



Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

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

COVID-19 vaccinations and risk spillovers: Evidence from Asia-Pacific stock markets

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ARTICLE INFO

JEL classification:

C51
C63
G15

Keywords:

COVID-19 vaccinations
Asia-Pacific stock markets
Volatility spillovers
Extreme risk spillovers
Complex network
Panic sentiment

ABSTRACT

This study investigates the impact of COVID-19 vaccinations on volatility (risk) spillovers among major Asia-Pacific stock markets. Utilizing both mean-based and quantile-based connectedness approaches, we examine the evolving patterns and network structure of risk spillovers not only on average but also in the extreme left and right tails. Risk spillovers are typically stronger under extreme shocks. A common regularity observed in the dynamics of standard (average) and extreme risk spillovers is that there are fewer risk spillovers after the launch of the COVID-19 vaccines. We also conduct a series of regression analyses to investigate the association between spillover levels and vaccination rates. The regression results support that an increase in vaccinations is associated with a decrease in standard risk spillovers. Besides, it is observed that vaccinations have an asymmetric impact on the extreme downside-tail and upside-tail risk spillovers. Further, panic sentiment is identified as a potential channel through which vaccinations affect spillovers. Our findings point to the role of COVID-19 vaccinations in stabilizing the Asia-Pacific stock markets by reducing risk spillovers.

1. Introduction

The ongoing global pandemic of coronavirus disease 2019 (COVID-19) is one of the most devastating pandemics in human history, with over 500 million cumulative infections after entering April 2022. Infectious disease was first reported in Wuhan, China, in late December 2019, and a new RNA virus from the family Coronaviridae was identified (Wu et al., 2020). An increasing number of countries have reported cases of infection. On March 11, 2020, the World Health Organization (WHO) declared the outbreak of a global pandemic and expressed deep concerns about alarming levels of spread (Cucinotta and Vanelli, 2020). The COVID-19 pandemic has caused numerous disturbances in the global economy, triggering intense discussions among scholars. The pandemic severely disrupts many aspects of the real economy, including international trade (Mena et al., 2022), airline and tourism industries (Florida-Benítez, 2021), and logistics performance (Choi, 2021). It is also noted that economic disruptions can be induced and reinforced by governmental responses (Brodeur et al., 2021). These disruptions undermine investor confidence, and COVID-19 risks are aggressively priced across various asset classes (Carlsson-Szlezak et al., 2020). The stock markets of major economies responded to the COVID-19

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pandemic immediately after its outbreak (Zhang et al., 2020a). Given the critical role played by finance in allocating resources and creating liquidity for economic operations, fluctuations in stock markets have attracted significant attention. Research on the impact of the COVID-19 pandemic on stock markets is in demand.

Earlier studies primarily discussed the role of the pandemic itself, including infections and casualties. Many researchers find a negative impact of increasing COVID-19 confirmed cases on stock prices (or returns) (e.g., Chatjuthamard et al., 2021; O'Donnell et al., 2021; Xue et al., 2021). Other researchers note that the climbing of cases amplifies stock market volatility (e.g., Albulescu, 2021; Uddin et al., 2021). Apart from case reports, other COVID-19-related news, such as lockdown policies, also affect stock market returns and volatilities (e.g., Ambros et al., 2021; Bannigidadmath et al., 2022; Cepoi, 2020; Scherf et al., 2022). In addition, the COVID-19 outbreak stimulates the spiking of return connectedness across asset classes (e.g., Bouri et al., 2021; Li et al., 2021a; Naeem et al., 2021). The intensification of risk (volatility or value-at-risk) spillovers is also observed among global stock markets (e.g., Abuzayed et al., 2021; Li, 2021) or across different financial markets (e.g., Corbet et al., 2021; Wang et al., 2022) after the outbreak of the COVID-19 pandemic. These studies show that market turbulence caused by the COVID-19 pandemic is remarkable at an early stage. More recent studies show signs of recovery in equity prices (e.g., Yarovaya et al., 2022), although the pandemic has not yet come to an end. The recovery may be partly contributed by governments' economic rescue packages that restore investors' confidence in stock markets (Seven and Yilmaz, 2021). Another essential factor that benefits the economic and financial recovery is the availability of COVID-19 vaccines.

The COVID-19 vaccine is a key weapon to combat the pandemic, allowing for the relaxation of strict restrictions, such as lockdowns, to resuscitate the depressed economy (Fu et al., 2022). The presence of COVID-19 vaccines also helps investors regain confidence in stock markets, which may affect stock market performance (Hartono, 2021). Several scholars have empirically investigated whether stock markets react to COVID-19 vaccine development. Rouatbi et al. (2021) were the first to test the effect of vaccination on stock market volatility and contend that mass vaccinations stabilize global equity markets by decreasing volatility. Other scholars have also discussed the impact on stock market returns. Khalfaoui et al. (2021) argue that COVID-19 vaccination in the US has a significant and positive influence on S&P 500 returns at most business cycle frequencies. Chan et al. (2022) find that prior to public inoculation, news of clinical trials on COVID-19 vaccines positively affects global equity returns. Similar findings were reported by Ho et al. (2022), who investigated the announcement effect of vaccine approvals on Chinese stock returns at the sectoral level. However, to our knowledge, few studies have discussed the impact of the COVID-19 vaccination on risk spillovers among regional and global stock markets. Risk spillovers are related to the financial stability and interest of international investors and policymakers. It is critical to conduct in-depth analyses to reveal the changes in risk spillovers after the occurrence of COVID-19 vaccines.

Our study is the first to focus on volatility (risk) spillovers among Asia-Pacific stock markets after the presence of COVID-19 vaccines. This contributes to two streams of literature. First, we add to the research on the influence of the COVID-19 vaccination on stock markets, which is inadequate, as mentioned above. The effects of vaccination on risk spillovers among regional stock markets are examined using multiple methods in this study. Second, there is research on the financial stability of the Asia-Pacific region. The Asia-Pacific region comprises many important economies, including the world's first and second largest countries, the US and China. The size of the Asian and Pacific economies contributes to over 40% of the world economy in terms of PPP-based GDP in 2021 (World Economic Outlook, April 2022). Since the beginning of the 2000s, the Asia-Pacific region has been an engine powering global economic growth (ESCAP, 2020). The stability of regional stock markets is always noteworthy for facilitating the sustainability of economic development. The pandemic itself has had an impact on the economic and financial stability of the Asia-Pacific region (ESCAP, 2020). Similar to the stock markets of other regions, the performance of Asia-Pacific stock markets is also affected by the COVID-19 outbreak (e.g., Rahman and Ai Mamun, 2021; Ibrahim et al., 2020). It is important to investigate whether the availability of COVID-19 vaccines may help restabilize regional stock markets. This study discusses the stability of regional stock markets from the perspective of risk spillovers among major markets. Specifically, we consider the stock markets in 12 economies: Australia, Canada, China, Japan, Malaysia, Mexico, Philippines, Russia, Singapore, South Korea, Thailand, and the US.

Our research questions were based mainly on the following three aspects. First, what is the evolving pattern of risk spillovers among the major Asia-Pacific stock markets in recent years? We consider the sample from January 2, 2019, to March 22, 2022, covering the period during which the COVID-19 vaccine is absent and the period during which the COVID-19 vaccine is available. Our analyses capture the dynamics of risk spillovers, not only on average but also on extreme tails. Diebold and Yilmaz (2009, 2012, 2014) standard approach is adopted to estimate spillover indices by decomposing the forecast error variance of the original mean-based vector autoregression (VAR). Furthermore, we follow Bouri et al. (2020) to extend the original approach of Diebold and Yilmaz (2012) by calculating the spillover indices based on quantile variance decomposition. This allows us to investigate the level of risk spillovers at both the left and right tails of the conditional distribution, which distinguishes the extreme spillovers from original mean-based estimators (i.e., standard "average" spillovers). Moreover, the estimated pairwise directional spillovers can be utilized in network topology (Diebold and Yilmaz, 2014), which visualizes the direction and intensity of connectedness. Network analysis is an important tool for measuring systemic risk across financial markets under turbulence (e.g., Kang and Lee, 2019; Lundgren et al., 2018), such as the outbreak of the COVID-19 pandemic (e.g., Aslam et al., 2020; Sui et al., 2022). In addition to constructing a network of standard spillovers, we describe the tail dependence structure. Full vaccination records were officially provided on December 13, 2020. In a static setting, our discussion centers on the changes in the overall views of risk spillovers across sub-periods before and after this date. For example, the weighted directed network of risk spillovers among selected Asia-Pacific markets was examined for two sub-samples. In the time-varying setting, we employ the rolling window approach to reflect the time variation in both mean-based and quantile-based spillover measures.

The second question is: Do COVID-19 vaccinations affect the extent of the Asia-Pacific stock market risk spillovers? Although evolving patterns of spillovers before and after the date on which the vaccination data is available can provide a preview of the

vaccination effect on risk spillovers, we adopt a series of panel data regressions to better answer this question. The data utilized in the regressions are from December 13, 2020 (the first date on which official data for the complete COVID-19 vaccinations is available) to March 22, 2022 (the end of the whole sample). The dependent variables can be either “TO” spillover indices of market i indicating the gross volatility spillovers transmitted to all other markets or “NET” spillover indices of market i indicating the differences between the gross volatility spillovers transmitted to and those received from all other markets. The main explanatory variable was the COVID-19 vaccination rate. Three vaccination-related variables¹ are alternatives to each other to ensure the robustness of our findings. Several variables are included in the regressions as controls to help better identify the impact of COVID-19 vaccinations. This discussion comprises three parts: (1) We analyze the effect of vaccinations on “average” spillovers (i.e., the standard spillover estimated within the mean-based VAR) and find the negative impact of mass vaccinations on spillovers; (2) The Social Attention (driven by economic uncertainty) and Market Uncertainty indices are employed in the heterogeneity test to determine whether the relationship between COVID-19 vaccinations and “average” risk spillovers is affected by these two factors; (3) We also explore the asymmetric effect of vaccinations on the downside and upside tails of spillovers (i.e., extreme spillovers).

Finally, what is the potential mechanism behind the influence of COVID-19 vaccinations on risk spillovers among major stock markets in the Asia-Pacific region? In this paper, we identify that investor sentiment may channel the vaccination effects on the “TO” and “NET” spillovers in each country. We construct a composite index of investor sentiment to mainly reflect the level of panic induced by the COVID-19 pandemic. And the two-stage regression is adopted to examine the association between COVID-19 vaccinations and panic sentiment as well as the association between panic sentiment and risk spillovers.

The remainder of this paper is organized as follows. The data and methodology are explained in Section 2. The empirical results of spillover estimations and regression analyses are presented in Sections 3 and 4, respectively. Section 5 presents the concluding remarks.

