Pacific-Basin Finance Journal 67 (2021) 101554

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

Policy uncertainty spillovers and financial risk contagion in the Asia-Pacific network

Yang LI, Jingqiu Luo, Yongmu Jiang *

Sichuan University, China

A R T I C L E I N F O

JEL classification:
D85
E66
G15

Keywords:
Economic policy uncertainty (EPU)
Financial risk
Spillover effects
Complex network analysis

A B S T R A C T

This study investigates the impact of policy uncertainties on the financial markets in the Asia-Pacific region using a complex network analysis. A new daily economic policy uncertainty (EPU) index was build using Global Database of Events, Language, and Tone data. The results show that China is the Asia-Pacific EPU network's center and the US stock market is the most important intermediary in the financial network. We also construct an uncertainty spillover network by combining the EPU and financial networks. The findings reveal that the US EPU and SPX indexes are the most important sources of uncertainties in the spillover network. The network dynamics show that during the US-China trade war, the correlations between the EPU and financial networks decreased significantly, while the COVID-19 outbreak has increased the combined network's density.

1. Introduction

In recent years, the global financial markets' and economic policies' uncertainties have increased significantly (Smales, 2020). Some major events, such as the United States' launching of "301 survey" against China, may have reversed the directions of policy uncertainties' spillovers between China and the United States and that no one wins in trade conflicts (Jiang et al., 2019). Moreover, the COVID-19 pandemic has created an enormous uncertainty shock, similar in magnitude to the rise in uncertainty during the Great Depression (Baker et al., 2020). This paper aims to study the impact of policy uncertainty on financial markets in the Asia-Pacific region, especially during the COVID-19 pandemic, when uncertainty and financial market turmoil have risen.

The COVID-19 pandemic has a huge impact on economic activities. The pandemic has caused the disruption of supply chains (Tisdell, 2020; Qin et al., 2020a, 2020b, 2020c), and has reduced the density and connectivity of world trade (Vidya and Prabheesh, 2020). The production cost has increased to varying degrees (He et al., 2020), and the manufacturing industry suffers the most negative impact (Gu et al., 2020). The pandemic also has a negative impact on company performance, especially when the company's investment scale or sales revenue is small (Shen et al., 2020). On the other hand, the pandemic has significantly decreased the mobility of households (Li et al., 2020), reduced their labor force participation (Yu et al., 2020), reduced their consumption (Liu et al., 2020a, 2020b, 2020c) and made their investment decisions more risk-averse (Yue et al., 2020; Yan and Qian, 2020). The exchange rate market has also been greatly impacted, such that daily data of the COVID-19 can predict the volatility and yield of currency exchange rates (Iyke, 2020a, 2020b, 2020c), and the overall bubble activity in the exchange rate market intensified while the market efficiency was relatively reduced (Narayan, 2020a, 2020b, 2020c). The pandemic has also affected the energy market (Ertuğrul et al., 2020; Polemis and Soursou, 2020; Gil-Alana and Monge, 2020), significantly

* Corresponding author.
E-mail addresses: liyangecon@scu.edu.cn (Y. LI), jiangyongmu@163.com (Y. Jiang).

https://doi.org/10.1016/j.pacfin.2021.101554
Received 18 September 2020; Received in revised form 9 April 2021; Accepted 12 April 2021
Available online 14 April 2021

increased the volatility of the oil market (Narayan, 2020a, 2020b, 2020c; Devpura and Narayan, 2020), changed the elasticity of investor sentiment (Huang and Zheng, 2020), affected the producers' behaviors (Iyke, 2020a, 2020b, 2020c), and may cause the decline of the oil prices (Prabheesh et al., 2020; Qin et al., 2020a, 2020b, 2020c).

While the world is responding to the unprecedented economic and social destruction caused by the COVID-19, financial markets have been severely affected as well. Yang and Deng (2021) studied 20 OECD countries and found that the increase in the number of confirmed cases have a significant negative impact on stock market returns, and government interventions have amplified such negative impact. Haroon and Rizvi (2020) studied emerging stock markets and found that the increase of the number of confirmed cases is related to the deterioration of financial market liquidity. Phan and Narayan (2020) pointed out the stock market overreacted to the evolution of COVID-19 at first, but will correct itself as the rescue policies are implemented.

Asian markets have experienced more negative abnormal returns compared to other markets (Liu et al., 2020a, 2020b, 2020c). Topcu and Gulal (2020) found that the impact of the epidemic is the largest in emerging Asian markets. Gil-Alana and Claudio-Quiroga (2020) found that the pandemic had a short-term effect on Nikkei 225 Index. However, for the Kospi and Shanghai Shenzhen indexes, the pandemic shock is permanent. Mishra et al. (2020) investigated the impact of COVID-19 on the Indian financial market and found that stock returns on all indexes during the COVID-19 outbreak were negative. Sharma (2020) found that there was a significant relationship between Asian regional stock market volatility and national stock market volatility. During the pandemic, emerging market portfolios reversed, and the withdrawal of foreign portfolio investment led to a sharp decline in emerging stock markets. Prabheesh (2020) found that during the COVID-19 period, there is a one-way causal relationship from Foreign Portfolio Investors to stock market returns in India. Lan et al. (2020) found that the outbreak has increased systemic risks in China's financial markets. Iyke (2020a, 2020b, 2020c) found that the pandemic has had a positive impact on EPU in China and South Korea, where most manufacturing activities are located in these countries. Therefore, the increasing uncertainty in these countries will not only disrupt economic activities there, but also disrupt economic activities in other parts of the world through interconnected global supply chains.

Besides Asian countries, the research target of this paper also includes important countries in the Pacific region, because these countries (such as the United States) have a pivotal position in the regional economy. One of our goals is to fully capture the correlations and dynamics of EPUs in the Asia-Pacific region. To achieve this, we expand the existing literature on EPU by constructing a complex network and studying the network topology. We also build a complex network of stock markets to represent the financial system in the Asia-Pacific region. Additionally, we study risk transmission or contagion from the economic policy network to the financial network by using partial correlations to construct an uncertainty spillover network.

The economic rationales behind the strong correlation between EPUs and the performance of financial markets have been thoroughly discussed by many theoretical works such as Bloom (2009), Pástor and Veronesi (2012, 2013). Most of the exiting literature considers the United States to be the main source of the spillover effect (Klößner and Sekkel, 2014; Christou et al., 2017; Chuliá et al., 2017; Li and Peng, 2017; Hu et al., 2018; Huang et al., 2018; Chiang, 2019). However, our findings show that China is the center of EPU spillovers in the network, consistent with Bai et al. (2019) results that highlighted China's increasing global economic and political influences since 2017. We also find that in the financial network, Hong Kong is the most important link in Asia and the US stock market serves as an important intermediary between American and Asian markets. Furthermore, our uncertainty spillover network combines policy uncertainties and stock markets, showing that US's EPU and SPX indexes are the most important sources of uncertainties in the combined spillover network. The network dynamics also show that during the US-China trade war, the correlations between the EPU and financial networks have decreased significantly, while the COVID-19 outbreak has increased the density of the whole network.

Although Marfatia et al. (2020) has constructed a static and dynamic EPU network across 17 developed and emerging economies, their network is built using monthly EPU indexes that may smooth out a lot of important information, especially when studying EPU's impact on high-frequency data such as stock market indexes. Because of daily EPU indexes' availability, we choose to build a new index. As such, one of our contributions lies in our development of a new daily EPU index of 17 Asia-Pacific economies using the Global Database of Events, Language, and Tone (GDELT) Summary in Global Online News Coverage, following Baker et al.'s (2016) exact standardization and normalization procedures. Another contribution stems from our attempt to construct an uncertainty spillover network of the Asia-Pacific stock markets and economic policies by combining a complex network analysis with partial correlations, based on Kenett et al.'s (2010) method. To the best of our knowledge, this paper is the first to study EPU's impact on stock markets under the framework of a complex network analysis. We also demonstrate that our results are robust by constructing two different kinds of networks, and the central network and the dependent network both reach similar conclusions.

The remainder of the paper is organized as follows. Section 2 explains how we built the daily EPU index and constructed the Asia-Pacific region's EPU network and Section 3 explains the stock market network's construction. Section 4 combines the two and assesses the spillover effect between the EPU and stock market networks. Finally, Section 5 offers our concluding remarks and some policy implications.

2. EPU network analysis

2.1. Daily EPU index

We follow Baker et al.'s (2016) method to construct a daily EPU index for 17 Asia-Pacific countries and regions that have available data from January 1, 2017, to June 30, 2020. We search GDELT's Global Online News Coverage for articles that contain terms of the three following categories: (1) economy and economic, (2) uncertainty and uncertain, and (3) policy-related terms. As those articles may present news from other countries, we also add a fourth criterion: (4) specific country name. In addition, we ensure that our keywords reflect country differences. For example, we use "White House" and "Kremlin" as keywords when searching the United States and Russia, respectively. The policy keywords applicable to all countries are "policy or government or regulation or deficit or spending or budget or rate or tax or tariff". Table 1 shows the country specific policy keywords for the 17 countries/regions.

Then, we scale the number of articles each day by the number of articles that meet the fourth criteria, representing the total number of articles reporting a home country each day. We subsequently standardize the series using standard deviations, from January 1, 2017, to June 30, 2020. Finally, we normalize the index to an average value of 100 in the time period. Fig. 1 shows the daily EPU indexes for the 17 countries.

Two of the 17 countries already have daily EPU indexes, stemming from previous papers: (1) the US index (Baker et al., 2016), based on the Newsbank news aggregator (USBBD index) and (2) China's index (Huang and Luk, 2020), retrieved from 114 local Chinese newspapers (CHINAHL index). The correlation between our US index and the USBBD index is 0.49, and between our China index and the CHINAHL index is 0.31. These differences occurred mainly due to different data bases and periods used for normalization. However, our indexes tend to move together with the USBBD and CHINAHL, respectively.

We also compare the indexes of 12 countries with monthly data, available from policyuncertainty.com, by considering the daily data's monthly average as that month's EPU index. Table 2's last column shows the correlations of our index and Baker's index. Overall, Table 2 presents the descriptive statistics of our daily EPU index. Hong Kong has the highest volatility and mean values, possibly because of the recent political turmoil. For all countries, the distribution of indexes has positive skew and hyper kurtosis values, and the Jarque-Bera statistics indicate that the daily EPUs for all countries are non-normally distributed.

