t_i\right)} \quad \tilde{\phi}^g_{ij,t}(J) = \frac{\phi^g_{ij,t}(J)}{\sum_{j=1}^{N} \phi^g_{ij,t}(J)}$$

with $\sum_{j=1}^{N} \tilde{\phi}^g_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}^g_{i,t}(J) = N$, where J represents the forecast horizon and l_i a selection vector with a one on the ith position and zero otherwise. Using the GFEVD, we construct the total connectedness index (TCI) by:

$$C_t^g(J) = 1 - N^{-1} \sum_{i=1}^{N} \Phi_{u,t}^g(J) \tag{3}$$

The ways in which an initial shock from one variable transmits to other variables are demonstrated through this method. We begin by considering the ways in which the shock in variable i percolates to other variables j, in what is known as the total directional connectedness to others:

$$C_{i \to j,t}^g(J) = \sum_{j=1, l \neq j}^{N} \Phi_{j,t}^g(J) \tag{4}$$

We then measure the transmissions received by variable i from variable j, in what is known as the total directional connectedness from others:

$$C_{i \leftarrow j,t}^g(J) = \sum_{j=1, i \neq j}^{N} \Phi_{ij,t}^g(J) \tag{5}$$

Finally, we calculate the net total directional connectedness, derived by subtracting the total directional connectedness to others from the total directional connectedness from others. This is the sum of influence which variable i transmits on the network of economic sectors in the study.

$$C_{i,t}^g = C_{i \to j,t}^g(J) - C_{i \leftarrow j,t}^g(J) \tag{6}$$

The equation above indicates that a net negative positive sum of the total directional connectedness indicates that variable i transmits influence on the network and is the higher influencer rather than the one being influenced by the network. On the contrary, a net negative sum of the total directional connectedness indicates that variable i is influenced by the network.

Nonetheless, we are also concerned about the "net pairwise directional connectedness (NPDC)" – because there is the possibility that there are other dynamics not detectable from the net sum of total directional connectedness as it is an aggregated measure of the network. Thus, we use a different calculation to generate the bilateral transmission process between variable i and variable j:

$$\mathrm{NPDC}_{ij}(J) = \widetilde{\phi}_{ji,t}(J) - \widetilde{\phi}_{ij,t}(J) \tag{7}$$

If $\mathrm{NPDC}_{ij}(J) > 0 \big(\mathrm{NPDC}_{ij}(J) < 0\big)$ variable i is driving (driven by) variable j.

Next, we run several robustness analyses across a 200-day rolling window VAR and a quantile VAR (QVAR) (Antonakakis *et al.*, 2019). The 200-observation rolling window is selected because of its close approximation to the TVP-VAR results (Diebold and Yılmaz, 2009, 2012). Nonetheless, the VAR model is sensitive to outliers. This is caused by the VAR's conditional mean-based procedure which is based on an equation-by-equation ordinary least squares used to estimate the unknown parameters. Therefore, to overcome the outliers, we focus on conditional median-based estimation instead, and in doing so, we estimate each equation using quantile regression.

3. Data and descriptive statistics

To investigate the interconnectedness between sectoral price return index, we use daily data from 10 May 2005 to 24 February 2021, which spans many volatile phases and disturbances,

including sharp swings in commodity futures markets and significant global incidents such as the GFC in years 2008–2009, the oil price crisis that started in 2014 and the COVID-19 global pandemic. The economic sectoral price index includes energy, finance, industry, technology, consumer cyclical, consumer non-cyclical, basic materials and utilities. This business sector price index classification is based on the data provided by Refinitiv Datastream. The study period includes 4,159 observations for each variable. We use logarithmic price returns index to estimate the spillovers and analyse the connectedness. For daily log-returns, it is calculated as the first log differences of closing prices of price index for each sector.

Figure 1 shows the dynamics of the eight business sectors price returns index in Malaysia's stock market. As illustrated in Figure 1, the index return series becomes more volatile during periods of high uncertainty about future economic growth and market performance as a result of the impact of the GFC in 2008 and the COVID-19 pandemic in 2020, respectively. These are characterised by significant fat tails during these intervals for all business sectors.