2. Data and methodology

2.1. Sample and data

This study examines the stock markets of 12 countries (Australia, Canada, China, Japan, Malaysia, Mexico, Philippines, Russia, Singapore, South Korea, Thailand, and the US) in the Asia-Pacific region. The entire sample period is from January 2, 2019, to March 22, 2022. This period covers the outbreak of the COVID-19 pandemic and the approval of COVID-19 vaccines. There are two key time points: January 23, 2020, was identified as the start of the COVID-19 pandemic, on which the city lockdown was imposed in Wuhan, and December 13, 2020, was identified as the start of the COVID-19 vaccination, on which the official WHO report of the COVID-19 full vaccination was available. To better serve the different purposes of empirical analyses, we extract different sub-samples from the whole sample, which will be elaborated on in the following sections.

We obtain economic and financial data for each country from the China Stock Market and Accounting Research (CSMAR) and Wind databases. Twitter-based measures are utilized, with macroeconomy-driving social attention proxied by the Twitter Economic Uncertainty index and market uncertainty proxied by the Twitter Market Uncertainty index. These measures are proposed by Baker et al. (2021) and thought to track perception of uncertainty using text messages based on a broad cross-section of social media users rather than journalist or experts. Daily observations are available from: http://www.policyuncertainty.com/twitter_uncert.html. Besides, the level of panic sentiment is reflected by a composite index constructed from three COVID-19 pandemic-related sentimental indicators provided by the Ravenpack (<https://coronavirus.ravenpack.com/>). COVID-19 vaccination statistics are manually collected through the World Health Organization (WHO) and country-by-country news reports.

2.2. Estimation of risk spillovers

Following Antonakakis and Kizys (2015), we use the natural logarithm of absolute daily returns, $\ln|R_{i,t}|$, to measure the stock market volatility of country i on day t . We examine volatility spillovers, a typical type of risk spillover, among 12 Asia-Pacific stock markets.

Diebold and Yilmaz (2009, 2012, 2014) proposed calculating spillover indices between variables by decomposing the forecast error variance of vector autoregression. The standard approach of the DY framework is based on original vector autoregression (VAR). Bouri et al. (2020) extend the standard (i.e., mean-based) approach of Diebold and Yilmaz (2012) connectedness to the quantile-based approach of connectedness, utilizing the quantile VAR model. This extension allows us to capture the extreme dependency at the tails of the variable distribution. Similar applications of quantile connectedness have also been seen in more recent studies (e.g., Ando et al., 2022; Chatziantoniou et al., 2021; Yousaf et al., 2022).

2.2.1. The quantile VAR model

According to Koenker and Bassett (1978), the n -variable quantile VAR process of the p th order, QVAR(p), can be outlined as follows:

¹ That is, *Vaccinated*, *Vaccinated_one* and *Vaccinated_100* variables. *Vaccinated* represents the percentage of the population fully vaccinated; *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and *Vaccinated_100* is calculated by vaccination doses per hundred people. More detailed information is presented in the Section 2.

$$y_t = \gamma(\tau) + \sum_{j=1}^p \Phi_j(\tau) y_{t-j} + \mu_t(\tau) \quad (1)$$

where $\tau \in (0, 1)$ denotes the quantile index, y_t and y_{t-j} are $n \times 1$ dimensional vectors of endogenous variables, p denotes the lag length of the QVAR model, $\gamma(\tau)$ and $\mu(\tau)$ represent the $n \times 1$ dimensional vectors of intercepts and residuals at quantile τ , respectively, and $\Phi_j(\tau)$ is the parameter matrix of the j th lagged coefficients at quantile τ (with $j = 1, \dots, p$).

Next, $\gamma(\tau)$ and $\Phi_j(\tau)$ can be estimated while assuming that the residuals fulfill the population quantile restrictions $Q_\tau(\mu_t(\tau)|y_{t-1}, \dots, y_{t-p}) = 0$, where the population τ th conditional quantile of response y is as follows:

$$Q_\tau(y_t|y_{t-1}, \dots, y_{t-p}) = \gamma(\tau) + \sum_{j=1}^p \widehat{\Phi}_j(\tau) y_{t-j} \quad (2)$$

Since each possible Eq. (2) contains the same variables on the right-hand side, the estimation problem is then solved on an equation-by-equation quantile regression basis, that is, at every quantile (Cecchetti and Li, 2008).

2.2.2. The spillover indices based on quantile VAR model

Inspired by Diebold and Yilmaz (2009, 2012, 2014), Bouri et al. (2020) computed spillover indices in each quantile τ based on quantile variance decomposition. Hence, the QVAR(p) in Eq. (1) can be rewritten as its QVMA (∞) representation based on Wold's theorem, as follows:

$$y_t = \kappa(\tau) + \sum_{i=1}^{\infty} A_i(\tau) \mu_{t-i}(\tau) \quad (3)$$

Where,

$$\kappa(\tau) = (I_n - \Phi_1(\tau) - \dots - \Phi_p(\tau))^{-1} \gamma(\tau) \quad (4)$$

$$A_i(\tau) = \begin{cases} 0, & i < 0 \\ I_n, & i = 0 \\ \Phi_1(\tau)A_{i-1} + \dots + \Phi_p(\tau)A_{i-p}, & i > 0 \end{cases} \quad (5)$$

Following this, the H-step-ahead generalized forecast error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998) is computed to show the impact of a shock in variable j on variable i :

$$\theta_{ij,\tau}^g(H) = \frac{\sigma(\tau)_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h(\tau) \sum(\tau) e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h(\tau) \sum(\tau) A_h(\tau)' e_j)^2} \quad (6)$$

$\theta_{ij,\tau}^g(H)$ indicates the contribution of the j th variable to the variance of the forecast error of the i th variable at horizon H based on the τ th quantile variance decomposition, Σ is the covariance matrix of the vector of errors, σ_{jj} is the j th diagonal element of the covariance matrix Σ , e_i represents a selection vector where the i th element is one and the others are zeros.

Then, each entry of the variance decomposition matrix is normalized as follows:

$$\widetilde{\theta}_{ij,\tau}^g(H) = \frac{\theta_{ij,\tau}^g(H)}{\sum_{j=1}^n \theta_{ij,\tau}^g(H)} \quad (7)$$

This normalization leads to the following two equalities: $\sum_{j=1}^n \widetilde{\theta}_{ij,\tau}^g(H) = 1$ and $\sum_{i=1}^n \sum_{j=1}^n \widetilde{\theta}_{ij,\tau}^g(H) = n$.

Within the framework of Diebold and Yilmaz (2012, 2014), various measures of connectedness (i.e., spillovers) can be formulated as follows (all indices are expressed in percentages).

Specifically, the total spillover index at each quantile τ , which can effectively reflect the overall market risk (Chatziantoniou et al., 2021), is given by:

$$TSI(\tau) = \frac{\sum_{i=1}^n \sum_{j=1, i \neq j}^n \widetilde{\theta}_{ij,\tau}^g(H)}{\sum_{i=1}^n \sum_{j=1}^n \widetilde{\theta}_{ij,\tau}^g(H)} \times 100 \quad (8)$$

Firstly, the total directional spillover *TO* others (i.e., “*TO*” spillover) at quantile τ , which represents the shocking effect variable i has on all other variables j , is given by:

$$TO_i(\tau) = \sum_{j=1, i \neq j}^n \widetilde{\theta}_{ji,\tau}^g(H) \times 100 \quad (9)$$

Secondly, the total directional spillover *FROM* others (i.e., “*FROM*” spillover) at quantile τ , which represents the shocking effect all other variables j has on variable i , is given by:

$$FROM_i(\tau) = \sum_{j=1, i \neq j}^n \widetilde{\theta}_{ij,\tau}^g(H) \times 100 \quad (10)$$

Thirdly, the *NET* total directional spillover (i.e., “*NET*” spillover) at quantile τ , which denotes the net impact variable i has on all other variables j is given by:

$$NET_i(\tau) = TO_i(\tau) - FROM_i(\tau) \quad (11)$$

Lastly, the pairwise *NET* directional spillover (i.e., “*Pairwise Net*” spillover) at quantile τ is given by:

$$PS_{ij}(\tau) = \tilde{\theta}_{ji,\tau}^g(H) - \tilde{\theta}_{ij,\tau}^g(H) \quad (12)$$

Time-varying connectedness can be obtained by rolling window sampling, as mentioned in Diebold and Yilmaz (2012, 2014). In this study, the spillover estimation is based on a VAR lag order of 2 (according to the Bayesian information criterion) and a 10-step ahead forecast, while the window is set as 100 days.

2.3. Regression model

As mentioned in Introduction section, regression analyses are used to answer the second and third research questions.

2.3.1. Baseline

To verify the effect of the COVID-19 vaccination on volatility (risk) spillovers, we employ different specifications of the following regression model:

$$RS_{i,t} = \alpha_0 + \beta_0 Vaccine_{i,t} + \gamma_0 Controls + \mu_i + \varphi_t + \varepsilon \quad (13)$$

$RS_{i,t}$ is one of six dependent variables: “*TO*” (standard) risk spillovers, “*NET*” (standard) risk spillovers, “*TO*” lower-tail risk spillovers, “*NET*” lower-tail risk spillovers, “*TO*” upper-tail risk spillovers and “*NET*” upper-tail risk spillovers for country i on day t .

$Vaccine_{i,t}$ is the primary explanatory variable reflecting the vaccination situation in country i on day t . It is proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people.

Controls is a vector of control variables, which are shown in prior studies to affect “*TO*” and “*NET*” risk spillovers (e.g., Yang et al., 2020). This vector includes the level of spillovers received by country i from other countries on trading day t in the risk network (*From*), the overall level of risk spillovers among the Asia-Pacific market (*AsiaNet*), MSCI European Monetary Economic Union Index (*Vol*), Gold ETF Volatility Index (*VIX_Gold*), Crude Oil ETF Volatility Index (*VIX_Oil*), S&P 500 Volatility Index (*VIX_SPX*), and the emerging market volatility index (*VIX_Emerging*). The above indicators not only reflect the volatility of the world's important capital markets but also help control the source of cyber risks, which allows us to better observe the impact of COVID-19 vaccination on risk spillovers.

In addition, we introduce country- and time-fixed effects to account for unobservable cross-sectional factors at the country level and macroeconomic conditions over the same period.

2.3.2. Two-stage procedure

Further, to investigate whether the investor panic sentiment is the channel through which the COVID-19 vaccination affects risk spillovers, we adopt the method of a two-stage regression outlined in Yi et al. (2022). The COVID-19-related sentiment index (*PanicSent*) in this paper is calculated as the mean of three components (Source: Ravenpack): (1) *PANIC_INDEX* measures the level of news chatter that makes reference to panic or hysteria alongside the Coronavirus; (2) *FAKE_NEWS_INDEX* measures the level of media chatter about the novel virus that makes reference to misinformation or fake news alongside COVID-19; (3) *INFODEMIC_INDEX* calculates the percentage of all entities (places, companies, organizations, etc.) that are reported in the media alongside COVID-19. The values of above-mentioned variables all range between 0 and 100.