We also divide the full sample period into three phases: January 1, 2017, to March 22, 2018 (before the US-China trade conflict); March 23, 2018, to January 14, 2020 (when the US-China rivalry began); and January 15, 2020, to June 30, 2020 (after the COVID-19 outbreak). As shown in Table 2, almost all countries' and regions' EPU indexes are increasing overtime, especially after the COVID-19 outbreak.

2.2. EPU centrality network

We first use the Minimum Spanning Tree (MST) method to study the EPU network's centrality. We consider each country as a note in the network, and as our daily EPU indexes follow a non-normal distribution, we adopt Kendall's τ to calculate $C(i,j)$, indicating the correlation between note i and note j. Then, we convert the correlation into distance $dis(i,j) = \sqrt{2(1 - C(i,j))}$, and use Prim's algorithm to construct the MST network that connects all nodes with minimum total edge weight and without closed loops.[1]

Fig. 2 shows the static results of the full sample and three sub-sample periods, illustrating the network's clear core structure. The findings indicate that the EPUs of countries with close geographical locations tend to be more closely related, consistent with the results of Balli et al. (2017), who used a monthly EPU index. China, on the other hand, has become the network's most important node in all sample periods and plays a crucial role in EPU connectivity across the Asia-Pacific region.

2.3. EPU dependency network

Kenett et al. (2010) built a dependency network using partial correlation technology, accounting for the influence of intermediate variables according to the partial correlation between source and target nodes. The approach is data-driven and semi/non-parametric. Following their method, we calculate the first-order partial correlation between two nodes i and j, with respect to a third node k. After removing the third node's influence, we obtain the partial correlation between the two nodes.

$$PC(i,j|k) = \frac{C(i,j) - C(i,k)C(j,k)}{\sqrt{(1 - C^2(i,k))((1 - C^2(j,k))}} \tag{1}$$

We modify the method of Kenett et al. (2010) by using Kendall's τ to calculate the partial correlation $C(i,j)$,as the EPU indexes are non-normally distributed. We define

$$d(i,j|k) = C(i,j) - PC(i,j|k) \tag{2}$$

in which $d(i,j|k)$is the dependency effect of note k on the correlation $C(i,j)$.The greater the $d(i,j|k)$, the greater the influence of node k on the correlation between nodes i and j. When there is a network with N nodes, the total influence of node k on node i is expressed as $D(i,k)$.[2]

$$D(i,k) = \frac{1}{N-1}\sum_{j\neq i}^{N-1} d(i,j|k) \tag{3}$$

As such, we can study both the magnitude and direction of the network dependencies, as the dependency matrix is asymmetric. We

[1] As we are studying countries and regions that span across 20 different time zones, we must address the possible time difference effect. In the GDELT, all articles' publication times are converted to GMT standard time and updated every 15 min. As such, we do not encounter time difference issues when collecting data. We also construct two EPU network versions: (1) using the same date for countries on both sides of the Pacific Ocean and (2) introducing a day lag on the west side of the Pacific Ocean. Our results show that the network without the day lag, connects better.

[2] $D(i, k)$ includes the case when j=k. So node k's direct influence on node i, $C(i, k)$, is included in $D(i, k)$.

Table 1
Summary of country specific policy keywords.

Countries/regions	Country specific policy keywords
USA	congress or legislation or "White House" or "Federal Reserve"
Australia	senate or legislation or parliament or "Reserve Bank of Australia"
Canada	senate or legislation or parliament or "Bank of Canada"
Chile	senate or congress or reform or "Central Bank"
China	president or legislation or "People's Bank of China"
Japan	congress or legislation or "Regulation Bank of Japan"
Korea	congress or legislation or "blue house" or "Bank of Korea"
Russia	Duma or Kremlin or legislation or "Central Bank"
Singapore	legislation or "Monetary Authority of Singapore" or MAS
India	legislation or "Central Bank"
Hong Kong	"Chief Executive" or legislation or "Hong Kong Monetary Authority"
Malaysia	senate or parliament or legislation or "Central Bank of Malaysia"
Mexico	congress or legislation or "Central Bank" or reserve
Taiwan	president or legislation or "Central Bank"
Thailand	parliament or legislation or "Bank of Thailand"
Indonesia	parliament or legislation or "Bank of Indonesia"
Vietnam	president or legislation or "State Bank of Vietnam"

The differences in country specific policy keywords are mainly because of different names of legislative bodies and central banks.

calculate three indicators following Wu et al. (2020): TO (total dependency impact of one node on others), FROM (total dependency impact transmitted from other nodes), and NET (net difference between TO and FROM). Based on this, one can clearly see which country or countries play the most important role in the system. In the full sample period, the biggest uncertainty transmitters of the EPU dependency network are China and the United States, as they have the highest NET values, and the EPU originators are Australia, China, India, Indonesia, South Korea, and the United States (positive NETs), while the others are recipients (negative NETs).

Fig. 3 presents a complete drawing of the EPU dependency matrix. We can see that in the full sample period, the most important uncertainty transmitter within the Asia-Pacific region is China, consistent with the centrality network's results. The dependency network also shows the same geographical links, proving the robustness of the results. However, our results differ from Marfatia et al.'s (2020). The authors studied 17 countries (including some European countries) from 1998 to 2018 and found that the United States is the most important contributor to the global EPU overflow and that China is mostly influenced by others. One possible explanation is that our research focuses on the Asia-Pacific region since 2017 and since then, many uncertainties have originated from the US-China relationship. Nonetheless, our results are consistent with Bai et al. (2019) findings that highlighted China's upward economic strength and outside global impact, since 2017.

Table 3 reports the NET indicators in the full-sample period and three phases. We can observe the changes in roles and importance for each country in the whole network in different time periods. Nonetheless, China remains the most important contributor of uncertainties in the dependency network in all three phases.

We plot the EPU dependency network for the three phases in Fig. 4. The network's density dropped dramatically during the US-China trade conflict period. This suggests that during the trade war, the correlation between different countries' economic policies decreased. A possible explanation is that the decline in trade links reduced the EPUs' dependencies, because trade shares are highly significant in determining the magnitudes of EPU spillovers (Balli et al., 2017). Also, Chile's and Vietnam's network importance actually increased in phase two, as a result of trade diversion. Regarding phase 3, we can compare the current pandemic to the previous financial crisis, when the financial and economic pressures made countries more dependent on each other (Klößner and Sekkel, 2014). Similarly, countries now have to coordinate with each other to fight against the global COVID-19 crisis.

3. Stock market network analysis

Using the same approach, we construct the financial centrality and dependency networks for the Asia-Pacific region. We collect the daily closing prices of the 17 countries' composite stock indexes and calculate the stock market return rates for each country based on its closing prices. Table 4 presents the descriptive statistics of the finance indexes. The United States has the highest average return on equities, while Mexico has the lowest. Regarding stock market risks, Russia has the highest volatility and Malaysia the lowest. The distribution of stock market indexes in all countries, except Chile, has a negative skew and hyper kurtosis. The Jarque-Bera statistics for these countries show that the financial indexes are all non-normally distributed.

As with EPU dependencies across countries, a third market may influence the correlation between two countries' stock market returns. Therefore, we need to calculate the third country's intermediary influence in the financial network. Due to stock markets closing according to local times and the obvious time difference effect on the financial network, we employ a day lag on the west side of the Pacific Ocean when constructing the network. Table 5 shows the NET index summaries for the 17 countries in the financial dependency network throughout the full-sample period and three sub-sample periods. According to our results, the top three influencers are Taiwan, Hong Kong, and South Korea. These countries also have the biggest net influencers according to the NET index. Furthermore, Australia, Canada, Chile, China, India, Indonesia, Mexico, Russia, Thailand, and Vietnam are the net recipients of stock market fluctuations, while the other countries are originators.