The descriptive statistics for the price return index series for each sector are shown in Table 1. We discover that the highest mean of index return is recorded by the basic material sector with 0.024, followed by consumer non-cyclical sector with a mean return of 0.023 and

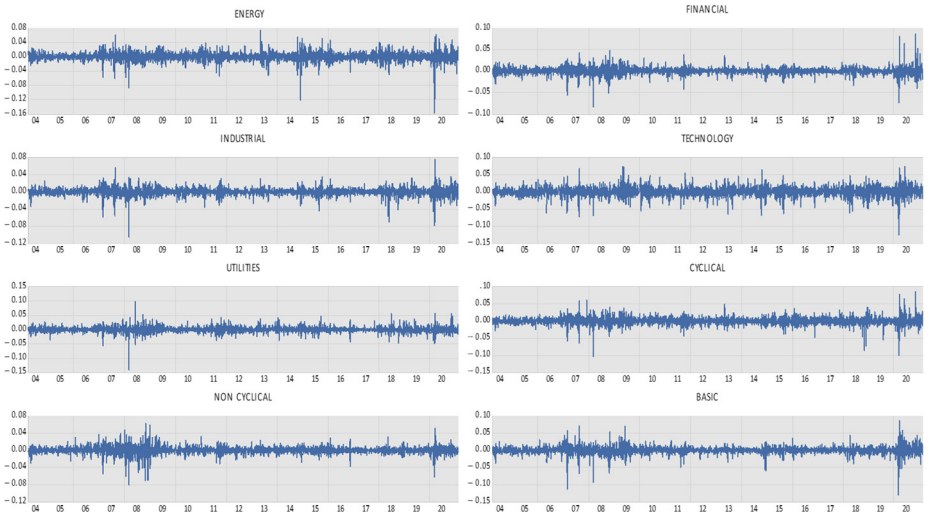


Figure 1.
Price return index for each sectors

Statistics	Energy	Financial	Industrial	Technology	Utilities	Cyclical	Non-cyclical	Basic
Mean	0.016	0.019	0.002	0.021	0.013	0.001	0.023	0.024
Variance	1.416	0.687	0.816	1.82	0.927	1.154	0.721	1.195
Skewness	-1.14^{***}	-0.11^{***}	-1.16^{***}	-0.44^{***}	-0.42^{***}	-0.56^{***}	-0.64^{***}	-1.09^{***}
Kurtosis	15.84^{***}	14.73^{***}	13.38^{***}	5.70^{***}	17.32^{***}	10.61^{***}	11.02^{***}	15.66^{***}
JB	$44{,}417.9^{***}$	$37{,}639.3^{***}$	$31{,}965.1^{***}$	$5{,}771.8^{***}$	$52{,}116.2^{***}$	$19{,}733.1^{***}$	$21{,}340.5^{***}$	$43{,}340.3^{***}$

Notes: ***denote significance at 1% significance levels

Table 1.
Summary statistics

technology sector with a mean return of 0.021. The consumer cyclical sector recorded the lowest average mean return of 0.001. Nevertheless, all return series show excess kurtosis, displaying elements of leptokurtosis. All series also show negative skewness, while the normality test of Jarque–Bera demonstrates that non-normal distribution exists in all the series.

4. Empirical result

4.1 Connectedness from time-varying parameter vector autoregressive

This section presents the empirical result based on the discussed methodology. Table 2 provides the average dynamic connectedness measures using the TVP-VAR approach for each series. From the table, we observe that industrial sector spillovers recorded the highest value of forecast error variance. When compared to off-diagonal elements, diagonal elements receive higher values. For example, industrial sector explains 12.07% of the forecast error variance of the energy sector and 13.42% of the financial sector. The lowest contribution is observed from the industrial sector to utilities sector, with 11.12%. On the contrary, the energy, financial and utilities sectors each explain 10.11%, 12.85% and 7.97% of industrial sector's forecast error variance, respectively. This indicates that the industrial sector is the primary net transmitter of spillovers in Malaysia's stock market across multiple economic sectors, as it demonstrates itself as the net pairwise transmitter of spillovers to the energy, financial and utilities sectors, respectively.