We first regress the *PanicSent* on *Vaccine* to get the value of *PanicSent* explained by *Vaccine*. The specification is shown as follows:

$$PanicSent_{i,t} = \alpha + \beta Vaccine_{i,t} + \gamma Controls + \mu_i + \varphi_t + \varepsilon \quad (14)$$

$$\widehat{PanicSent}_{i,t} = \hat{\alpha} + \hat{\beta} Vaccine_{i,t} + \hat{\gamma} Controls \quad (15)$$

$\widehat{PanicSent}_{i,t}$ reflects the level of COVID-19-related sentiment index in country i on day t . The control variables are consistent with the benchmark model (Eq. (13)).

Secondly, we regress the *RS* on estimated *PanicSent*:

$$RS_{i,t} = \alpha_1 + \beta_1 \widehat{PanicSent}_{i,t} + \gamma_1 Controls + \mu_i + \varphi_t + \varepsilon_{1i,t} \quad (16)$$

3. Spillover results analysis

The results of volatility (risk) spillovers estimated within the mean-based and quantile-based VAR models are presented and discussed in this section.

3.1. Static analysis: spillover tables

To illustrate the changes in Asia-Pacific stock market risk spillovers induced by the availability of COVID-19 vaccines during the COVID-19 pandemic, which began on January 23, 2020, as mentioned in Section 2.1, we present snapshots for two sub-periods: 23/01/

2020–12/12/2020 (before the vaccine was launched) and 13/12/2020–22/03/2022 (after the vaccine was launched). First, we demonstrate the results of the spillover matrices estimated by the mean-based approach in Table 1 and the quantile-based approach in Tables 2–4. Variation in the level of connectedness across quantiles can be understood as a regime-switching process, allowing the connectedness associated with extreme downside shocks (at 0.05 quantile) and extreme upside shocks (at 0.95 quantile) to be captured. Specifically, the standard approach of Diebold and Yilmaz (2012) estimates volatility shock propagation in the conditional mean. By applying the quantile-based approach, we obtain risk spillovers estimated at the conditional median (see Table 2), lower tail (see Table 3), and upper tail (see Table 4).

In each spillover table, the i th entry in the i th row and j th column, called pairwise directional spillovers, represents the spillover effects of market i from market j . The off-diagonal row sums are presented in the last column labelled “FROM,” indicating the total directional spillover received by market i from all other markets, namely “FROM” spillovers. Similarly, the off-diagonal column sums are presented on the last row labelled “TO,” indicating the total directional spillover transmitted by market i to all other markets, namely “TO” spillovers. The total spillover index is shown in the lower right corner of the table. It is calculated as the sum of all “TO” spillovers (or “FROM” spillovers) relative to the sum of all entries in the matrix.

Overall, compared to the first-stage pandemic period (Panel A) before the presence of COVID-19 vaccines, there are obviously fewer volatility spillovers in the second stage (Panel B) in spillover tables estimated at the conditional mean and median (Table 1–2). Especially in Table 1, the total spillover index across 12 stock markets is 76.2% in Panel A; however, it is only 32.3% in Panel B. The results suggest that the appearance of vaccines plays an important role in preventing the continuing spread of pandemic-induced panic and in reducing the total risk spillover among the Asia-Pacific stock markets. A possible explanation for this phenomenon is as follows. As we all know, investors' risk attitudes toward certain events might vary considerably, thus leading to an increase in “irrational” investment decisions. The launch of the COVID-19 vaccination rebuilds public optimism, especially investors' confidence in global economic recovery, which positively influences global stock markets, and the systemic risk spillover effects also fell significantly. Besides, the results of the quantile-based approach show that the spillovers estimated at extreme tails (Table 3–4) are generally larger than those estimated at the conditional median. For example, in the second stage of the COVID-19 pandemic (post-vaccination period), the total spillover index is 79.5% at the extreme lower quantile ($\tau = 0.05$) and 90.5% at the extreme upper quantile ($\tau = 0.95$), whereas the figure is only 41.6% at the conditional median. A possible explanation for this is that extreme shocks are more likely to cause changes in investors' expectations and trigger herding behavior than median shocks. These results highlight the strong impact of

Table 1
Volatility spillovers in the mean VAR.

	AUS	CAN	JPN	USA	SIN	RUS	MAL	THA	CHN	MEX	PHI	KOR	FROM
Panel A: Pre-Vaccination period (23/01/2020–12/12/2020)													
AUS	18.8	13.2	4.4	9.9	9.8	6.7	5.7	7.8	5.4	8.5	4.1	5.9	81.2
CAN	10.5	20.2	4.3	13	8	8.2	5.8	7.6	4.1	9.1	4.1	5.1	79.8
JPN	7	11.7	29.1	10.1	6.5	4.4	4.5	5.9	3.4	7.3	3.7	6.5	70.9
USA	9.3	16	3.8	21.5	7.2	6.5	6.2	7.4	4.7	8.8	3.7	4.8	78.5
SIN	10.2	11.1	3.8	7.2	20.3	6.2	6.8	8.3	6.9	7.7	3.9	7.6	79.7
RUS	9	13.4	3.1	9.4	6.7	24.3	4.4	6.5	3.4	10	4.9	5.1	75.7
MAL	8.1	10.2	3.5	7.2	8.8	5.2	22.3	9.5	4.4	6.4	6	8.4	77.7
THA	8.3	10.6	3.7	7.4	9.5	6.1	8.4	21.4	4.9	7.2	6.2	6.3	78.6
CHN	8	7.7	2.8	6.8	10.9	5.6	5.5	6.9	30.2	4.8	3.5	7.3	69.8
MEX	9.1	12	3.9	9.1	8.7	7.8	5.7	7.8	3.5	23.1	4.4	4.7	76.9
PHI	7.1	8	3.7	5.4	6.1	6.5	6.8	7.8	3.4	6.5	31.3	7.5	68.7
KOR	7.9	8.4	4.6	5.8	10	6.1	8.6	6.8	6.1	5.9	6	23.8	76.2
TO	94.6	122.2	41.6	91.3	92.2	69.3	68.4	82.3	50.2	82.2	50.3	69.2	913.8
NET	13.4	42.4	−29.3	12.8	12.5	−6.5	−9.4	3.7	−19.6	5.3	−18.3	−7	TSI = 76.2
Panel B: Post-Vaccination period (13/12/2020–22/03/2022)													
AUS	60.4	5.6	6.6	4	8.4	4.1	1.2	0.4	0.5	3.1	0.6	5.1	39.6
CAN	5.9	53.2	2.6	11.3	6.1	6.8	1.5	1.4	1.4	4.9	1.3	3.6	46.8
JPN	9.1	4	62.7	5.6	4.1	1.8	1.2	1.2	2.7	1.1	1.4	5.1	37.3
USA	5	13	3.8	58.4	3	2.4	0.7	1.1	2.4	3.6	1.1	5.5	41.6
SIN	7.2	5.3	4.9	2.4	61.4	2.7	2.8	1	0.6	2.5	1.1	8.1	38.6
RUS	4.6	8.5	1.2	1.6	3	67.4	1.3	4.5	0.6	5.3	0.5	1.4	32.6
MAL	2.4	2.3	2	0.7	5.3	2.8	77.4	2.1	1.2	1.2	0.9	1.7	22.6
THA	0.9	2.4	1.8	1.4	1.2	4.1	1.7	78.3	2.7	3.1	1.4	1	21.7
CHN	1.5	1.5	3.3	3.5	1.2	0.6	0.9	1.1	77.2	2.3	1.5	5.5	22.8
MEX	3.3	5.7	2.1	3.9	2.6	5.4	0.9	1.3	1.3	69.7	1	2.8	30.3
PHI	1	1.4	0.7	1.3	0.9	1.4	0.8	1	2.3	1.6	84.4	3	15.6
KOR	3	3.9	4.1	5.9	8.2	1.5	1.1	1	4.3	4.2	1.4	61.4	38.6
TO	43.9	53.4	33	41.5	44	33.7	14.2	16.1	20.1	32.8	12.4	42.9	388.1
NET	4.3	6.6	−4.3	−0.2	5.4	1.1	−8.4	−5.5	−2.6	2.5	−3.2	4.3	TSI = 32.3

Notes: This table reports the volatility spillovers among the 12 Asia-Pacific stock markets in the mean VAR, based on the standard approach of Diebold and Yilmaz (2012), during the pre-vaccination and post-vaccination periods. “FROM” measures the gross directional volatility spillovers received from other stock markets, “TO” measures the gross directional volatility spillovers transmitted to other stock markets, “NET” measures the net directional volatility spillovers received from or transmitted to other markets, and “TSI” measures the total level of the volatility spillovers among the 12 Asia-Pacific stock markets.

Table 2
Volatility spillovers in the quantile VAR (median $\tau = 0.5$).