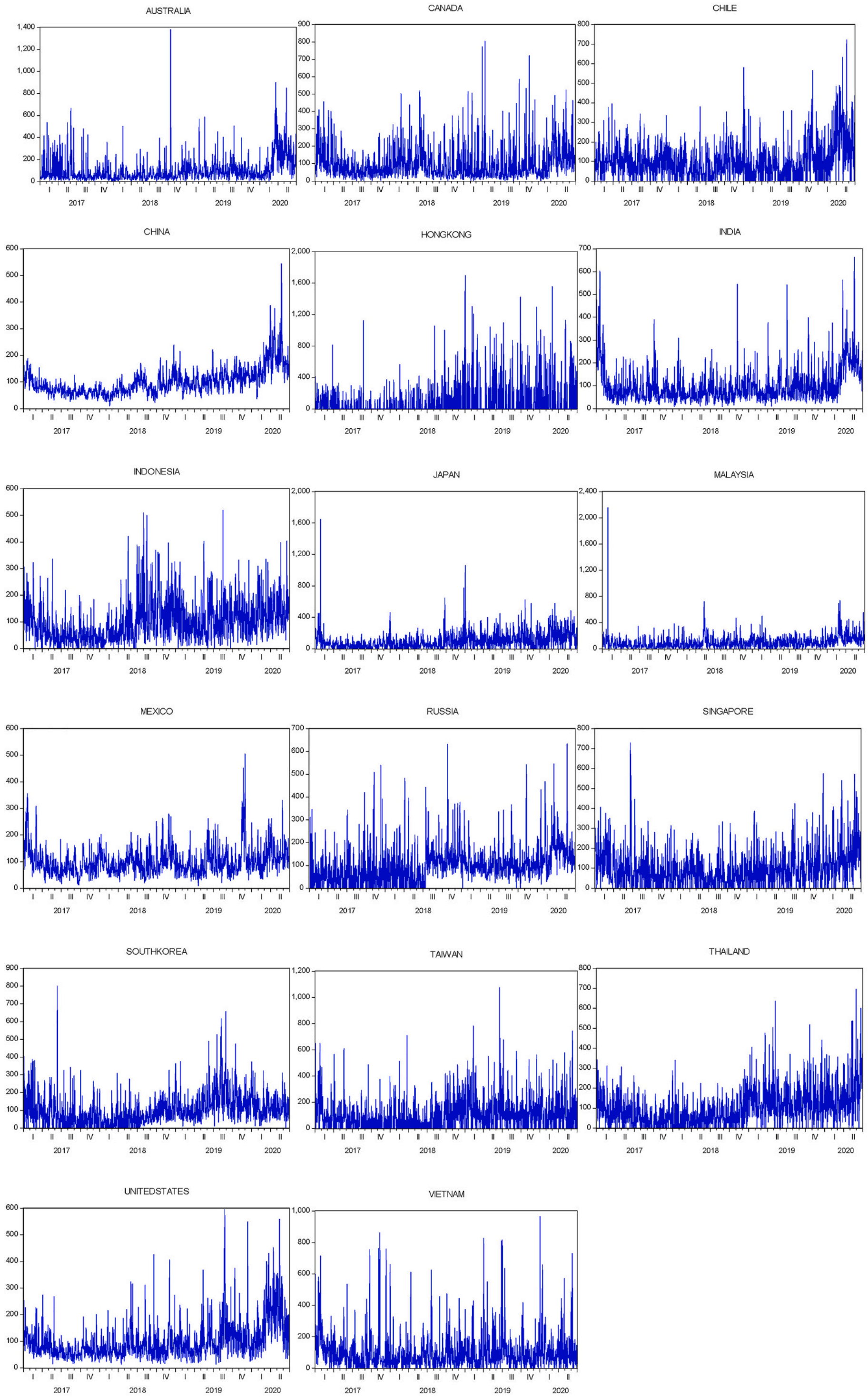

Fig. 1. Daily EPU indexes of 17 Asia-Pacific countries/regions.
The 17 Asia-Pacific countries/regions include Australia, Canada, Chile, China (Mainland), Hong Kong, India, Indonesia, Japan, Malaysia, Mexico, Russia, Singapore, South Korea, Taiwan, Thailand, United States and Vietnam. Data sets are available upon request.

Fig. 5 illustrates the financial dependency networks for the full sample period. We can see that Hong Kong, South Korea, and Taiwan have the highest importance in the financial network son the west coast of the Pacific Ocean, while on the other side, the United States holds the most influence. The financial networks, similar to EPU networks, show significant geographic segmentation.

Table 2
Descriptive statistics of the daily EPU indexes.

Countries/regions	Mean	Mean (phase 1)	Mean (phase 2)	Mean (phase 3)	Std. Dev	Skew.	Kurt.	J.-B.	Corr. w/Baker's
AUS	100	76.18	85.76	219.42	113.72	3.33	22.60	22811***	0.83
CAN	100	94.75	92.13	144.97	97.61	2.35	10.94	4530***	0.61
CHI	100	95.08	82.13	183.58	95.32	1.63	7.07	1446***	0.44
CHN	100	71.52	99.32	178.29	49.82	1.94	11.13	4320***	0.73
HKG	100	44.22	123.50	155.33	214.75	3.06	14.62	9170***	0.57
IND	100	92.58	85.66	176.31	76.01	2.28	11.17	4660***	0.69
INA	100	63.38	114.62	139.54	79.24	1.37	5.55	744***	–
JPN	100	63.32	106.63	171.20	112.42	3.68	36.68	63220***	0.77
MAS	100	75.96	94.79	184.41	107.89	6.64	108.13	597516***	–
MEX	100	92.93	99.94	118.97	53.31	1.88	9.54	3029***	0.74
RUS	100	66.26	106.06	165.66	83.02	1.80	9.18	2723***	0.67
SIN	100	99.16	85.37	159.95	95.07	1.60	7.06	1423***	0.50
KOR	100	73.42	115.00	111.35	88.35	1.83	9.57	3016***	0.93
TWN	100	76.42	112.62	112.80	122.53	2.09	9.88	3449***	–
THA	100	65.38	106.02	168.17	92.91	1.56	7.13	1425***	–
USA	100	74.72	97.51	176.94	71.45	2.28	10.61	4193***	0.87
VIE	100	99.64	98.45	107.08	117.08	3.04	15.96	10902***	–

*** indicates significance at the 1% level. Baker's Chile and Mexico indexes are updated to February 2020 and September 2019, respectively. As such, the presented correlations are partial for these two countries. There are three monthly EPU indexes for China, namely (1) Baker et al.'s (2016) CHINABBD, based on The South China Morning Post in Hong Kong, (2) David et al.'s CHINADLS, based on Renmin Daily and Guangming Daily, and (3) Huang and Luk's (2020) CHINAHL index based on 10 mainland Chinese newspapers (all three indexes are available at policyuncertainty.com). The correlations between our CHN index and the CHINABBD, CHINADLS, and CHINAHL are 0.73, 0.46, and 0.60, respectively.

Almost all countries' dependencies have increased over time and the entire financial dependency network's connections have been reinforced significantly, especially after the COVID-19 outbreak. Before the US-China trade conflict, the TOTAL indexwas1.06. This number rose to 1.90 during the trade war and surged to 3.85 after the COVID-19 outbreak. As shown in Fig. 6, the dependency network density changes also exhibit these dynamics. The United States and Canada have a significant influence in the American continent, while Hong Kong is the most important link in the Asian markets. Nonetheless, the US stock market serves as an important intermediary between American and Asia countries.

4. EPU's and Asia-Pacific stock markets' uncertainty spillover network

As shown in the EPU and financial networks, a third country can affect the correlations of EPUs or stock markets. Similarly, many studies have proved the existence of spillover effects between a country's EPU and another country's stock market. To fully capture how the spillover effects are transmitted between the EPU and financial networks, we construct an uncertainty spillover network by combining the former two networks.[3]Aside from the domestic correlation between a country's EPU and its stock market (Bloom, 2009; Pástor and Veronesi, 2012, 2013), a country's EPU can also directly affect other countries' stock markets, through international capital flows and trades, while its stock market can influence foreign countries' EPUs, especially when foreign companies are listed in that stock market.

We compute both domestic and cross-country impacts between EPU and stock markets, finding that the correlation between the two indexes can be either positive or negative. In most cases, a higher policy uncertainty has a negative impact on the stock market, but sometimes, capital will flow back to the home country or to a safer market to avoid risks, bringing up the stock market indexes. The spillover effect of country A's EPU on country B's stock market can be divided into three ways. Firstly, there is direct effect, as country A and B may have close political and economic relations. Secondly, country A's EPU may influence other countries through the EPU network, and these other countries EPUs may have influence over country B's stock market. Thirdly, country A's EPU may have spillover effect to other countries' stock indexes and then pass on to B's stock index through the financial network. The spillover effect of country A's stock market on country B's EPU is inverted.

We combine the EPU and financial networks by computing the correlation between EPU and stock market indexes. We introduce weight adjustments to all the correlations that run across networks. As we standardized and normalized the EPU data and stock market indexes, respectively, there is no need to adjust edge weights when constructing the EPU and financial networks separately. However, when combining the two networks and calculating the correlation between a country's EPU and a stock market's rate of return, weight adjustments are necessary. As Balli et al. (2017) and Trung (2019) highlighted, the two main factors behind the heterogeneity across countries, found in the spillover effects between EPU and stock markets, are trade and capital flows. We find the bilateral trade data from UN Comtrade and IMF Direction of Trade Statistics. However, as the bilateral capital flow data are missing for a number of countries in the network, we use stock market capitalization instead, obtaining the data from the World Federation of Exchanges.

[3] As EPU indexes produce data on weekends and holidays when the stock markets are not trading, we match the average weekend or holiday EPU index as well as the day when stock markets reopen, with their opening day's stock market index to capture the possible effect of policy uncertainties on stock markets over the weekend or holidays.

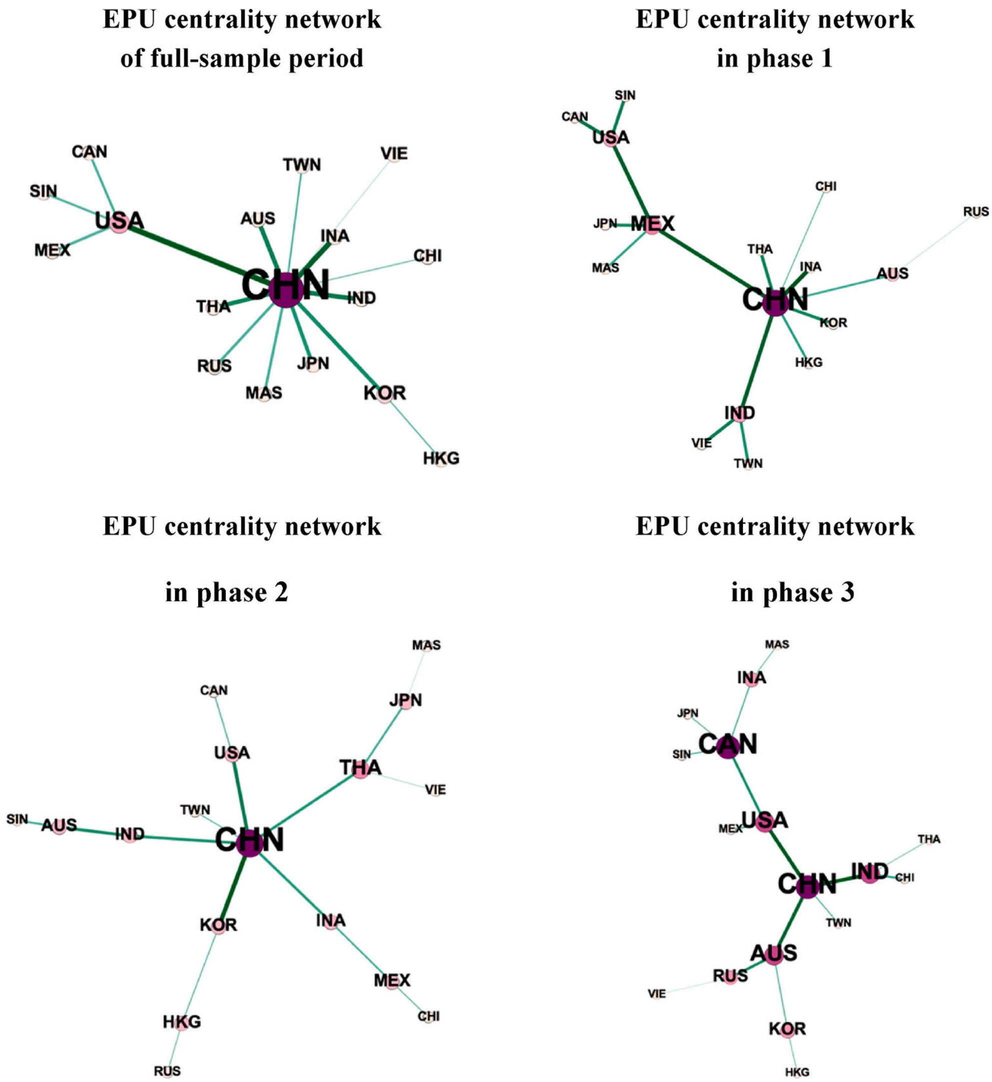

Fig. 2. EPU centrality networks.
The color depth of an edge represents the size of the impact, and the size of a node represents its importance in the network.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