Furthermore, the industrial sector is the primary source of price return index spillovers, followed by the financial sector, basic material sector and consumer cyclical sector, respectively. The negative value of NET shows the net receiver, which means, the utilities sector becomes the main net receiver of price return index spillovers followed by technology, consumer non-cyclical and energy sectors, respectively. The TCI indicates that the average influence of all other variables on one variable's forecast error variation across time is 66.7%. This means that returns in one business sector affect returns in other business sectors. Thus, returns in different business sectors are not independent of one another; whereas the average effect of one business sector to another business sector is 66.7%. The result may imply that network theory can explain the connection and link between various business sectors, as well as the direct direction between them.

Table 2.
Full-sample connectedness table

	From								
Sectors	Energy	Financial	Industrial	Technology	Utilities	Cyclical	Non-cyclical	Basic	From others
Energy	34.17	11.19	12.07	7.72	6.57	9.61	8.13	10.54	65.83
Financial	9.88	28.95	13.42	7.64	7.9	11.81	9.92	10.47	71.05
Industrial	10.11	12.85	27.97	9.24	7.97	10.8	9.64	11.42	72.03
Technology	8.49	9.65	12.24	39.05	5.04	8.06	6.88	10.58	60.95
Utilities	7.6	10.56	11.12	5.27	39.01	9.24	9.3	7.9	60.99
Cyclical	9.03	12.68	12.14	6.92	7.52	32.03	9.75	9.93	67.97
Non-cyclical	8.41	11.52	11.76	6.23	7.91	10.63	33.21	10.33	66.79
Basic	9.94	10.94	12.8	8.95	6.21	9.81	9.33	32.02	67.98
To others	63.46	79.39	85.55	51.98	49.13	69.97	62.95	71.17	TCI
Net	−2.37	8.34	13.52	−8.97	−11.86	2	−3.85	3.2	*66.7*

Notes: Values reported are variance decompositions for estimated TVP-VAR model. Variance decompositions are based on 10-step-ahead forecasts

Next, we look at the results for the dynamic TCI as shown in Figure 2. This spillover plots are based on various connectedness measures (TVP-VAR, VAR and QVAR) as described in Section 2. The overall connectedness index has a high range of variance, making it very vulnerable to major economic shocks. The highest value of TVP-VAR reaches more than 80% between years 2007 and 2009 and across year 2020.This shows that high spillovers occur during the global financial crises of 2008–2009 and the shock event of COVID-19 pandemic in 2020. This finding is consistent with Polat (2021) that total return connectedness is high for the BRICS (Brazil, Russia, India, China and South Africa) and Turkish stock markets in 2020. Apart from that, it can be observed that there are also sharp fluctuations around years 2015 and 2018, respectively. This might be due to the shock events of rapid fall in oil prices in 2015 and trade uncertainty between China and the USA in 2018 which caused impacts to the sectoral price index. It is important to note that this dynamic of TCI shows that there are certain events (e.g. economic shocks) that have a particular impact on their interconnectedness. This highlights the need to examine the time-varying behaviour of connectedness measures to fully comprehend the sectoral index return transmission mechanism among business sectors.

In Figure 3, the spillovers *TO* other business sectors emergent from the price return index is visible. The sum total of connectedness in its dynamic directionality can be seen here. Contrastingly, in Figure 4, the spillovers *from* other business sectors stemming from the price return index is shown. The sum total of connectedness in its dynamic directionality can also be seen here. Both figures demonstrate how the spillovers respond disparately over time whether or not they arise *from* or *to* the network of other business sectors. Heterogeneity is the distinct feature observed here in the directionality, similar to the one observed in dynamic total connectedness. Similar to what we have seen in Figure 2, all the business sectors exhibit patterns of spillover transmissions which fluctuate over the period of time. We see that the transmission of spillovers from each sector to others increased between years 2006 and 2007 which in turn, created an impact to the sectoral price index for most of the business sectors. The impact of COVID-19 in 2020 also shows the value of connectedness index had increased sharply for all sectors, which suggests that the index return responded quickly to the shock event. We also observed that the industrial sectors provide the largest area, from 50 to more than 100 of the value of TVP-VAR, VAR and