	AUS	CAN	JPN	USA	SIN	RUS	MAL	THA	CHN	MEX	PHI	KOR	FROM
Panel A: Pre-Vaccination period (23/01/2020–12/12/2020)													
AUS	36.85	7.96	3.88	7.65	7.69	4.94	4.29	5.21	6.65	7.04	3.19	4.64	63.15
CAN	5.86	35.6	2.54	17.63	4.93	6.22	4.43	6.43	3.37	6.7	3.24	3.06	64.4
JPN	4.46	7.08	44.53	8.29	4.25	2.57	4.88	6.95	3.85	3.43	3.3	6.4	55.47
USA	4.47	18.11	2.82	37.48	4.41	4.09	4.99	5.66	4.29	6.92	3.75	3.01	62.52
SIN	6.6	6.66	3.02	5.2	36.15	4.63	6.17	6.51	9.41	6	2.83	6.81	63.85
RUS	4.12	8.28	2.19	6.03	5.1	46.92	4.15	4.54	3.92	6.72	4.83	3.2	53.08
MAL	4.14	6.01	4.63	5.93	6.66	3.57	38.94	7.39	4.75	4.36	6.9	6.71	61.06
THA	4.43	7.21	4.25	5.27	7.25	4.69	6.81	40.23	4.75	4.29	5.39	5.44	59.77
CHN	5.88	4.14	2.89	5.2	10.99	4.31	5.44	5.03	41.79	3.61	3.41	7.31	58.2
MEX	5.97	7.28	3.32	7.04	7.19	5.58	4.94	6.1	3.52	41.77	3.8	3.49	58.23
PHI	3.67	3.04	3.32	3.85	3.44	3.79	8.05	5.58	3.33	3.82	50.83	7.27	49.1
KOR	4.66	4.93	4.87	4.51	8.05	3.66	7.38	5.46	7.22	4.47	6.45	38.34	61.66
TO	54.25	80.71	37.75	76.59	69.96	48.06	61.53	64.85	55.07	57.35	47.1	57.34	710.56
NET	-8.89	16.31	-17.72	14.07	6.12	-5.02	0.47	5.08	-3.14	-0.88	-2.07	-4.33	TSI = 59.21
Panel B: Post-Vaccination period (13/12/2020–22/03/2022)													
AUS	56.89	7.77	4.18	4.21	6.67	5.28	2.46	1.47	1.61	3.36	0.97	5.14	43.11
CAN	5.42	46.53	2.28	7.96	6.48	8.38	3.59	4.13	1.58	7.09	1.93	4.62	53.47
JPN	6.82	4.86	52.95	10.25	5.69	1.3	3.27	1.21	2.97	1.92	1.31	7.44	47.05
USA	9.28	9.38	3.2	49.7	5.04	3.79	4.31	3.18	1.79	3.91	0.65	5.78	50.3
SIN	6.18	6.75	4.42	2.13	57.95	4.23	2.36	2.09	1.81	4.75	0.87	6.46	42.05
RUS	5.45	10.21	1.12	2.86	4.6	58.94	3.63	3.27	1.08	5.45	0.97	2.41	41.06
MAL	1.8	6.14	3.47	1.31	4.29	4.83	63.48	6.69	3.37	1.4	1.19	2.05	36.52
THA	1.94	6.3	1.45	3.59	3.11	3.62	6.38	64.52	2.91	2.67	1.23	2.26	35.48
CHN	2.34	2.8	2.47	4.09	2.34	1.29	3.3	4.47	65.88	3.41	1.83	5.79	34.12
MEX	3.44	7.15	2.53	4.6	4.6	5.47	1.31	2.01	0.98	59.96	3.78	4.17	40.04
PHI	1.93	4.94	1.27	1.76	2.39	2.42	2.12	2.35	4.53	2.9	68.07	5.32	31.93
KOR	4.03	4.29	4.44	6.34	6.86	2.93	2.13	1.9	5.44	4.05	2.08	55.52	44.48
TO	48.62	70.59	30.81	49.09	52.07	43.55	34.89	32.78	28.07	40.93	16.8	51.42	499.62
NET	5.5	17.12	-16.24	-1.21	10.02	2.48	-1.63	-2.7	-6.04	0.89	-15.13	6.94	TSI = 41.63

Notes: This table reports the volatility spillovers among the 12 Asia-Pacific stock markets in the quantile VAR (median $\tau = 0.5$) during the pre- and post-vaccination periods. “FROM” measures the gross directional volatility spillovers received from other stock markets, “TO” measures the gross directional volatility spillovers transmitted to other stock markets, “NET” measures the net directional volatility spillovers received from or transmitted to other markets, and “TSI” measures the total level of the volatility spillovers among the 12 Asia-Pacific stock markets.

extreme shocks on the volatility spillover system. Comparing the results of sub-samples at lower and upper tails, the decrease in total spillover index at the second stage (Panel B) is smaller under extreme upside shocks than under extreme downside shocks. This suggests the asymmetric effect of COVID-19 vaccination.

Regarding the divergence in market reactions across different countries, Table 1-3 that during the pre-vaccination period, compared with emerging markets, developed markets, except Japan, have relatively high levels of volatility spillovers transmitted to other regional markets. More specifically, Japan is the weakest producer of volatility risk and a minor receiver (especially in the left tail) among developed markets. The inferior position of the Japanese stock market in Asia-Pacific information leadership has been reported in some previous studies (Kim, 2005). This implies that the volatility linkages between the Japanese and other major stock markets are not as close as expected (Wang et al., 2022). Moreover, the Canadian stock market serves as the strongest producer of volatility spillovers to other markets at the conditional mean and median (see Table 1-2) during both subperiods. In particular, it delivered the highest volatility among all foreign stock markets in the U.S. market in these two tables. By comparison, within mean-, median-, and lower-tail-based VARs (see Table 1-3), the Philippines is the weakest producer and the least receiver of volatility spillover during the post-vaccination period. Given that volatility spillovers involved with the Philippines are also small during the pre-vaccination period, this may be because the Philippines is a small country in Asia and its openness level is limited. Thus, the Philippine stock market is more resilient to external shocks such as the COVID-19 pandemic. Other emerging markets, such as China, Thailand, and Malaysia, are also relatively less influenced by volatility spillovers from other markets.

If we focus on the results for negative news shocks shown in Table 3 and compare the “TO” risk spillovers between Panels A and B, we find that the total spillovers transmitted from several emerging markets, including Malaysia, Thailand, China, and the Philippines, are significantly reduced after the availability of vaccines, while little vaccination effects appear in most developed markets. In addition, we find that China's spillover effect on other markets is as high as 117.44% in Panel B of Table 4. This result indicates that China, as an emerging power, has an important impact on the Asia-Pacific region when the market experiences intense news in the right tail. This may be related to the prompt response of the Chinese government to the pandemic outbreak, such as a series of measures that restrict the deterioration of the pandemic and thus mitigate the damage to economic activities.

3.2. Static analysis: spillover networks

To provide a more intuitive analysis, Fig. 1 and Fig. 2 describe the “Pairwise Net” volatility (risk) spillovers among the 12 Asia-

Table 3Volatility spillovers in the quantile VAR (lower $\tau = 0.05$).

	AUS	CAN	JPN	USA	SIN	RUS	MAL	THA	CHN	MEX	PHI	KOR	FROM
Panel A: Pre-Vaccination period (23/01/2020–12/12/2020)													
AUS	17.43	8.14	6.7	7.61	8.94	6.57	7.15	7.59	8.23	7.64	6.3	7.7	82.57
CAN	8.12	17.81	5.72	12.3	7.12	8.18	7.03	7.69	6.39	8.44	5.19	6.01	82.19
JPN	7.47	6.85	19.87	7.33	7.33	5.66	8.13	7.65	7.17	7.12	6.38	9.04	80.13
USA	7.45	12.2	6.22	17.85	6.94	6.86	7.55	7.68	7.14	8.33	5.7	6.09	82.15
SIN	8.58	6.93	6.29	6.59	17.04	6.6	8.17	8.05	9.27	7.72	6.08	8.68	82.96
RUS	7.43	9	5.55	7.79	7.36	19.53	6.74	6.94	7.1	9.06	6.46	7.03	80.47
MAL	7.09	6.96	7.13	7.22	8.33	5.85	17.48	8.62	7.78	6.77	8.08	8.7	82.52
THA	7.55	7.62	6.8	7.35	8.47	6.2	8.74	17.72	7.66	7.21	7.25	7.44	82.28
CHN	8.31	6.49	6.38	7.13	9.61	6.52	7.97	7.72	17.86	6.79	6.47	8.74	82.14
MEX	7.66	8.44	6.32	8.37	8.12	8.25	7.14	7.49	6.95	18.1	6.58	6.59	81.9
PHI	7.12	5.88	6.38	6.24	7.18	6.6	9.1	8.22	7.21	7.1	20.29	8.7	79.71
KOR	7.73	6.03	7.99	6.08	8.99	6.27	8.92	7.5	8.56	6.37	7.9	17.66	82.34
TO	84.52	84.54	71.48	83.99	88.39	73.56	86.63	85.14	83.47	82.54	72.39	84.71	981.36
NET	1.95	2.35	−8.64	1.84	5.43	−6.91	4.11	2.86	1.33	0.64	−7.32	2.37	TSI = 81.78
Panel B: Post-Vaccination period (13/12/2020–22/03/2022)													
AUS	18.77	8.94	8.16	7.69	8.65	7.54	6.35	6.24	5.61	7.54	5.58	8.93	81.23
CAN	8.86	18.29	6.8	9.06	8.07	8.7	6.59	7.35	5.66	7.88	4.49	8.26	81.71
JPN	8.76	7.52	20.04	7.75	7.65	6.5	7.47	5.84	6.69	6.53	5.55	9.7	79.96
USA	8.07	10.11	7.64	19.93	7.08	6.44	5.52	7.06	6.1	8.3	5.01	8.75	80.07
SIN	8.96	8.7	7.41	6.74	19.86	7.5	6.9	6.75	5.8	8.28	3.99	9.1	80.14
RUS	8.3	9.85	6.4	6.46	7.86	20.65	7.26	7	5.1	8.82	5.1	7.2	79.35
MAL	7.34	7.8	7.93	5.65	7.69	7.7	21.8	8.07	6.76	6.4	5.93	6.93	78.2
THA	6.8	8.67	6.09	7.42	7.15	7.23	7.89	21.46	6.88	7.56	5.52	7.33	78.54
CHN	6.6	6.83	7.42	7.1	6.62	5.48	7.11	7.56	22.45	6.77	6.67	9.39	77.5
MEX	7.82	8.49	6.16	8.04	8.25	8.42	5.95	7.01	5.72	19.74	6.12	8.28	80.2
PHI	6.99	6.16	6.76	6.37	5.04	6.2	6.91	6.58	7.24	8	25.16	8.58	74.8
KOR	8.24	8.08	8.67	8	8.47	6.28	5.84	6.35	7.72	7.75	6.25	18.35	81.65
TO	86.74	91.16	79.44	80.28	82.53	77.98	73.78	75.82	69.28	83.82	60.21	92.46	953.51
NET	5.51	9.46	−0.53	0.21	2.39	−1.37	−4.42	−2.73	−8.26	3.56	−14.63	10.81	TSI = 79.46

Notes: This table reports the volatility spillovers among the 12 Asia-Pacific stock markets in the quantile VAR (median $\tau = 0.05$) during the pre- and post-vaccination periods. “FROM” measures the gross directional volatility spillovers received from other stock markets, “TO” measures the gross directional volatility spillovers transmitted to other stock markets, “NET” measures the net directional volatility spillovers received from or transmitted to other markets, and “TSI” measures the total level of the volatility spillovers among the 12 Asia-Pacific stock markets.

Pacific stock markets before and after the launch of the COVID-19 vaccines, respectively, through network visualization. The division of subperiods is consistent with that in Section 3.1. In each figure, part (a) shows the results of the standard approach of Diebold and Yilmaz (2012), while parts (b), (c), and (d) show the results of the quantile VAR approach in the middle, left, and right tail quantiles, respectively. Each node represents a stock market. The arrow indicates the direction of “Pairwise Net volatility spillover between the two stock markets. The edge size (i.e., the thickness of the arrow) reflects the magnitude of the “Pairwise Net” spillover between two stock markets. The magnitude is also reflected in the color types of the edge: dark (strong) versus light (weak).