We follow the methods from Bhattacharya et al. (2007), Fagiolo et al. (2010), Barigozzi et al. (2011), and others in the International Trade Network literature to determine the weights. If the spillover effect between EPUs and stock markets is cross-country, then the weight-adjusted correlation between stock market i and country k's EPU is

$$\widetilde{C}(i,k) = C(i,k)\left(\frac{Bilateral\ Trade(i,k)}{2 \times Total\ Trades} + \frac{SMC(i+k)}{2 \times Total\ SMC}\right) \tag{4}$$

If the spillover effect is domestic and stock market i belongs to country k, then

$$\widetilde{C}(i,k) = C(i,k)\left(\frac{Trade(k)}{2 \times Total\ Trades} + \frac{SMC(k)}{Total\ SMC}\right) \tag{5}$$

where *Bilateral Trade* (i, k) is the export from country k to country i, plus the exports from country i to country k. *SMC* (i+k) is the market capitalization of stock market k and i. Trade(k) is country k's total exports and imports. *SMC* (k) is stock market k's market capitalization. *Total trades* and *Total SMC* are the total trades and market capitalization of the network containing 17 Asian-pacific economies and stock markets.

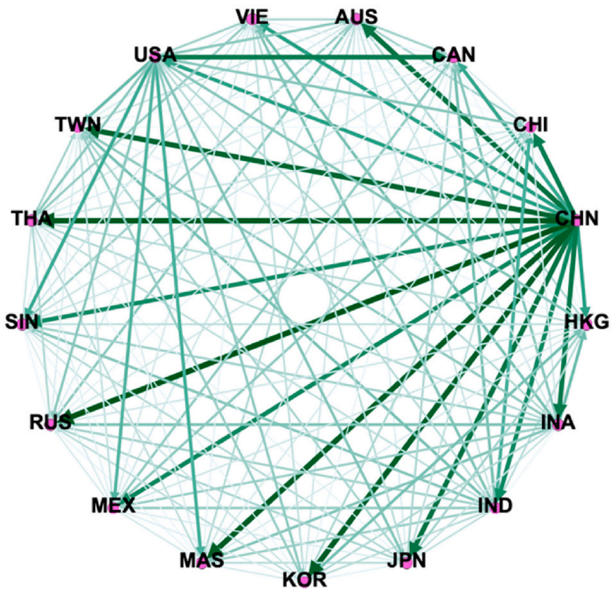

Fig. 3. EPU dependency network of full sample period.
The color depth of an edge represents the size of the impact, and the direction of an arrow represents the direction of the impact.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
NET EPU dependency indexes.

Countries/regions	Full-sample	Phase 1	Phase 2	Phase 3
AUS	0.0199	−0.0528	0.0205	0.0459
CAN	−0.0814	−0.0225	−0.0196	0.0687
CHI	−0.0816	−0.0135	−0.0281	−0.0347
CHN	0.3378	0.1373	0.0699	0.1766
HKG	−0.0788	−0.0488	−0.0297	−0.0024
IND	0.0696	0.0350	0.0215	0.0891
INA	0.0617	0.0356	0.0103	−0.0182
JPN	0.0042	−0.0045	−0.0041	−0.0646
MAS	−0.0638	−0.0551	−0.0298	−0.0437
MEX	−0.0241	0.0295	−0.0029	−0.0647
RUS	−0.0683	0.0366	−0.0239	−0.0770
SIN	−0.0546	−0.0532	−0.0031	−0.0506
KOR	−0.0088	−0.0086	0.0527	−0.0647
TWN	−0.0825	−0.0431	−0.0319	−0.053
THA	−0.0100	−0.0298	0.0025	−0.0377
USA	0.1341	0.0791	0.0220	0.1192
VIE	−0.0733	−0.0212	−0.0263	0.0116

This table represents the EPU dependency indexes following Wu et al. (2020). The NET index is the net difference between TO and FROM indexes, where TO index is the total dependency impact of one node on others and FROM index is the total dependency impact transmitted from other nodes.

4.1. Spillover centrality network

We first construct a spillover centrality network to identify the most important connection between the EPU and financial networks. Fig. 7 shows the results of the full-sample period and the three subsample periods. In the full sample period, the strongest connection between the two networks is through the US stock market and Vietnam's EPU. As a result of China's increasing labor costs, many foreign companies are shifting their investments from China to other Asian countries, and the US-China trade war has accelerated this process. Vietnam has become the biggest beneficiary of the trade war, with a flow of nearly \$4.3 billion foreign direct investments into its industrial and economic zones from January to May 2020[4] despite the COVID-19 pandemic. As a result, Vietnam's EPUs are strongly correlated with the movements in the US stock market.

However, the situation in the three subsample periods is different. We can see that the strongest link between the EPU and financial

[4] Reported by the Vietnam Economic Zone and the Industrial Zone Development Steering Committee.

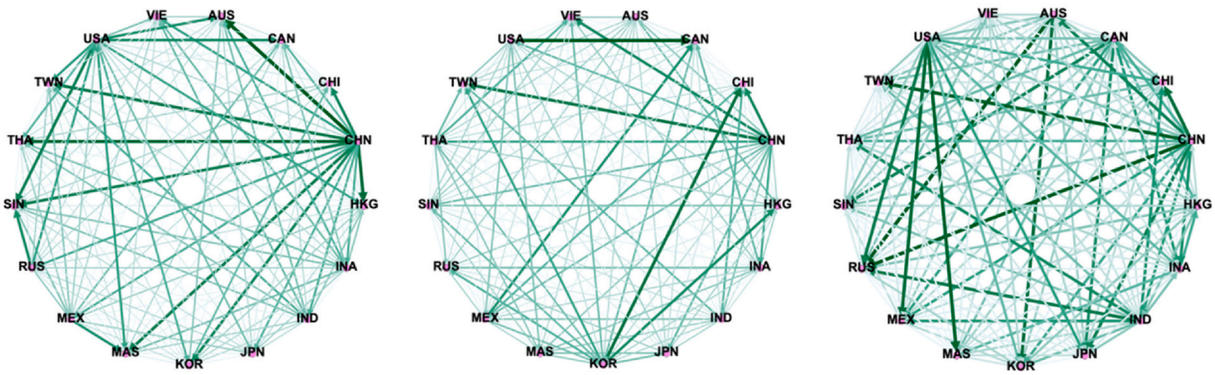

Fig. 4. EPU dependency networks in three phases.
The color depth of an edge represents the size of the impact, and the direction of an arrow represents the direction of the impact.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Descriptive statistics for the finance indexes.

Indexes	Mean	Mean (phase 1)	Mean (phase 2)	Mean (phase 3)	Std. Dev.	Skew.	Kurt.	J.-B.
AXJO	0.00004	0.00015	0.00034	−0.00138	0.01	−1.74	22.86	15456***
GSPTSE	−0.00000	0.00005	0.00021	−0.00097	0.01	−2.24	51.98	91937***
SPIPSA	−0.00004	0.00092	−0.00023	−0.00186	0.01	−2.44	39.87	52563***
SSEC	−0.00004	0.00016	−0.00010	−0.00033	0.01	−0.24	6.83	565***
HIS	0.00012	0.00108	−0.00015	−0.00140	0.01	−0.48	6.28	443***
BSESN	0.00030	0.00067	0.00051	−0.00153	0.01	−2.34	35.51	40985***
JKSE	−0.00008	0.00052	0.00002	−0.00212	0.01	−0.76	11.14	2606***
N225	0.00017	0.00038	0.00023	−0.00063	0.01	−0.12	10.18	1963***
KLSE	−0.00010	0.00042	−0.00036	−0.00043	0.01	−0.48	21.00	12343***
MXX	−0.00021	0.00011	−0.00012	−0.00143	0.01	−0.76	9.32	1608***
IRTS	0.00006	0.00028	0.00051	−0.00234	0.02	−1.56	17.05	7872***
FTWISGPL	−0.00005	0.00073	−0.00012	−0.00187	0.01	−0.57	15.23	5733***
KS11	0.00004	0.00065	−0.00023	−0.00050	0.01	−0.28	17.42	7908***
TWII	0.00025	0.00054	0.00021	−0.00039	0.01	−0.63	12.30	3345***
SETI	−0.00016	0.00048	−0.00027	−0.00142	0.01	−3.03	40.97	56176***
SPX	0.00035	0.00062	0.00041	−0.00062	0.01	−1.23	26.03	20375***
VNI	0.00024	0.00178	−0.00041	−0.00132	0.01	−1.17	9.57	1848***

*** indicate significance at the 1% level. AXJO is the stock index of Australia, GSPTSE of Canada, SPIPSA of Chile, SSEC of China, HIS of Hong Kong, BSESN of India, MXX of Mexico, IRTS of Russia, FTWISGPL of Singapore, KS11 of South Korea, TWII of Taiwan, SETI of Thailand, JKSE of Indonesia, KLSE of Malaysia, N225 of Japan, SPX of US, and VNI of Vietnam.

networks in phase 1is the correlation between Russia's EPU and the US stock market. After the Crimea incident in April 2014, the United States began to sanction Russia and capital started to flow out of Russia. In July 2017, the Trump-Russia investigation led to a sharp drop in US stock markets. Thus, we can observe the aforementioned dominant connection as a result of these incidences. Furthermore, the US-China trade war has changed the spillover centrality network's structure. The correlation between Vietnam's EPU and US stock market became dominant in phase 2, due to trade diversions and international capital reallocation. As Siregar et al. (2019) reported, Vietnam has benefited from US' trade diversion away from China, and Chinese firms 'production reallocation, investment, and further integration into regional supply chains.