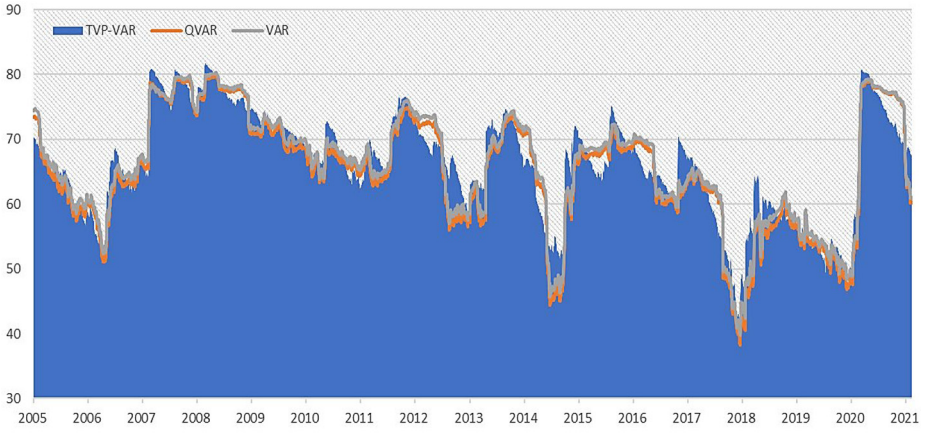
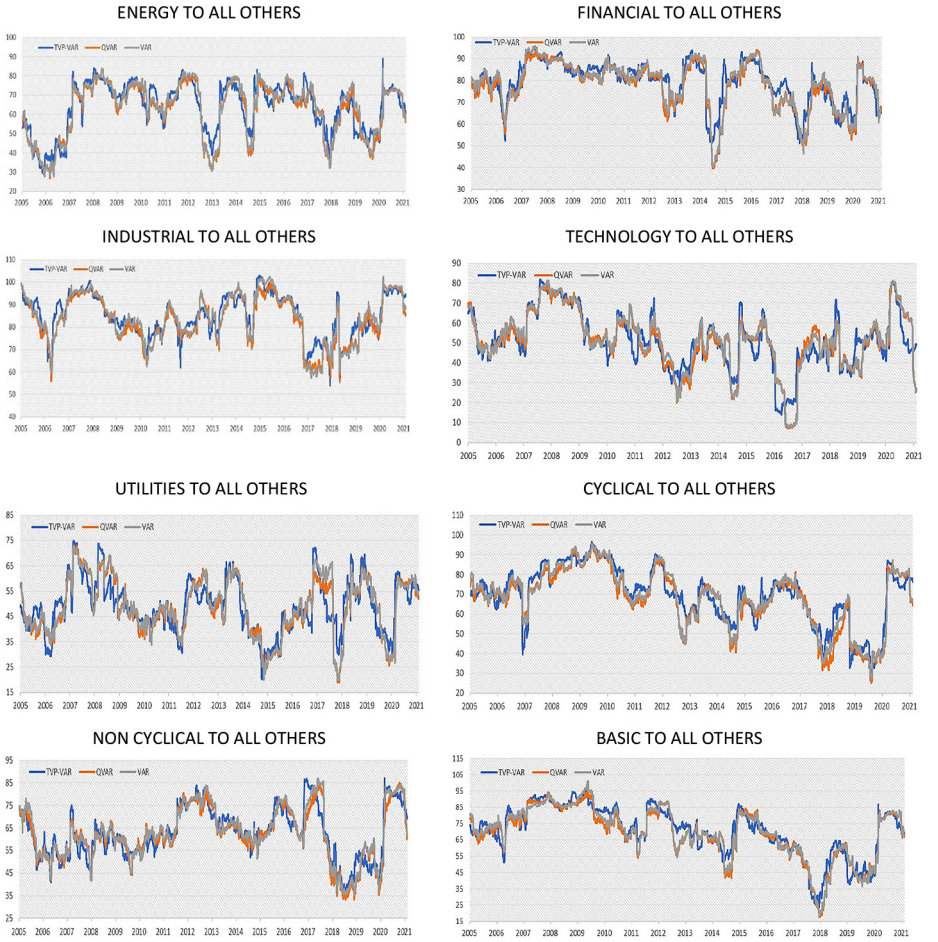