Comparing the networks for two sub-periods presented in Fig. 1 and Fig. 2, there is a common feature existing in the “average” spillover networks (from the standard approach) and the quantile spillover networks: the connections of the network are relatively sparse during the post-vaccination period (see Fig. 2), with the directed edges thinner during this period than it was before. This suggests a weakening of network connectedness after the presence of COVID-10 vaccines, which may be associated with economic recovery and market confidence to resist shocks. Notably, in both Fig. 1 and Fig. 2, relative to the mean- and median-based spillover networks (parts (a) and (b)), the extreme tail network (parts (c) and (d)) has a more complex structure, with more edges indicating stronger spillovers in color and size. This finding suggests that the volatility linkages between stock markets are more susceptible to extreme events. Generally, the graphical visualization of “Pairwise Net” volatility spillover is in line with the results in Table 1–4. From the perspective of economic significance, the quantile network is more accurate and contains richer information than the standard network. As mentioned in Bouri et al. (2020), the tail risk propagation is extremely useful for regulators and investors to more effectively manage significant effects arising from extreme shocks, which cannot be fully uncovered by the standard connectedness approach.

Focusing on the direction of the spillover arrows, we can see that the structure of spillovers is quite different before and after the launch of vaccines. For instance, as shown in Fig. 1(a), before the vaccines are launched, the volatility spillovers among the U.S., Japan, and Canada are strong, while Canada is the net transmitter, with all arrows being outward, indicating that it transmits more volatility spillovers to all other markets. However, after the vaccines are launched, as shown in Fig. 2(a), the volatility spillovers among Russia, Malaysia, Thailand, and South Korea are strong, while Russia seems to be the net transmitter. These two findings point out that the “average” level of volatility linkages between stock markets in the same economic region is relatively high. Furthermore, when there is plenty of strong upside news in the market during the pre-vaccination period (see Fig. 1(d)), we find that the US, Singapore, and Mexico are significant contributors to volatility spillovers. More specifically, the main thick arrows are directed from the US to South Korea, Mexico to South Korea, Mexico to Malaysia, Singapore to Russia, and Singapore to South Korea, indicating that the fluctuations

Table 4Volatility spillovers in the quantile VAR (upper $\tau = 0.95$).

	AUS	CAN	JPN	USA	SIN	RUS	MAL	THA	CHN	MEX	PHI	KOR	FROM
Panel A: Pre-Vaccination period (23/01/2020–12/12/2020)													
AUS	8.7	8.91	8.59	9.27	8.95	7.63	7.51	7.84	8.19	8.94	8.13	7.35	91.3
CAN	8.07	9.54	8.68	9.15	8.68	7.75	7.56	8.37	7.97	9.14	7.98	7.11	90.46
JPN	7.96	8.87	9.35	9.24	8.4	7.34	7.83	8.43	7.95	9.37	8.09	7.15	90.65
USA	8.26	9.45	8.46	9.92	8.8	7.64	7.23	8	7.95	9.17	8.05	7.07	90.08
SIN	7.98	9.2	8.77	8.78	9.39	7.35	7.66	8.51	7.98	9.14	8.14	7.1	90.61
RUS	8.09	9.01	8.69	8.91	9.19	8.22	7.3	8.4	8.1	8.83	8.21	7.03	91.78
MAL	8.2	8.56	9.12	8.56	8.71	7.53	8.43	8.32	7.94	9.24	8.11	7.3	91.57
THA	8.07	8.92	8.89	8.86	8.86	7.57	7.39	8.9	7.99	9.03	8.25	7.26	91.1
CHN	8.01	8.87	8.55	8.83	8.78	7.72	7.32	8.16	8.98	8.97	8.35	7.45	91.02
MEX	8.26	8.83	8.67	9.03	8.55	7.64	7.47	8.1	7.99	10.15	8.14	7.18	89.85
PHI	8.09	8.73	8.43	8.81	8.79	7.71	7.6	8.25	8.07	9.2	9.1	7.22	90.9
KOR	8.41	8.78	8.46	8.88	8.92	7.57	7.46	7.75	8.19	9.02	8.47	8.1	91.9
TO	89.42	98.13	95.31	98.31	96.63	83.44	82.33	90.14	88.32	100.04	89.92	79.21	1091.21
NET	−1.89	7.67	4.67	8.22	6.02	−8.34	−9.24	−0.96	−2.69	10.2	−0.98	−12.68	TSI = 90.93
Panel B: Post-Vaccination period (13/12/2020–22/03/2022)													
AUS	8.89	8.92	7.56	8.81	9.4	7.05	7.4	7.89	10.31	7.86	7.6	8.31	91.11
CAN	7.76	10.47	7.8	8.87	8.29	7.16	7.47	8.04	10.61	8.12	6.73	8.67	89.53
JPN	7.98	9.81	8.31	8.74	8.88	7.2	7.47	8.66	9.52	8.08	7.53	7.82	91.69
USA	7.73	9.62	7.24	9.17	8.52	6.92	7.51	8.76	10.52	8.04	7.55	8.41	90.83
SIN	8.17	9.09	7.8	8.4	10.35	7.06	7.62	8.69	9.3	8.5	7.22	7.78	89.65
RUS	7.66	8.75	7.56	7.96	9.11	7.72	7.93	8.69	11.1	7.94	7.79	7.8	92.28
MAL	8.38	8.8	7.39	8.18	9.59	7.16	8.67	8.92	9.25	8.08	8.26	7.33	91.33
THA	7.61	8.94	7.44	8.07	9.19	6.94	7.42	9.7	11.42	7.81	7.91	7.55	90.3
CHN	7.08	8.37	7.64	8.21	8.88	6.43	7.67	8.68	13.97	7.14	7.26	8.69	86.03
MEX	7.21	8.54	7.56	7.94	9.33	6.74	7.38	8.69	11.71	8.73	8.46	7.72	91.27
PHI	6.77	8.21	6.98	7.65	8.82	6.59	7.92	9.02	14.48	6.78	8.39	8.38	91.61
KOR	7.87	9.57	7.43	8.57	8.83	7.19	7.84	8.48	9.22	8.21	7.4	9.4	90.6
TO	84.2	98.61	82.39	91.39	98.84	76.45	83.65	94.53	117.44	86.56	83.71	88.47	1086.24
NET	−6.91	9.08	−9.3	0.55	9.2	−15.83	−7.69	4.24	31.4	−4.72	−7.9	−2.13	TSI = 90.52

Notes: This table reports the volatility spillovers among the 12 Asia-Pacific stock markets in the quantile VAR (median $\tau = 0.95$) during the pre- and post-vaccination periods. “FROM” measures the gross directional volatility spillovers received from other stock markets, “TO” measures the gross directional volatility spillovers transmitted to other stock markets, “NET” measures the net directional volatility spillovers received from or transmitted to other markets, and “TSI” measures the total level of the volatility spillovers among the 12 Asia-Pacific stock markets.

at the upper quantile in these economies' stock markets are closely correlated. Volatility spillovers in the Asia-Pacific region are mainly attributed to several major markets (nodes) and spillovers (edges). Conversely, during the post-vaccination period (see Fig. 2(d)), China is the key contributor to volatility spillovers to the Philippines, Russia, Mexico, Australia, and the US. This finding is consistent with the observation in Panel B of Table 4 that the Chinese stock market plays a crucial role in transmitting volatility risks to other regional markets in the upper tails during the post-vaccination period. This further confirms that China's initiative to fight the COVID-19 pandemic enhances its financial influence in the Asia-Pacific region. Move on to the negative shocks, comparing Fig. 1-(c) and Fig. 2-(c), we also find that the network of volatility spillovers for post-vaccination samples is less complex than that for pre-vaccination samples, suggesting the vaccination effects on stabilizing Asia-Pacific regional stock markets by weakening the system-wide connectedness.

To complement our discussion on the network of “Pairwise Net” volatility spillovers, we also present the network of pairwise directional volatility spillovers among the 12 Asia-Pacific stock markets in the Appendix. In these figures, the node size reflects the overall magnitude of the transmission for each market. The magnitude is also reflected in the color of the node: dark (strong) versus light (weak). The arrow indicates the direction of the pairwise volatility spillover, while thickness and color reflect the strength of the spillovers.

3.3. Dynamic analysis: rolling-window spillover plots

It is insufficient to focus only on risk spillovers in a static setting. To better understand the time-varying characteristics of volatility (risk) spillovers among the 12 stock markets, we employ dynamic analysis using a rolling window approach. This approach was applied to the entire sample period (i.e., January 2, 2019, to March 22, 2022) to observe the impact of the COVID-19 outbreak as well as the impact of the COVID-19 vaccination. The time-varying volatility connectedness is estimated at the conditional mean, median, lower tail, and upper tail. Figs. 3 and 4 summarize the results of the total spillover index (TSI). This index summarizes the system-wide spillovers among 12 Asia-Pacific stock markets and reflects the overall financial stability of this system. Generally, Fig. 3 shows that the TSI at the conditional mean and middle quantile varies considerably, ranging between 35% and 88%. In contrast, Fig. 4 shows that TSI at both the left and right tails is much higher, but the range of fluctuations is much smaller, from 78% to 88% and from 88% to 93%, respectively. These observations are consistent with the volatility spillover matrices presented in Tables 1–4. Such a high level of system-wide risk spillover at both the lower and upper tails reveals an increase in the sensitivity of the Asia-Pacific stock markets to