The COVID-19 outbreak has caused tremendous panic to the global financial markets. In March 2020, the US stock trading halt was triggered four times. To stabilize the financial market, the US government announced a series of stimulating monetary and fiscal policies, including an unprecedented unlimited QE program. Consequently, the correlation between the US EPU and the US stock market became the strongest link in phase 3.

4.2. Spillover dependency network

We modify Kenett et al.'s (2010) method to construct a spillover dependency network. Initially, we calculate the first-order partial correlation between two stock markets i and j, with respect to country k's EPU. After removing the influence of country k's EPU, we obtain the partial correlation between the two stock markets:

Table 5
NET Financial dependency indexes.

Stock market indexes	Full-sample	Phase 1	Phase 2	Phase 3
AXJO	−0.0922	0.0309	−0.1304	−0.2959
GSPTSE	−0.1014	−0.0064	−0.1418	−0.1265
SPIPSA	−0.2051	−0.1121	−0.1854	−0.4911
SSEC	−0.1277	−0.1057	−0.0935	−0.2314
HIS	0.2845	0.2177	0.3082	0.2851
BSESN	−0.1317	0.0056	−0.1909	−0.0531
JKSE	−0.1177	−0.1178	−0.1294	0.0832
N225	0.1510	0.0503	0.2282	−0.0463
KLSE	0.0617	0.0358	0.0305	0.1596
MXX	−0.1618	−0.0988	−0.1339	−0.4042
IRTS	−0.2183	−0.1232	−0.2066	−0.5559
FTWISGPL	0.2136	0.0557	0.2305	0.6407
KS11	0.2524	0.0854	0.2524	0.5689
TWII	0.3395	0.1757	0.3463	0.6758
SETI	−0.0712	−0.0879	−0.1112	0.1478
SPX	0.1345	0.1251	0.1167	0.0012
VNI	−0.210	−0.1302	−0.1898	−0.3579

This table presents the financial dependency indexes following Wu et al. (2020). The NET index is the net difference between TO and FROM indexes, where TO index is the total dependency impact of one node on others and FROM index is the total dependency impact transmitted from other nodes.

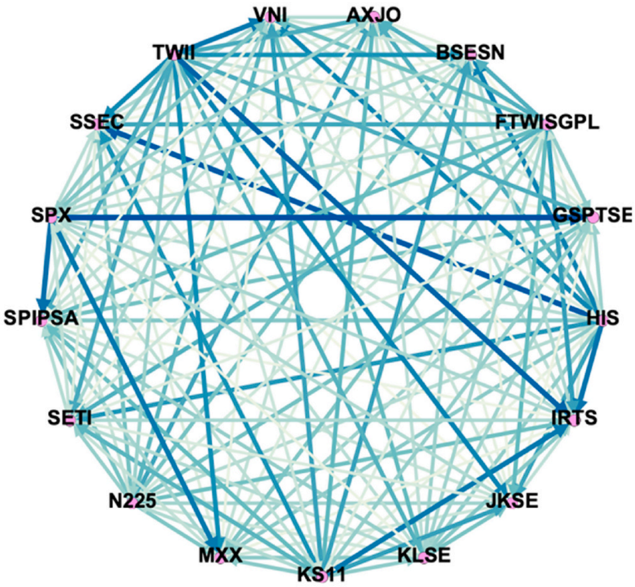

Fig. 5. Financial networks of full-sample period.
The color depth of an edge represents the size of the impact, and the direction of an arrow represents the direction of the impact.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$PC(i,j|k) = \frac{C(i,j) - \widetilde{C}(i,k)\widetilde{C}(j,k)}{\sqrt{\left(1 - \widetilde{C}^2(i,k)\right)\left(\left(1 - \widetilde{C}^2(j,k)\right)\right.}} \tag{6}$$

Then, we define

$$d(i,j|k) = C(i,j) - PC(i,j|k) \tag{7}$$

in which$d(i,j|k)$isthe dependency effect of country k's EPU on the correlation $C(i,j)$.When a financial network has N nodes, the total influence of country k's EPU on stock market i through the financial network is expressed as:

$$D^{Stock}(i,k) = \frac{1}{N-1}\sum_{j\neq i}^{N-1} d(i,j|k) \tag{8}$$

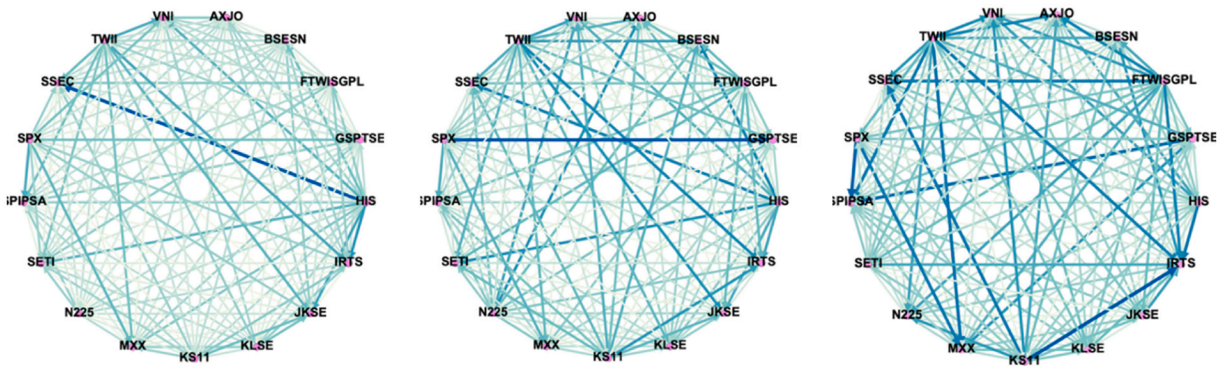

Fig. 6. Dynamics of the financial dependency networks.
The color depth of an edge represents the size of the impact, and the direction of an arrow represents the direction of the impact.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

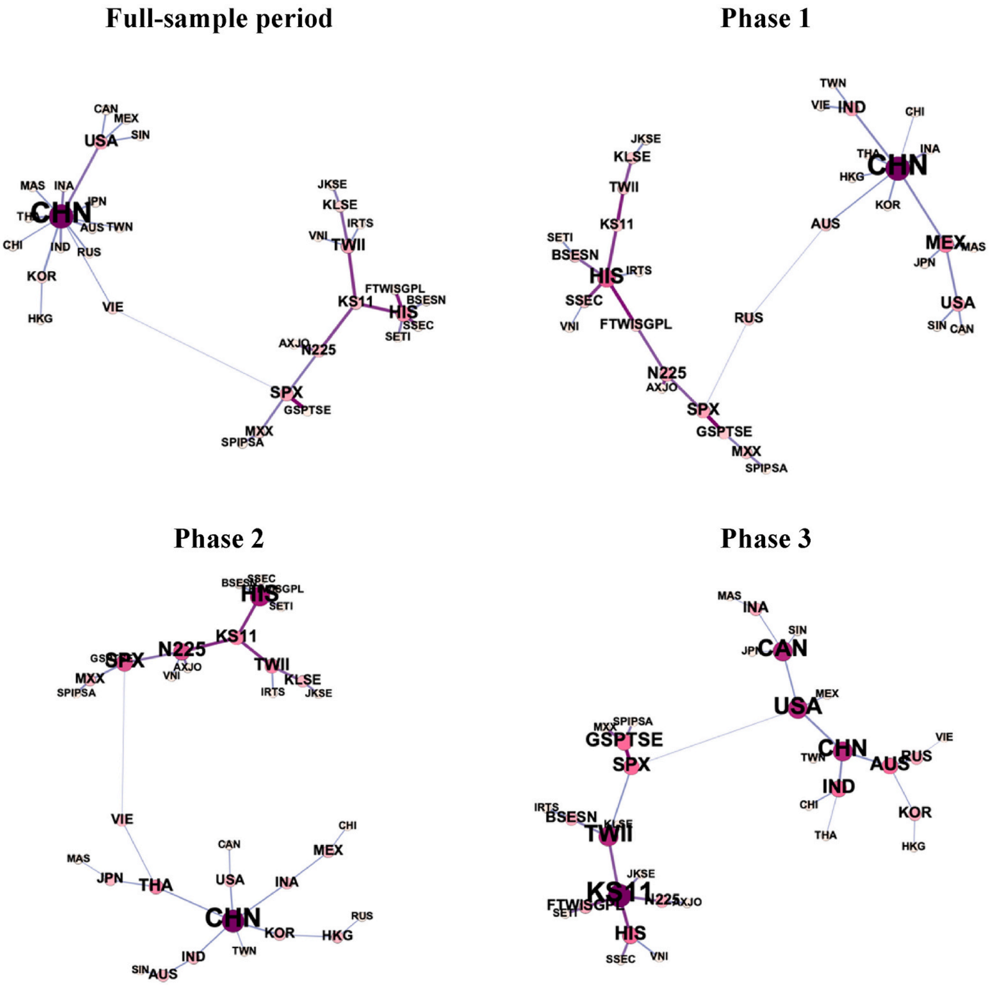

Fig. 7. Spillover centrality networks.
The color depth of an edge represents the size of the impact, and the size of a node represents its importance in the network.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Next, we consider the spillover effect of country k's EPU on stock market i through the EPU network. We calculate the first-order partial correlation between stock market i and country g's EPU, with respect to country k's EPU. The partial correlation between stock market i and country g's EPU is:

$$PC(i,g|k) = \frac{\widetilde{C}(i,g) - \widetilde{C}(i,k)C(g,k)}{\sqrt{\left(1-\widetilde{C}^2(i,k)\right)\left((1-C^2(g,k)\right)}} \tag{9}$$