Figure 2.
Dynamic total connectedness

Note: Blue line indicates the total connectedness index (TCI) based on the TVP-VAR model

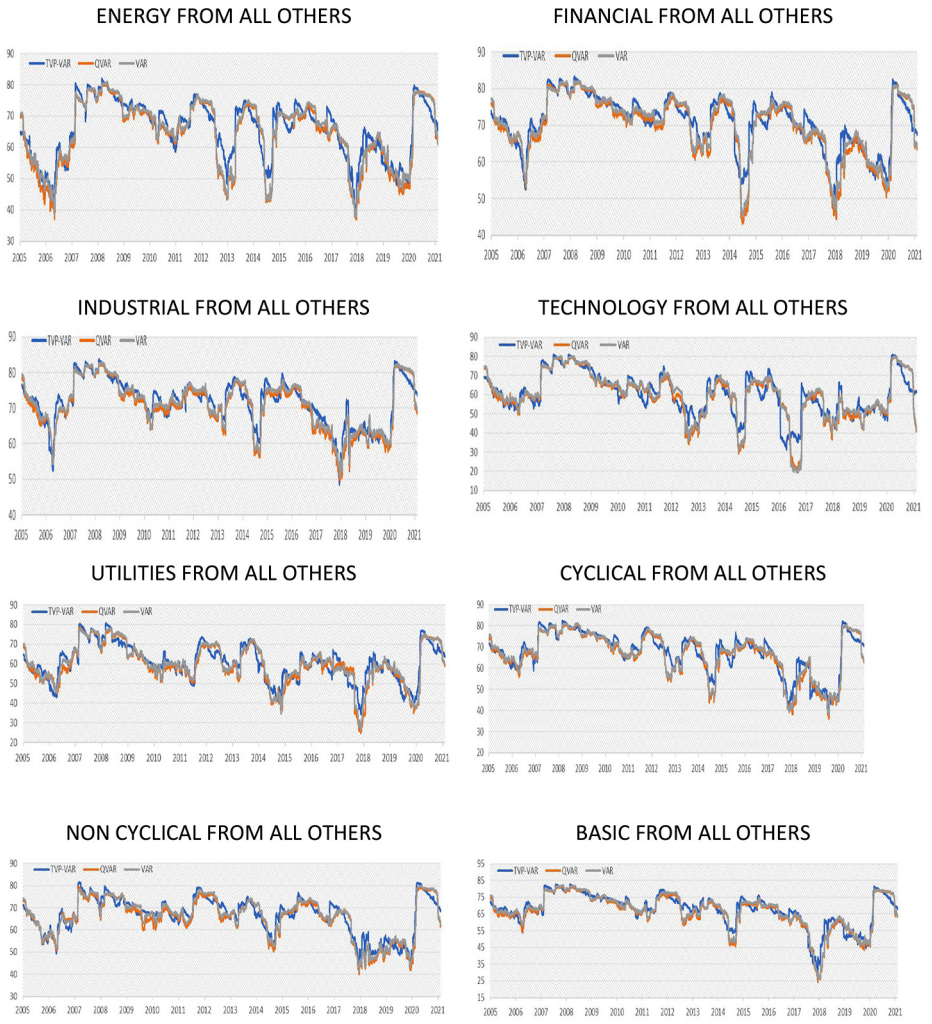


Notes: The blue line indicates the connectedness emergent from the directionality to each of the multiple business sector measured using our main TVP-VAR model, i.e. equation (4). Robustness is indicated from the grey line and red line, respectively. The grey line arises from the rolling-window measurement based on the VAR model (VAR), and the red line is measured from the rolling-window Quantile VAR model (QVAR). (Readers are referred to the web version of our journal for a full interpretation of the colour references in this figure legend.)

Figure 3.
Total directional connectedness *TO* others

QVAR, respectively. This suggests that industrial sectors play an important role as transmitter of spillovers to other economic sectors. Overall, we can conclude that the magnitude of price return index spillovers transmission varies over time and has a large swing during shock events.