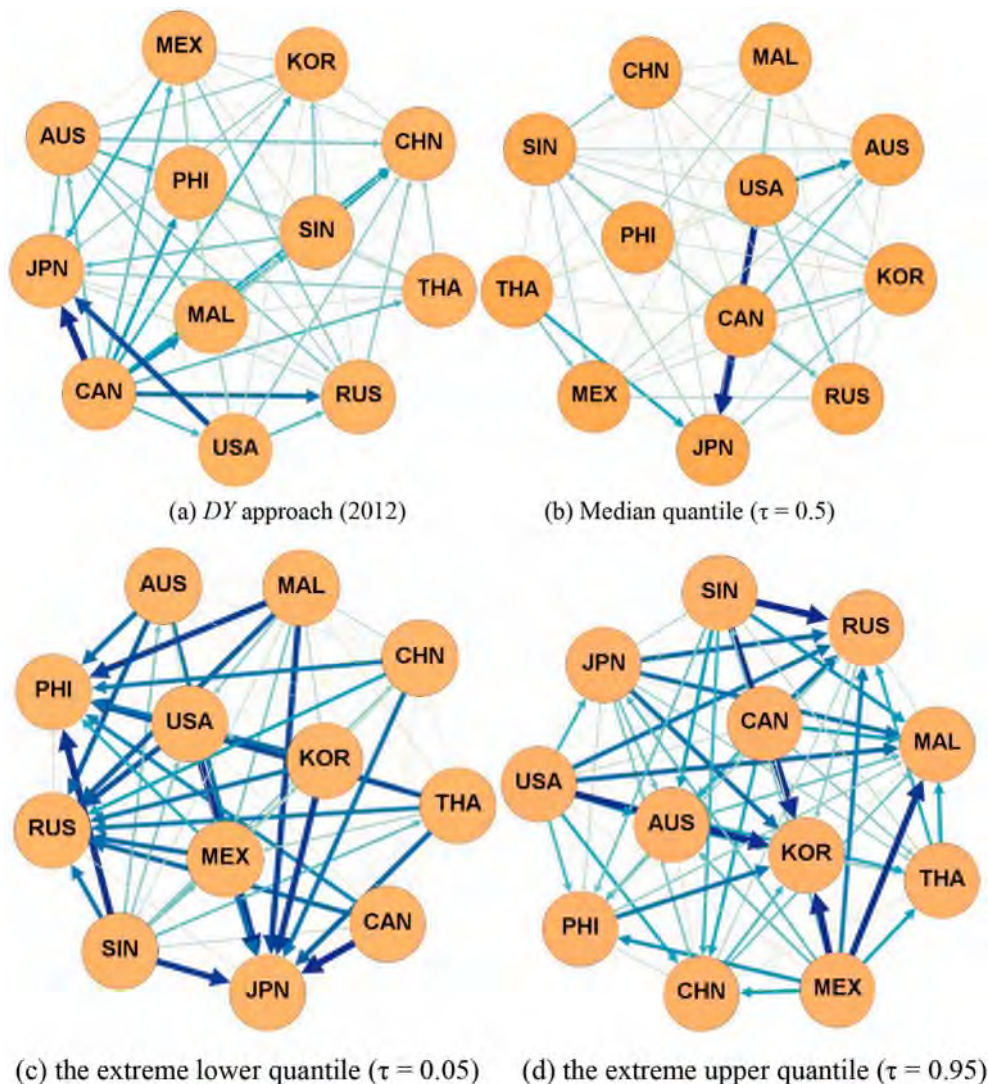


Fig. 1. Net pairwise directional volatility spillovers network among the 12 stock markets during the pre-vaccination period.

both extremely downside and upside volatility shocks.

In terms of the time-varying characteristics of volatility spillovers, the *TSI* estimated by the standard approach of Diebold and Yilmaz (2012) peaks in mid-March 2020 (see the left-side picture of Fig. 3), when the World Health Organization labelled the COVID-19 outbreak a global pandemic. Almost all stock markets experienced violent fluctuations from March to June 2020. This implies that the COVID-19 outbreak shocks added to large uncertainty in the investment environment and hence caused strong volatility connectedness in the system. There are two possible explanations for this observation. First, the effects of COVID-19 on the overall economy will not only significantly influence domestic demand but also limit supply, negatively impact firms' future cash flows, and foster public pessimism about the future (Goodell, 2020). Second, this strong spillover connectedness is often caused by some “irrational” behavior, such as financial panic, confidence loss, herding behavior, and increased risk aversion.

The right-side picture in Fig. 3 contains similar information to the left side, with some unique findings: (1). A significant drop in the level of *TSI* after July 2020. It indicates that the negative shocks of COVID-19 pandemic were noticeably weakened in several months after the global outbreak. This may be due to governmental responses to fight against the spread around the world at the early stage. (2). Another significant decrease occurred around April 2021, reaching a *TSI* value of <40%. It is noted that World Health Organization (WHO) highlighted the urgent need to improve vaccine access in the Immunization Agenda 2030 (IA2030) on 26 April 2021 (WHO, Twitter²). Meanwhile, the Asia-Pacific countries were gradually recovering their economies (IMF, Transcript³). As investor confidence

² <https://twitter.com/who/status/1386715756440719372>.

³ <https://www.imf.org/en/News/Articles/2021/04/14/tr041321-transcript-of-april-2021-asia-and-pacific-department-press-briefing>.

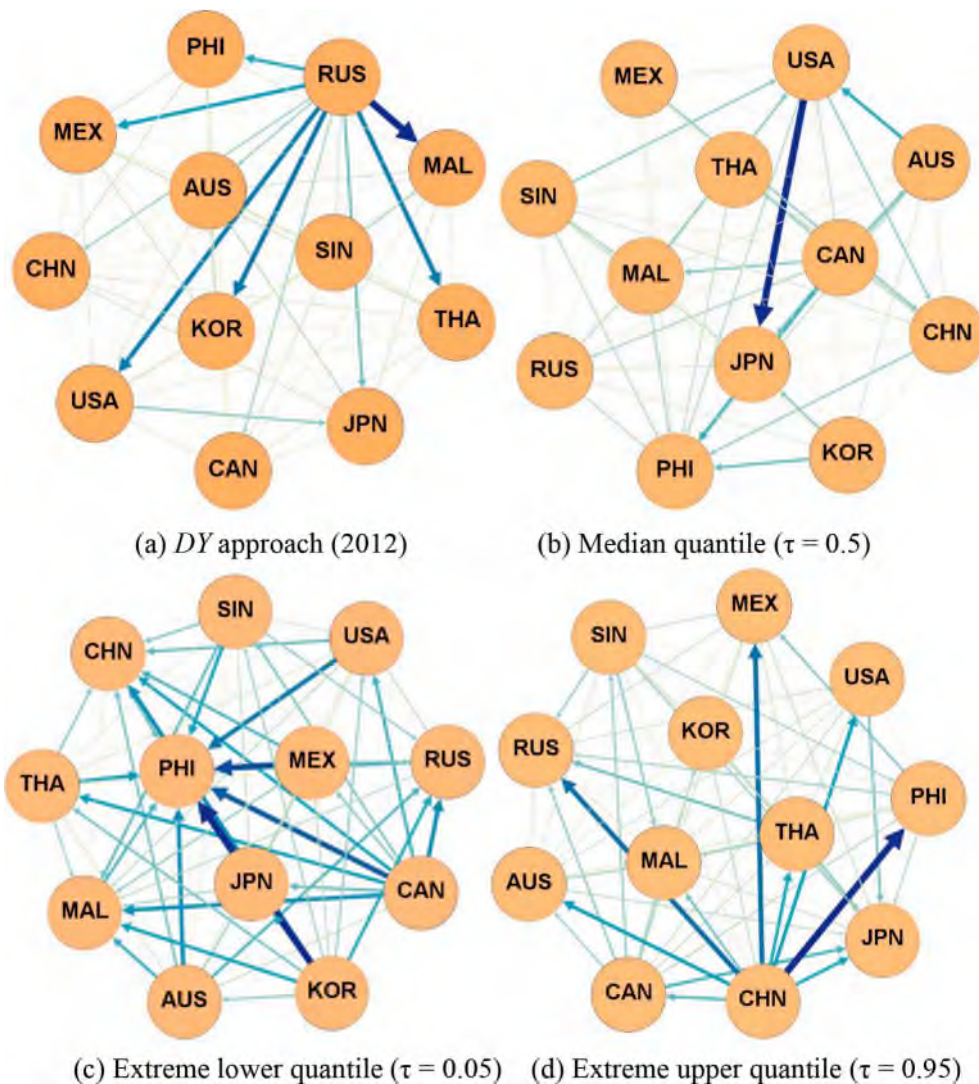


Fig. 2. Net pairwise directional volatility spillovers network among the 12 stock markets during the post-vaccination period.

was restored, stock markets became more resilient, thereby reducing the spread of panic across markets. Overall, the above findings are consistent with prior studies (Hanif et al., 2021; Hung and Xuan, 2021; Lin and Su, 2021; Wang et al., 2021).

The analysis of *TSI* helps to understand the general situation of dynamic risk spillovers among the Asia-Pacific stock markets. Next, we conduct a further analysis by estimating time-varying net total directional spillover (i.e., “*NET*” spillover), which is used to depict the changing role (a net transmitter or a net receiver) of each market within the system. The “*NET*” volatility (risk) spillover of each stock market is obtained by the quantile-based approach, and the results for the middle, extreme lower, and extreme upper quantiles are presented in Fig. 5, Fig. 6, and Fig. 7, respectively.

According to the normal pattern at the conditional median presented in Fig. 5, we observe the following empirical regularities.

- (1) First, changes in “*NET*” volatility spillovers are observed in most stock markets after the COVID-19 pandemic outbreak in early 2020. The magnitudes of spillovers are reinforced in many markets. Stock markets in Australia (AUS) and Mexico (MEX) transform from net receivers (negative “*NET*” spillovers) to net transmitters (positive “*NET*” spillovers), while stock markets in China (CHN) and Malaysia (MAL) change from net transmitters to net receivers. This finding may be associated with arguments in Li et al., 2021b which indicate that the changes in the spillover level of different countries in response to the COVID-19 pandemic is related to factors such as economic development, industrial structure and policy formulation.
- (2) Second, we find three groups of markets in Fig. 5: the first includes Canada (CAN), the United States (USA), and Singapore (SIN), which are net transmitters during almost the entire sample period; the second refers to stock markets that are net receivers of volatility spillovers almost all the time, such as Japan (JPN) and the Philippines (PHI); other stock markets change their roles between net transmitters and net receivers during different periods of the whole sampling time. Hence, the major net

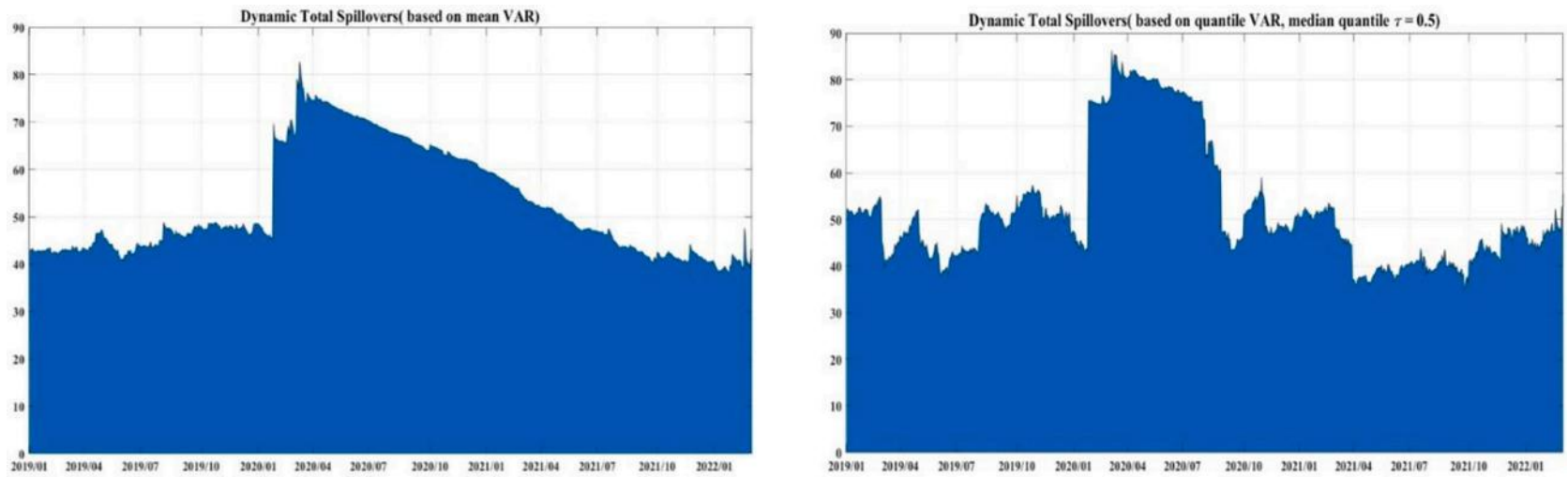


Fig. 3. Total volatility spillovers: (left)-based on the standard approach of [Diebold and Yilmaz \(2012\)](#). (right)-based on the quantile VAR (median quantile $\tau = 0.5$).