Then, we define

$$d(i,g|k) = \widetilde{C}(i,g) - PC(i,g|k) \tag{10}$$

in which d(i, j| k)is the dependency effect of country k's EPU on the correlation $C(i,g)$.When an EPU network has N nodes, the spillover effect of country k's EPU on stock market i through the EPU network is expressed as:

$$D^{EPU}(i,k) = \frac{1}{N-1}\sum_{g\neq k}^{N-1} d(i,g|k) \tag{11}$$

In addition to the direct effect $\widetilde{C}(i,k)$, the total spillover effect of country k's EPU on stock market i is represented as:

$$D(i,k) = \frac{(N-1)\left(D^{Stock}(i,k) + D^{EPU}(i,k)\right) + \widetilde{C}(i,k)}{2N-1} \tag{12}$$

The spillover effect of stock market i on country k's EPU is inverted. Accordingly, we calculate the mutual spillover effects of the EPU and financial networks. Table 6 shows the results of the full sample period and the three subsample periods. These results are consistent with the current economic and political situations of the Asia-Pacific region. Overall, the US EPU has the highest total influence over the stock markets.[5] In Asia, Hong Kong and Japan's EPUs have the highest direct effect and indirect effect through the financial network over the stock markets. Also, Mainland China and Japan's EPUs have the highest total effect and indirect effect through the EPU network over the stock markets. Our results differ from Tsai's (2017), who found that China's EPU is the biggest source of fluctuations in the global stock market. This difference is perhaps due to the increasing volatility of the US EPU in recent years, caused by varying events, such as the USMCA negotiation, the trade conflict with China, and the COVID-19 pandemic. On the other hand, although SPX is the most influential stock market index, with the highest direct, indirect, and total spillover effect over the EPU network, Hong Kong's HIS and Japan's N225 are the two most influential stock market indexes in Asia.

EPUs from different countries have heterogeneous effects over the financial markets. EPUs in Hong Kong, India, Mexico, Singapore, South Korea, Taiwan, Thailand, and the United States have negative total spillover effects over the financial markets, while those in Australia, Canada, Chile, China, Indonesia, Japan, Malaysia, Russia, and Vietnam have positive influences. In other words, the

Table 6
NET uncertainty spillover effects.

Countries/regions	Full sample	Phase 1	Phase 2	Phase 3	Indexes	Full sample	Phase 1	Phase 2	Phase 3
AUS	−0.0008	−0.0013	−0.0014	−0.0029	AXJO	0.0005	0.0009	0.0008	0.0022
CAN	−0.0009	−0.0017	−0.0029	−0.0027	GSPTSE	0.0006	0.0010	0.0006	0.0048
CHI	−0.0008	−0.0012	−0.0009	−0.0039	SPIPSA	−0.0000	0.0004	0.0003	0.0012
CHN	−0.0002	−0.0006	−0.0019	−0.0088	SSEC	0.0009	0.0011	0.0027	0.0124
HKG	−0.0031	−0.0016	−0.0042	−0.0118	HIS	0.0023	0.0024	0.0025	0.0093
IND	−0.0006	−0.0006	−0.0011	−0.0059	BSESN	0.0005	0.0010	0.0010	0.0049
INA	−0.0006	−0.0003	−0.0012	−0.0040	JKSE	0.0003	0.0002	0.0010	0.0042
JPN	−0.0012	−0.0011	−0.0022	−0.0136	N225	0.0021	0.0017	0.0042	0.0103
MAS	−0.0012	−0.0018	−0.0019	−0.0027	KLSE	0.0007	0.0008	0.0006	0.0068
MEX	−0.0004	−0.0005	−0.0012	−0.0036	MXX	0.0001	0.0003	0.0006	0.0013
RUS	−0.0012	−0.0042	−0.0013	−0.0029	IRTS	0.0001	0.0002	0.0003	0.0016
SIN	−0.0008	−0.0016	−0.0012	−0.0081	FTWISGPL	0.0006	0.0008	0.0011	0.0042
KOR	−0.0007	−0.0005	−0.0010	−0.0087	KS11	0.0009	0.0006	0.0018	0.0059
TWN	−0.0008	−0.0017	−0.0030	−0.0049	TWII	0.0010	0.0008	0.0015	0.0099
THA	−0.0004	−0.0005	−0.0010	−0.0025	SETI	0.0003	0.0001	0.0005	0.0069
USA	−0.0019	−0.0021	−0.0031	−0.0271	SPX	0.0066	0.0099	0.0118	0.0299
VIE	−0.0015	−0.0006	−0.0023	−0.0059	VNI	−0.0001	−0.0001	0.0003	0.0039
EPU Network	−0.0171	−0.0218	−0.0315	−0.1197	Financial Network	0.0171	0.0218	0.0315	0.1197

The calculation of uncertainty spillover effects follows Wu et al. (2020). The NET index is the net difference between TO and FROM indexes, where TO index is the total dependency impact of one node on others and FROM index is the total dependency impact transmitted from other nodes.

[5] The United States also has the greatest direct influence and indirect influence (through both the financial and EPU networks). The table of direct and indirect effects can be obtained from the author.

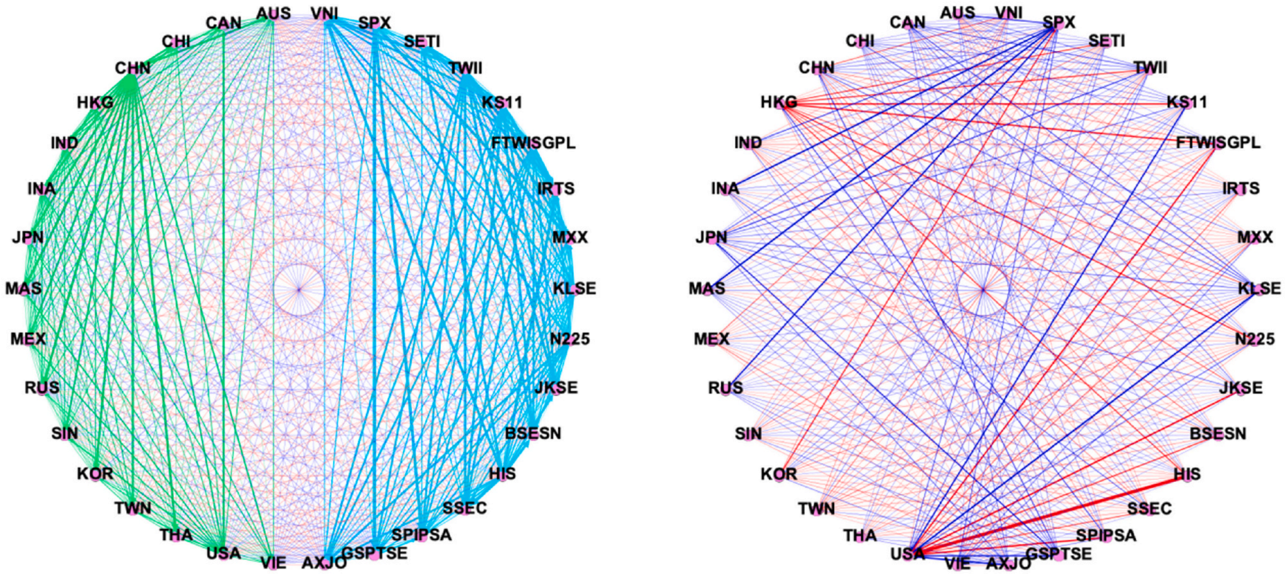

Fig. 8. Spillover dependency network of the full-sample period.
The green connections represent the EPU network; the cyan connections depict the financial network; and in the spillover effects across the two networks, a red line represents a net negative correlation and a blue line represents a net positive correlation. The color depth of an edge represents the size of the impact, and the direction of an arrow represents the direction of the impact.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

financial markets tend to consider rising uncertainties as risks in the former economies and as speculative opportunities in the latter economies. Stock market indexes also have heterogeneous effects over the EPU network. AXJO, GSPTSE, KLSE, IRTS, KS11, TWII, and SPX have positive overall spillover effects over the EPU network, while other stock market indexes have negative overall influences. In other words, higher return rates in the former stock market indexes will encourage economies to adopt more active monetary and fiscal policies, thereby increasing the EPUs, while higher return rates in the latter stock market indexes encourage economies to adopt more conservative economic policies, thereby decreasing the EPUs.

Fig. 8 plots the spillover dependency network. As can be seen from the right side of the figure, the financial network has a greater impact on the EPU network, and SPX is the biggest contributor of spillover effects in the combined network and Hong Kong's EPU is the biggest receiver.

For the three subsample periods, Fig. 9 illustrates the dynamics of the spillover dependency network. When considering the uncertainty spillover from the EPU network to the financial network, the United States, China, and Japan are the top three exporters in all three subsample periods. Their cross-network influences on the financial network declined during the trade war and rose after the COVID-19 outbreak. When studying the impact of stock market indexes on the EPU network, the largest sources of spillovers are SPX, SSEC, HIS, and N225. In phase 1, SPX, SSEC, and HIS played the leading roles in the spillover dependency network, while in phases 2 and 3, N225 replaced HIS.

The spillover dependency is asymmetric, as the financial network's impact is always stronger than that of the EPU network, throughout the three subsample periods. The impact of the EPU network on the financial network declined during the trade war, which was due to the decline in the correlation of EPUs during that period. While many countries see the trade war as an unstable factor, some regard it as an opportunity to develop their own manufacturing industry. After the outbreak of the pandemic, the spillover effect of the EPU network on the financial network has increased significantly. As Choi (2020) pointed out, the impact of the pandemic has even exceeded the impact of the global financial crisis. In order to mitigate such impact, countries have launched similar recue policies, which in a way have improved the policy coordination and the density of the EPU network. Governments have implemented various levels of lockdown in economic activities and relief plans to rescue businesses and unemployed (Phan and Narayan, 2020). For example, the Chinese government has provided liquidity support to the private sector (mainly small and medium enterprises) through the People's Bank of China, financial institutions and various government agencies (Zhang et al., 2020). By lowering the benchmark interest rate to a historically low level, Australia's monetary policy actions have achieved the expected results and have been transmitted to households and businesses (Debelle, 2020). Moreover, there is no safe haven for funds to escape; the responses of financial markets are highly consistent upon the pandemic. The stock indexes of many countries and regions have recorded the largest single-day decline, and the stock indexes of more than 10 countries have triggered the circuit breaker mechanism. On the second day after the pandemic was announced, 71 stock markets observed negative returns (Liu et al., 2020a, 2020b, 2020c). Therefore, the correlation of the financial network has also been increased. Consequently, the spillover effect of the financial network on the EPU network has increased sharply.