In Figure 4, the total sum of spillovers that each business sector receives (*FROM*) is presented. It is clearly shown here how most of the business sectors are constantly on the receiving end of the spillovers throughout the entire period of the economic crises (2007–2008, 2018) and COVID-19 pandemic (2020), respectively, than during the period when shock



Notes: The blue line indicates the connectedness emergent to the directionality of each business sector from all the multiple business sectors measured using our main TVP-VAR model, i.e. equation (5). Robustness is indicated from the grey line and red line, respectively. The grey line arises from the rolling-window measurement based on the VAR model (VAR), and the red line is measured from the rolling-window Quantile VAR model (QVAR). (Readers are referred to the web version of our journal for a full interpretation of the colour references in this figure legend.)

Figure 4.
Total directional connectedness *FROM* others

events are absent. For example, from 2008 to 2012, the TVP-VAR graph for the energy sector remained relatively stable between 60 and 80. However, it increased dramatically from 48 to 80 in 2020. Nonetheless, we have seen previously that most business sectors demonstrated a substantial increase in their transmission of spillovers. This denotes a

significant rise in stock market efficiency. Interestingly, we also observed that industrial sectors provide contrast results as shown in Figure 3 where the value of all three measurements are between 50 and 85. This suggests that the industrial sector receives less spillovers than it transmits.

Figure 5 shows the dynamic net total directional connectedness for all business sectors. We see that energy, technology, utilities and non-cyclical sectors are mostly net receivers of spillovers during our sample period, whereas the utilities sector is receiving the highest