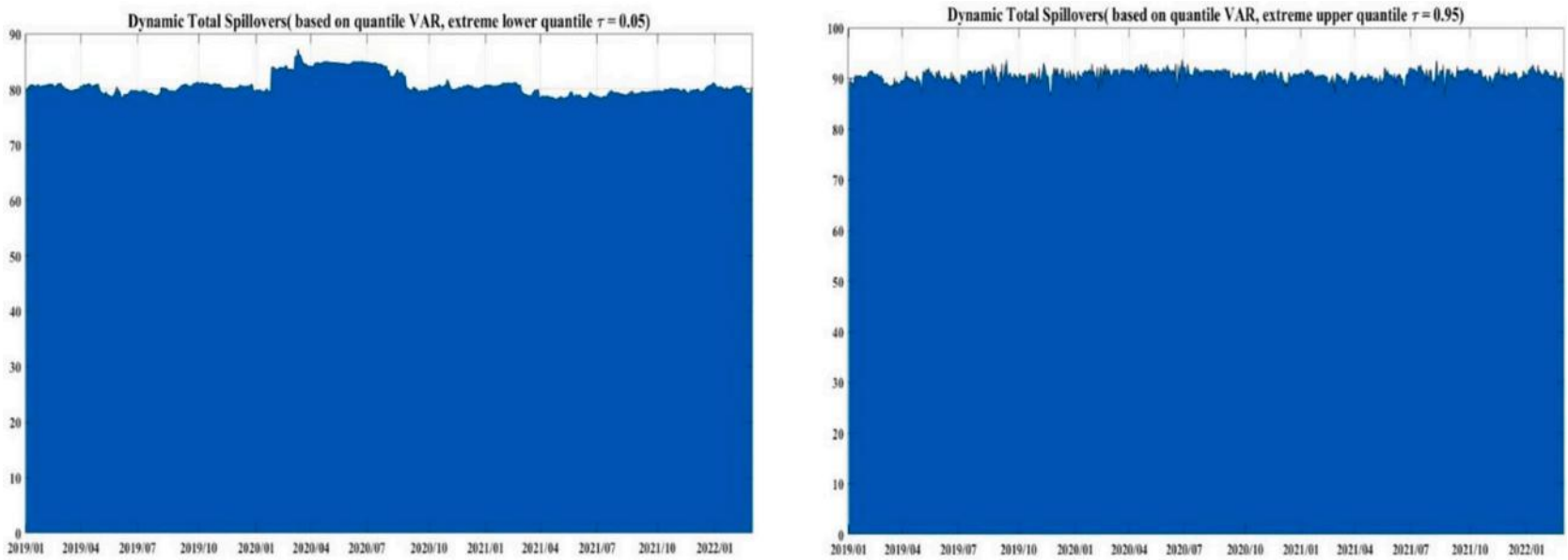


Fig. 4. Total volatility spillovers: (left)-based on the quantile VAR (extreme lower quantile $\tau = 0.05$); (right)-based on the quantile VAR (extreme upper quantile $\tau = 0.95$).

Net volatility spillovers in the quantile VAR (median $\tau = 0.5$)

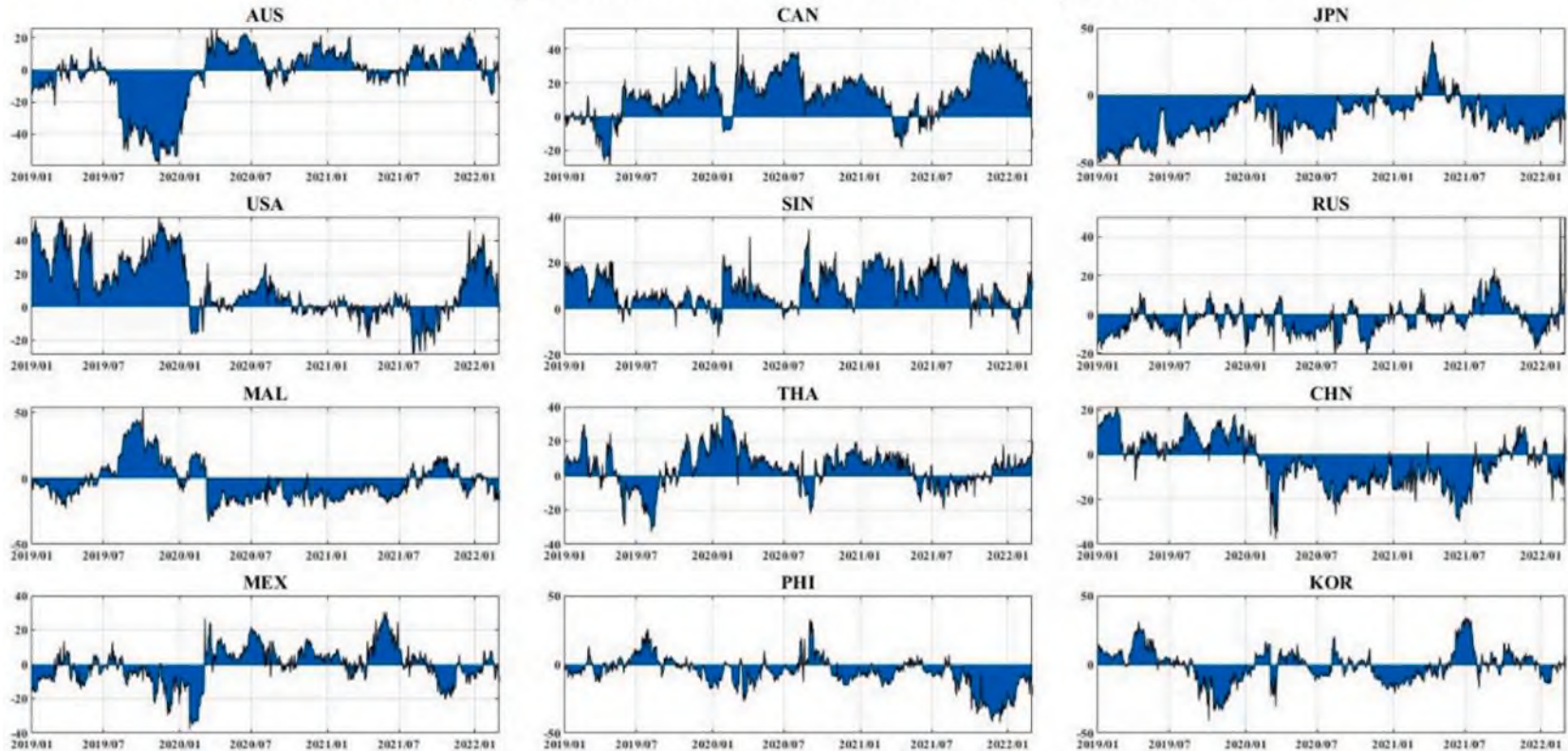


Fig. 5. Net total directional volatility spillovers in the quantile VAR (median quantile $\tau = 0.5$).

Net volatility spillovers in the quantile VAR (lower $\tau = 0.05$)

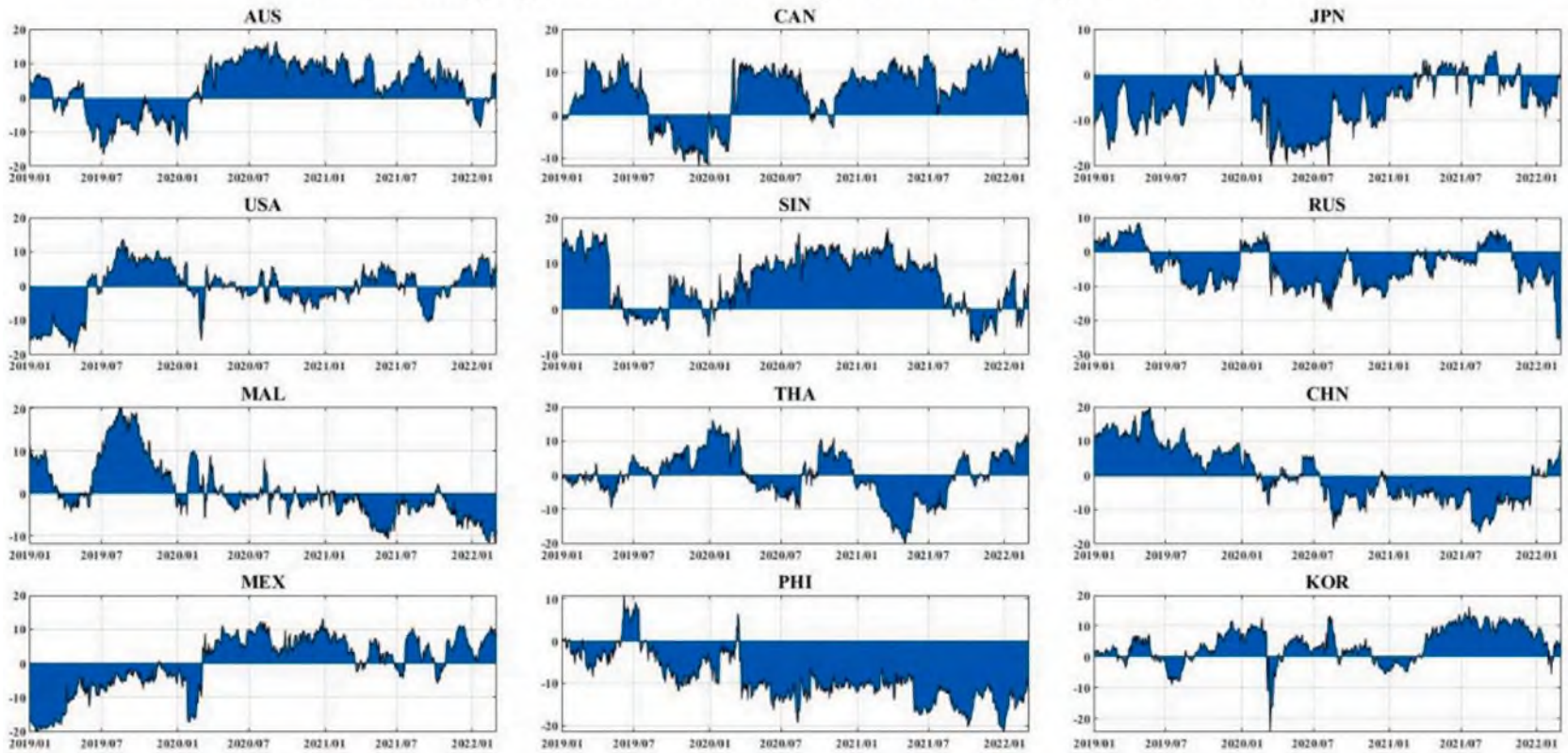


Fig. 6. Net total directional volatility spillovers in the quantile VAR. (extreme lower quantile $\tau = 0.05$.)