5. Conclusion and policy implications

This paper studies policy uncertainty spillover and financial risk contagion in the Asia-Pacific region through a network analysis. Different from Baker et al.'s (2016) EPU index, we build a daily EPU index using GDELT data on 17 Asia-Pacific countries and regions from January 1, 2017, to June 30, 2020. Based on the daily EPU and stock market indexes, we then construct the EPU and stock market networks separately and analyze the network topologies, respectively. We find that both the EPU and financial networks show geographic segmentation, such that economies with close geographical locations tend to be more closely related. We also discover that China is the center of the EPU network, and that China and the United States are the two biggest uncertainty transmitters in the network. In the financial network, we find Hong Kong the most important link in Asian markets and the United States the most influential on the east coast of the Pacific Ocean. Also, the US stock market is the most important intermediary in the financial network.

By dividing the sample period into three sub-sample periods, we study the network dynamics before and after the US-China trade war, and after the COVID-19 outbreak. Our results reveal that during the US-China trade war, the correlation between different countries' economic policies decreased, while the COVID-19 outbreak increased the EPU network's density. On the other hand, the financial network's dynamics indicate that almost all countries' dependencies increased over time. Especially after the COVID-19 outbreak, the entire financial dependency network's connections strengthened significantly. These results further prove the importance of national cooperation in fighting the ongoing global pandemic.

We also combine the EPU and financial networks to construct an uncertainty spillover network. Our results show that the two networks have asymmetric spillover effects, and that the spillover from the financial to the EPU network is always stronger than the other way around. Additionally, the United States, China, and Japan are the three largest transmitters of uncertainty spillovers from the EPU network. When considering the spillover effects from the financial to the EPU network, SPX plays the most important role, while SSEC, HIS, and N225 are more influential than other stock market indexes in Asia. Similar to the results of the EPU and financial networks' dynamics, we also find that the spillover effects between the EPU and financial networks declined during the US-China trade war and rose after the COVID-19 outbreak. By comparing the results of the EPU and financial networks separately and simultaneously, we find that although China has become the center of the EPU network, the USEPU is still the biggest source of uncertainty for the Asia-Pacific financial market. Also, SPX is the dominant source of uncertainty in the financial and combined spillover dependency networks. Lastly, our research results reveal that although China's political and economic influence is gradually rising, the United States is still the absolute political and financial center of the Asia-Pacific region.

Based on our results, it is clear that EPUs and stock market returns have very complex interrelationships. The uncertainties

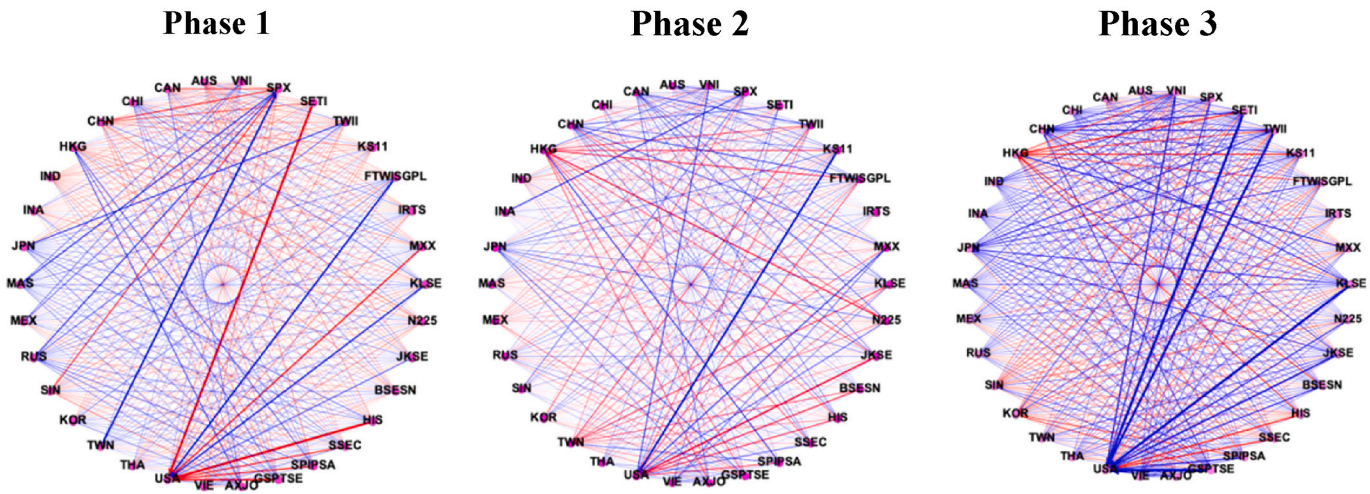

Fig. 9. Highlights of the Spillover effects of the subsample periods.
A red line represents a net negative correlation and a blue line represents a net positive correlation. The color depth of an edge represents the size of the impact, and the direction of an arrow represents the direction of the impact.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

originate from important regional powers that often cast long shadows over neighboring countries and trigger a chain reaction of regional economic policy changes. In addition, the close network of financial markets makes it easy for regional financial risks to spread. Policy makers should remain vigilant to the fluctuations of foreign EPUs and international financial markets. At the same time, policy makers also need to enhance policy coordination and cooperation among themselves, as this is the only way to deal with systemic crises, such as the present COVID-19 pandemic. As the pandemic continues to evolve, its impact on the global economy has not yet been fully revealed. Further research is needed to study such impact when more data becomes available. And most importantly, how should we coordinate our policy network to better respond to this pandemic.

References

Bai, L., Zhang, X., Liu, Y., Wang, Q., 2019. Economic risk contagion among major economies: new evidence from EPU spillover analysis in time and frequency domains. Phys. A: Stat. Mech. Applic. 535, 122431. https://doi.org/10.1016/j.physa.2019.122431.

Baker, S., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636. https://doi.org/10.1093/qje/qjw024.

Baker, S., Bloom, N., Davis, S.J., Terry, S.J., 2020. Covid-Induced Economic Uncertainty. NBER Working Paper No. 26983. http://www.nber.org/papers/w26983.

Balli, F., Uddin, G.S., Mudassar, H., Yoon, S., 2017. Cross-country determinants of economic policy uncertainty spillovers. Econ. Lett. 156, 179–183. https://doi.org/10.1016/j.econlet.2017.05.016.

Barigozzi, M., Fagiolo, G., Mangioni, G., 2011. Identifying the community structure of the international-trade multi network. Phys. A: Stat. Mech. Applic. 390 (11), 2051–2066. https://doi.org/10.1016/j.physa.2011.02.004.

Bhattacharya, K., Mukherjee, G., Saramaki, J., Kaski, K., Manna, S.S., 2007. The international trade network: weighted network analysis and modelling. J. Stat. Mech.: Theory Exp. 41, 139–147 (707.4343). http://ideas.repec.org/p/arx/papers/0707.4343.html.

Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–685. https://doi.org/10.3982/ECTA6248.

Chiang, T.C., 2019. Economic policy uncertainty, risk and stock returns: evidence from G7 stock markets. Financ. Res. Lett. 29, 41–49. https://doi.org/10.1016/j.frl.2019.03.018.

Choi, S., 2020. Industry volatility and economic uncertainty due to the COVID-19 pandemic: evidence from wavelet coherence analysis. Financ. Res. Lett., 101783 https://doi.org/10.1016/j.frl.2020.101783.

Christou, C., Cunado, J., Gupta, R., Hassapis, C., 2017. Economic policy uncertainty and stock market returns in Pacific rim countries: evidence based on a Bayesian panel VAR model. J. Multinatl. Financ. Manag. 40, 92–102. https://doi.org/10.1016/j.mulfin.2017.03.001.

Chuliá, H., Gupta, R., Uribe, J.M., Wohar, M.E., 2017. Impact of US uncertainties on emerging and mature markets: evidence from a quantile-vector autoregressive approach. J. Int. Financ. Mark. Inst. Money 48, 178–191. https://doi.org/10.1016/j.intfin.2016.12.003.

Debelle, G., 2020. The Reserve Bank of Australia's policy actions and balance sheet. Econ. Anal.Policy 68, 285–295. https://doi.org/10.1016/j.eap.2020.10.001.

Devpura, N., Narayan, P.K., 2020. Hourly oil price volatility: the role of COVID-19. Energy Res. Lett. 1 (2), 13683 https://doi.org/10.46557/001c.13683.

Ertuğrul, H.M., Güngör, B.O., Soytaş, U., 2020. The effect of the COVID-19 outbreak on the Turkish diesel consumption volatility dynamics. Energy Res. Lett. 1 (3) https://doi.org/10.46557/001c.17496.

Fagiolo, G., Reyes, J., Schiavo, S., 2010. International trade and financial integration: a weighted network analysis. Quant. Financ. 10 (4), 389–399. https://doi.org/10.1080/14697680902882420.

Gil-Alana, L.A., Claudio-Quiroga, G., 2020. The COVID-19 impact on the Asian stock markets. Asian Econ. Lett. 1 (2) https://doi.org/10.46557/001c.17656.

Gil-Alana, L.A., Monge, M., 2020. Crude oil prices and COVID-19: persistence of the shock. Energy Res. Lett. 1 (1), 13200 https://doi.org/10.46557/001c.13200.

Gu, X., Ying, S., Zhang, W., Tao, Y., 2020. How do firms respond to COVID-19? First evidence from Suzhou, China. Emerg. Mark. Financ. Trade 56 (10), 2181–2197. https://doi.org/10.1080/1540496X.2020.1789455.

Haroon, O., Rizvi, S.A.R., 2020. Flatten the curve and stock market liquidity—An inquiry into emerging economies. Emerg. Mark. Financ. Trade 56 (10), 2151–2161. https://doi.org/10.1080/1540496X.2020.1784716.

He, P., Niu, H., Sun, Z., Li, T., 2020. Accounting index of COVID-19 impact on Chinese industries: a case study using big data portrait analysis. Emerg. Mark. Financ. Trade 56 (10), 2332–2349. https://doi.org/10.1080/1540496X.2020.1785866.