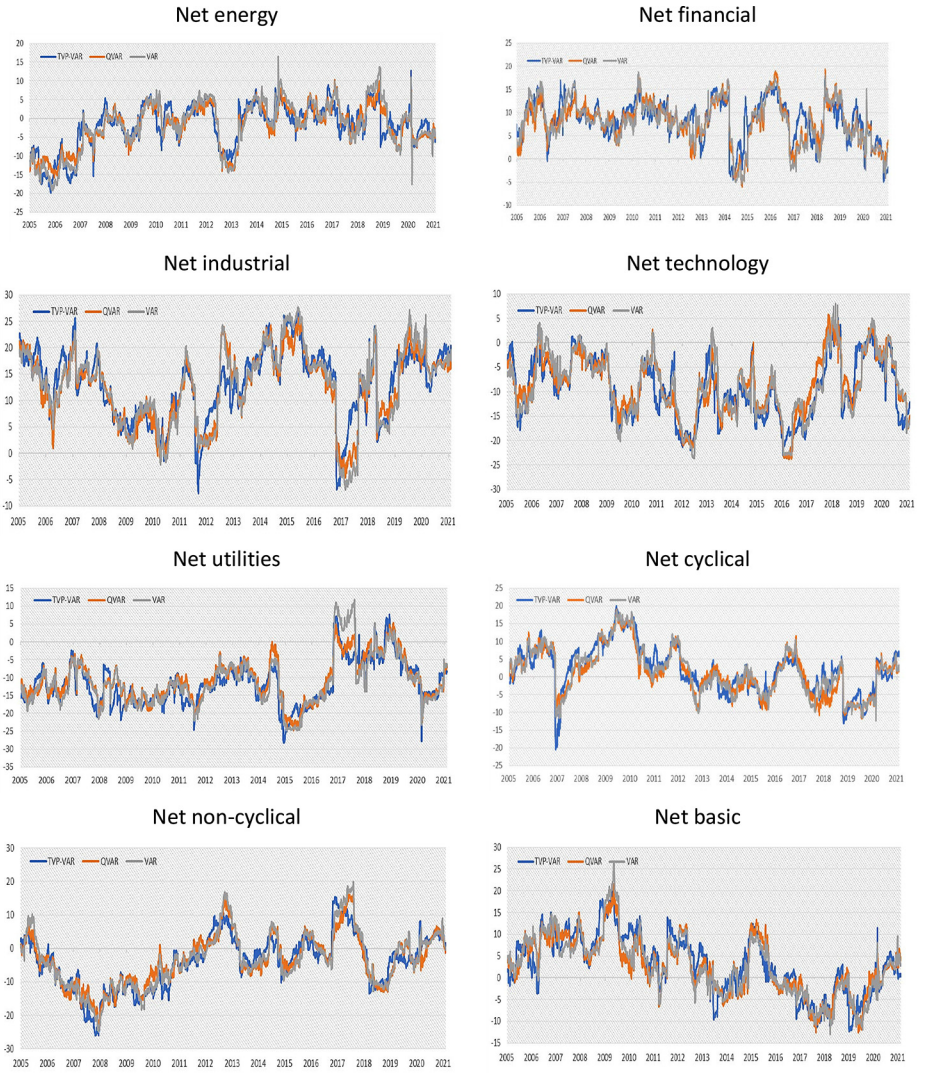


Figure 5.
Net total directional connectedness

Notes: The figure shows the net total directional connectedness based on TVP-VAR together a rolling-window VAR model (VAR) and a rolling-window quantile VAR (VAR)

spillover than other sectors. The industrial sector recorded mostly positive value throughout the sample period which suggests that it is the largest transmitter of the index return to other business sectors. This result is supported by Tiwari *et al.* (2020) who found that returns on the industrial price index transmit more than they receive from all of the other markets (food, beverage, agricultural, metal, fuel). Furthermore, Lee *et al.* (2020) documented that the number of COVID-19 cases and deaths in the US market had a substantial link with the Industrial Product and Utilities sectors' performance on Bursa Malaysia. However, because of the limitation of that research, it cannot identify which sector became transmitter or receiver of the price index spillovers.

The findings are consistent with tail risk spillover theory, which has been discussed in a number of papers. Numerous studies have shown the interconnectivity of tail risk at various aggregation levels, including national, industry and firm levels. The tail risk connection between countries is, arguably, the most well-known theme in this research. Examples are Kenourgios *et al.* (2011) and Cappiello *et al.* (2014). According to studies on tail risk linkages at the industrial level, the financial industry tends to dominate (Adams *et al.* (2014), Wang *et al.* (2017). Studies on tail risk correlations at the firm level (Betz *et al.*, 2016; Billio *et al.*, 2012) disproportionately concentrate on financial firms. The aforementioned discussion demonstrates that, aside from research in the financial sector, the industry and business levels have paid little attention to the tail risk connectivity (Nguyen *et al.*, 2021). Our study contributes to this strand of literature by constructing a complete tail risk connectedness network among all industries in the Malaysian economy.

4.2 Robustness test

As mentioned in Section 2, we also perform some robustness analyses. In addition to the TVP-VAR-based connectedness results, we also present results from the 200-day rolling window VAR and the QVAR. This window size is also used as a benchmark model in Diebold and Yılmaz (2009, 2012), Antonakakis *et al.* (2019) and it closely matched the TVP-VAR results. It must be made clear here, however, that although all three models of calculations share similarities, the TVP-VAR model performs faster adjustment as compared to its alternatives. This was also emphasised by Antonakakis and Gabauer (2017), Korobilis and Yilmaz (2018) and Antonakakis *et al.* (2019).

5. Conclusion and implications

In this study, we examined the sectoral price return index spillovers across different economic sectors in Malaysia stock market over the period of 10 May 2005 to 24 February 2021 based on a TVP-VAR methodology. Our empirical results indicate that spillover price returns in the economic sector are a key source of changes in the price index. We found that the magnitude of price return index spillovers varies over time, with peaks occurring during the COVID-19 pandemic in 2020. Furthermore, the dominant transmitters of price return index spillover is the industrial sector, while the utilities sector is the dominant receivers of price return index spillovers. This finding contributes to the robust body of literature in this field which proposes that the determination of shock-transmitters and shock-receivers will intensify the effectiveness of portfolio management for market participants.