Hu, Z., Kutan, A.M., Sun, P., 2018. Is U.S. economic policy uncertainty priced in China's A-shares market? Evidence from market, industry, and individual stocks. Int. Rev. Financ. Anal. 57, 207–220. https://doi.org/10.1016/j.irfa.2018.03.015.

Huang, Y., Luk, P., 2020. Measuring economic policy uncertainty in China. China Economic Review 59. https://doi.org/10.1016/j.chieco.2019.101367.

Huang, W., Zheng, Y., 2020. COVID-19: structural changes in the relationship between investor sentiment and crude oil futures price. Energy Res. Lett. 1 (2), 13685 https://doi.org/10.46557/001c.13685.

Huang, Z., Tong, C., Qiu, H., Shen, Y., 2018. The spillover of macroeconomic uncertainty between the U.S. and China. Econ. Lett. 171, 123–127. https://doi.org/10.1016/j.econlet.2018.07.018.

Iyke, B.N., 2020a. Economic policy uncertainty in times of COVID-19 pandemic. Asian Econ. Lett. 1 (2) https://doi.org/10.46557/001c.17665.

Iyke, B., 2020b. COVID-19: the reaction of US oil and gas producers to the pandemic. Energy Res. Lett. 1 (2), 13912 https://doi.org/10.46557/001c.13912.

Iyke, B.N., 2020c. The disease outbreak channel of exchange rate return predictability: evidence from COVID-19. Emerg. Mark. Financ. Trade 56 (10), 2277–2297. https://doi.org/10.1080/1540496X.2020.1784718.

Jiang, Y., Zhu, Z., Tian, G., Nie, H., 2019. Determinants of within and cross-country economic policy uncertainty spillovers: Evidence from US and China. Financ. Res. Lett. 31 https://doi.org/10.1016/j.frl.2019.08.004.

Kenett, D.Y., Tumminello, M., Madi, A., Gur-Gershgoren, G., Mantegna, R.N., 2010. Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market. PLoS One 5 (12), 1–14. https://doi.org/10.1371/journal.pone.0015032.

Klößner, S., Sekkel, R., 2014. International spillovers of policy uncertainty. Econ. Lett. 124 (3), 508–512. https://doi.org/10.1016/j.econlet.2014.07.015.

Lan, C., Huang, Z., Huang, W., 2020. Systemic risk in China's financial industry due to the COVID-19 pandemic. Asian Econ. Lett. 1 (3) https://doi.org/10.46557/001c.18070.

Li, X., Peng, L., 2017. US economic policy uncertainty and co-movements between Chinese and US stock markets. Econ. Model. 61, 27–39. https://doi.org/10.1016/j.econmod.2016.11.019.

Li, J., Song, Q., Peng, C., Wu, Y., 2020. COVID-19 pandemic and household liquidity constraints: evidence from micro data. Emerg. Mark. Financ. Trade 56 (15), 3626–3634. https://doi.org/10.1080/1540496X.2020.1854721.

Liu, M., Choo, W.-C., Lee, C.-C., 2020a. The response of the stock market to the announcement of global pandemic. Emerg. Mark. Financ. Trade 56 (15), 3562–3577. https://doi.org/10.1080/1540496X.2020.1850441.

Liu, H., Manzoor, A., Wang, C., Zhang, L., Manzoor, Z., 2020b. The COVID-19 outbreak and affected countries stock markets response. Int. J. Environ. Res. Public Health 17 (8), 2800. https://doi.org/10.3390/ijerph17082800.

Liu, T., Pan, B., Yin, Z., 2020c. Pandemic, mobile payment, and household consumption: micro-evidence from China. Emerg. Mark. Financ. Trade 56 (10), 2378–2389. https://doi.org/10.1080/1540496X.2020.1788539.

Marfatia, H., Zhao, W., Ji, Q., 2020. Uncovering the global network of economic policy uncertainty. Res. Int. Bus. Financ. 53, 101223. https://doi.org/10.1016/j.ribaf.2020.101223.

Mishra, A.K., Rath, B.N., Dash, A.K., 2020. Does the Indian financial market nosedive because of the COVID-19 outbreak, in comparison to after demonetisation and the GST? Emerg. Mark. Financ. Trade 56 (10), 2162–2180. https://doi.org/10.1080/1540496X.2020.1785425.

Narayan, P.K., 2020a. Did bubble activity intensify during COVID-19? Asian Econ. Lett. 1 (2) https://doi.org/10.46557/001c.17654.

Narayan, P.K., 2020b. Oil price news and COVID-19—Is there any connection? Energy Res. Lett. 1 (1), 13176 https://doi.org/10.46557/001c.13176.
Narayan, P.K., 2020c. Has COVID-19 changed exchange rate resistance to shocks? Asian Econ. Lett. 1 (1) https://doi.org/10.46557/001c.17389.
Pástor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. J. Financ. 67 (4), 1219–1264. https://doi.org/10.1111/j.1540-6261.2012.01746.x.
Pástor, L., Veronesi, P., 2013. Political uncertainty and risk premia. J. Financ. Econ. 110 (3), 520–545. https://doi.org/10.1016/j.jfineco.2013.08.007.
Phan, D.H.B., Narayan, P.K., 2020. Country responses and the reaction of the stock market to COVID-19—A preliminary exposition. Emerg. Mark. Financ. Trade 56 (10), 2138–2150. https://doi.org/10.1080/1540496X.2020.1784719.
Polemis, M., Soursou, S., 2020. Assessing the impact of the COVID-19 pandemic on the Greek energy firms: an event study analysis. Energy Res. Lett. 1 (3) https://doi.org/10.46557/001c.17238.
Prabheesh, K.P., 2020. Dynamics of foreign portfolio investment and stock market returns during the COVID-19 pandemic: evidence from India. Asian Econ. Lett. 1 (2) https://doi.org/10.46557/001c.17658.
Prabheesh, K.P., Padhan, R., Garg, B., 2020. COVID-19 and the oil price—Stock market nexus: evidence from net oil-importing countries. Energy Res. Lett. 1 (2), 13745 https://doi.org/10.46557/001c.13745.
Qin, M., Liu, X., Zhou, X., 2020a. COVID-19 shock and global value chains: is there a substitute for China? Emerg. Mark. Financ. Trade 56 (15), 3588–3598. https://doi.org/10.1080/1540496X.2020.1855137.
Qin, M., Zhang, Y.C., Su, C.W., 2020b. The essential role of pandemics: a fresh insight into the oil market. Energy Res. Lett. 1 (1), 13166 https://doi.org/10.46557/001c.13166.
Qin, M., Zhang, Y.C., Su, C.W., 2020c. The essential role of pandemics: a fresh insight into the oil market. Energy Res. Lett. 1 (1), 13166 https://doi.org/10.46557/001c.13166.
Sharma, S.S., 2020. A note on the Asian market volatility during the COVID-19 pandemic. Asian Econ. Lett. 1 (2) https://doi.org/10.46557/001c.17661.
Shen, H., Fu, M., Pan, H., Yu, Z., Chen, Y., 2020. The impact of the COVID-19 pandemic on firm performance. Emerg. Mark. Financ. Trade. https://doi.org/10.1080/1540496X.2020.1785863.
Siregar, R., Ma, G., Hu, Y., Feng, P., 2019. Vietnam: Navigating US-China Trade Tensions. ASEAN Economic Views, IIF. July 30.
Smales, L.A., 2020. Examining the relationship between policy uncertainty and market uncertainty across the G7. Int. Rev. Financ. Anal. 71, 101540. https://doi.org/10.1016/j.irfa.2020.101540.
Tisdell, C.A., 2020. Economic, social and political issues raised by the COVID-19 pandemic. Econ. Anal. Policy 68, 17–28. https://doi.org/10.1016/j.eap.2020.08.002.
Topcu, M., Gulal, O.S., 2020. The impact of COVID-19 on emerging stock markets. Financ. Res. Lett. 36, 101691. https://doi.org/10.1016/j.frl.2020.101691.
Trung, N.B., 2019. The spillover effects of US economic policy uncertainty on the global economy: a global VAR approach. N. Am. J. Econ. Financ. 48, 90–110. https://doi.org/10.1016/j.najef.2019.01.017.
Tsai, I., 2017. The source of global stock market risk: a viewpoint of economic policy uncertainty. Econ. Model. 60, 122–131. https://doi.org/10.1016/j.econmod.2016.09.002.
Vidya, C.T., Prabheesh, K.P., 2020. Implications of COVID-19 pandemic on the global trade networks. Emerg. Mark. Financ. Trade 56 (10), 2408–2421. https://doi.org/10.1080/1540496X.2020.1785426.
Wu, F., Zhao, W., Ji, Q., Zhang, D., 2020. Dependency, centrality and dynamic networks for international commodity futures prices. Int. Rev. Econ. Financ. 67, 118–132. https://doi.org/10.1016/j.iref.2020.01.004.
Yan, L., Qian, Y., 2020. The impact of COVID-19 on the Chinese stock market: an event study based on the consumer industry. Asian Econ. Lett. 1 (3) https://doi.org/10.46557/001c.18068.
Yang, H., Deng, P., 2021. The impact of COVID-19 and government intervention on stock markets of OECD countries. Asian Econ. Lett. 1 (4) https://doi.org/10.46557/001c.18646.
Yu, Z., Xiao, Y., Li, Y., 2020. The response of the labor force participation rate to an epidemic: evidence from a cross-country analysis. Emerg. Mark. Financ. Trade 56 (10), 2390–2407. https://doi.org/10.1080/1540496X.2020.1787149.
Yue, P., Korkmaz, A.G., Zhou, H., 2020. Household financial decision making amidst the COVID-19 pandemic. Emerg. Mark. Financ. Trade 56 (10), 2363–2377. https://doi.org/10.1080/1540496X.2020.1784717.
Zhang, Z.A., Tsoi, V., Pang, C., 2020. COVID-19 Aid Plan: China Has Issued a Package of Financial Policies to Help Affected Enterprises. White & Case. https://www.whitecase.com/publications/alert/covid-19-chinese-government-financial-assistance-measures.