As posited by Kang *et al.* (2019), relying on either a long or short portfolio strategy based on shock-transmitters and receivers, respectively, will enable investors to control risks in their portfolio. They further suggest that a strategy, which is long on shock-receivers and short on shock-transmitters, will provide better hedging effectivity while also necessitating lower expenses. Thus, our research finding is useful for investors when choosing to buy (long) stock in the utilities sector or sell (short) stock in the industrial sector. However, there

are several caveats with this idea. Firstly, short selling restriction is imposed in Bursa Malaysia; hence, it effectively limits the practicability of this strategy. Second, in a Muslim-majority country like Malaysia, adherence to the Islamic principles means that investment in non-Shariah compliant stocks is not permitted among those who strictly follow faith-based instruments. Third, there are also differences in opinions (khilaf) about the permissibility of short selling. Most scholars view that such transaction is invalid because of the element of uncertainty (gharar). In Malaysia, however, the Shariah Advisory Council of the Securities Commission Malaysia deems Regulated Short Selling as Shariah-compliant as the implementation of Securities Borrowing and Lending can mitigate gharar. Regardless, the use of proper diversification strategies such as mean-variance or Black–Litterman model with complex-constrained optimisation (to capture factors such as round lot, trading costs and cardinality constraints) are also important to ensure that the generated portfolios can yield the best risk-return trade-off along the efficient frontier. Investors can also consider combining utilities stock and commodities, which, in comparison to other combinations, can provide a larger return (lower cost) potential over time.

Portfolio managers should use the strategies in the same way. They can factor in the fact that industrial sector is the primary transmitter of price return index spillover, whereas the utilities sector is the dominant receiver. Indeed, diversification would yield better return per risk if the sectors were less affected by spillover that are dominant in portfolios. They should also look at the spillover on a firm level for the most impacted sectors, taking into account the market capitalisation of the companies within, assuming that small businesses will be more affected by the pandemic than larger businesses. To alleviate country-level systematic risk, return and volatility spillovers among advanced economies and emerging markets (for example, see Aziz *et al.*, 2022) can be considered for portfolio formation, allowing for international diversification benefits.

It is important to note that the preceding argument is valid only if the market is said to be efficient. Existing studies on the efficiency of the financial markets, including Bursa Malaysia, however, remain mixed (Gillet and Renault, 2019; Hanauer *et al.*, 2022; Nor and Wickremasinghe, 2017; Nor and Zawawi, 2020; Shahzad *et al.*, 2017; Wang *et al.*, 2022, to name a few). If there are indeed predictable patterns and/or intrinsic value-market price departures, investors should instead use proper strategies such as fractals, momentum, moving averages and oscillators to discern patterns in the financial time series, or use price multiples and dividend discount models, among others, to find undervalued stocks and generate abnormal return. High frequency and big data as well as machine learning can be applied to capture the non-linear dynamics in the variables. Furthermore, investors should pay great attention to the consequences of shock events likes COVID-19, as well as their potential negative effects, recognise potential hazards and proper stop-loss mechanisms.

Our results have important policy implications. Our findings suggest that cross-sector connectivity was high during the GFC of 2007–2008, and throughout the year 2020 of the COVID-19 pandemic, but low during normal economic conditions. This implies that when the economy experiences extreme negative movements, all eight sectoral connectedness increased. Therefore, the findings could be used to assess the efficacy of policies. The analysis of pairwise spillovers between multiple sectors is significant in helping policymakers design the best targeted policies for each business sector. In our findings, for example, the industrial sector's net connectedness is positive, and it has become one of the most important contributors of index return spillover shocks to other sectors. This means that industrial reforms have a positive impact on other sectors. Policymakers will find that the insights presented in this research will support the formulation of sector-specific policy reforms.

Policymakers, in particular, can respond in a variety of ways. To begin, increasing transaction costs should be considered to decrease the impact of spillover during the pandemic era, albeit this may result in a series of long-term difficulties. These costs can also curb speculators from exploiting mispricing and hence promote market efficiency, allowing investors to make informed decisions. Short selling can also be widely permitted (with some limitations to ensure efficiency and compliance with Islamic principles) to allow for arbitrage strategies and provide a more accurate forecast of future asset prices. As a result, it improves pricing possibilities in both the stock and commodities markets and potentially reduce the herding behaviour between them.

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Corresponding author

Hazrul Shahiri can be contacted at: hizuan@ukm.edu.my

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