Net volatility spillovers in the quantile VAR (upper $\tau = 0.95$)

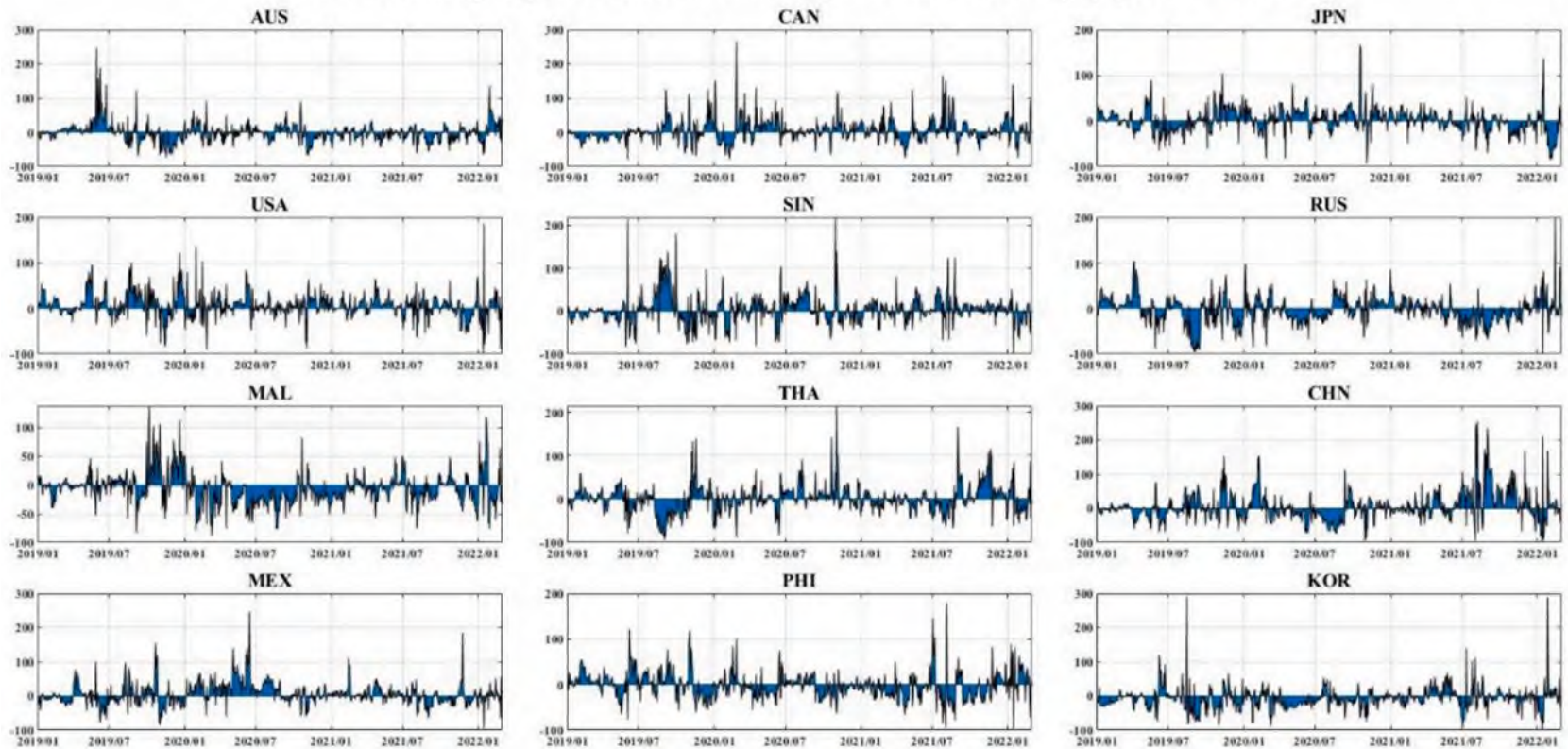


Fig. 7. Net total directional volatility spillovers in the quantile VAR. (extreme upper quantile $\tau = 0.95$.)

transmitters and recipients mentioned above should be emphatically monitored by investors and regulators if the historical pattern underlined by the volatility linkages across Asia-Pacific stock markets at the conditional median continues in the future. The above findings are somewhat in line with earlier studies (Zhang et al., 2019; Zhang et al., 2020a, 2020b; Li et al., 2021b).

When considering extreme events (i.e., in both tails) in the Asia-Pacific stock markets, the extreme patterns of net spillovers are quite different from the normal patterns mentioned above. Specifically:

- (1) Firstly, when comparing Figs.6 and 7, there are obvious divergences in the dynamic patterns and magnitudes of the “NET” volatility spillovers at the left and right tails across Asia-Pacific stock markets. This result suggests asymmetry in the responses of net spillovers across Asia-Pacific stock markets to extreme downside and upside shocks. The asymmetric behavior is also observed in volatility spillovers among other financial markets during the COVID-19 pandemic (e.g., Billah et al., 2022; Liu et al., 2021; etc.), as uncertain economic activity may affect market responses.
- (2) Secondly, when there are extreme events on the upside (see Fig. 7), we find that there are no clear major net transmitters or recipients during the entire sampling period. The role (net transmitter or net recipient) of each market alternates very frequently. Our findings are consistent with previous studies (Bouri et al., 2020; Yousaf et al., 2022) examining the net connectedness among global financial markets under extreme market conditions. Thus, under extreme events (especially at the right tail), investors and policymakers should continuously follow the dynamic net spillovers of volatility shocks in the Asia-Pacific economies.

However, the above figures only provide a general view of the time-varying spillovers over recent years and the effect of COVID-19 vaccinations is still ambiguous, for which regression analyses are needed.

4. Regression results analysis

Rouatbi et al. (2021) discuss stock market risk from the perspective of market volatility and find that mass COVID-19 vaccination helps stabilize stock markets by reducing volatility. Few studies have investigated the impact of vaccination on volatility (risk) spillovers among stock markets during the COVID-19 pandemic. We attempted to provide further insights into this topic. Section 3.3 presents the fluctuations in (system-wide) total spillover indices (Fig. 3 & Fig. 4) and country-specific “NET” spillover indices (Fig. 5 & Fig. 6 & Fig. 7) over the whole sample period. In this section, to better understand the association between vaccinations and “TO” (or “NET”) risk spillovers at the country level, we adopt regression model and estimation method as shown in Eqs. (13)–(16) in section 2.3.

We discuss the following four aspects: (1) panel-data analysis of COVID-19 vaccinations and mean-based risk spillovers (also known as standard risk spillovers); (2) heterogeneous tests for the impact of social attention and market uncertainty on the relationship between vaccinations and standard risk spillover; (3) the effect of COVID-19 vaccinations on extreme risk spillovers obtained by the quantile-based approach. (4) the channel which potentially mediates the vaccination effect on stock market risk spillovers.

Table 5
Descriptive statistics.

Variable	Mean	Std.	Min	p50	Max	Obs.
<i>TRS</i>	3.922	1.829	0.732	3.773	8.843	3588
<i>NRS</i>	−0.005	1.006	−1.578	−0.230	3.114	3588
<i>Vaccinated</i>	0.316	0.315	0.000	0.201	0.864	3588
<i>Vaccinated_one</i>	0.389	0.327	0.000	0.373	0.886	3588
<i>Vaccinated_100</i>	76.273	70.968	0.000	59.305	231.84	3588
<i>From</i>	3.936	1.147	1.418	4.016	5.995	3588
<i>AsiaNet</i>	47.200	6.653	38.54	46.15	61.45	3588
<i>Vol</i>	0.153	0.057	0.078	0.147	0.404	3588
<i>VIX_Gold</i>	17.020	2.228	14.53	16.41	28.01	3588
<i>VIX_Oil</i>	40.268	8.193	21.56	37.93	77.29	3588
<i>VIX_SPX</i>	20.646	4.459	15.10	19.36	35.13	3588
<i>VIX_Emerging</i>	23.318	4.252	17.65	22.30	40.44	3588

Note: This table reports the descriptive statistics of the variables used in the analysis. The regression analyses were applied to the period from December 13, 2020, to March 22, 2022 (i.e., the end of the whole sample), during which the COVID-19 vaccination information is available, and all continuous variables are winsorized at the 1% and 99% levels. The total directional spillover transmitted by market *i* to all other markets, namely “TO” risk spillovers (denoted as *TRS*). The net directional volatility spillovers received from or transmitted to other markets, namely “NET” risk spillovers (denoted as *NRS*). Vaccination status are proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people. The control variables include the level of spillovers received by country *i* from other countries on trading day *t* in the risk network (*From*), the overall level of risk spillovers among the Asia-Pacific market (*AsiaNet*), MSCI European Monetary Economic Union Index (*Vol*), Gold ETF Volatility Index (*VIX_Gold*), Crude Oil ETF Volatility Index (*VIX_Oil*), S&P 500 Volatility Index (*VIX_SPX*), and the emerging market volatility index (*VIX_Emerging*).

4.1. Preliminaries before regression: descriptive statistics and correlation analysis

4.1.1. Descriptive statistics

Regression analyses were applied to observations at the second stage of the COVID-19 pandemic, from December 13, 2020, to March 22, 2022, during which the COVID-19 vaccination rates are available. This subsample consists of 299 trading days in 12 countries, with a total of 3588 valid data.

As aforementioned, “TO” and “NET” spillover indices in the risk spillover network are considered dependent variables in this study. The baseline regression model focuses on the spillover indices obtained by the standard approach of Diebold and Yilmaz (2012). Table 5 provides the descriptive statistics of the main data used for the baseline analysis. *TRS* denotes the “TO” mean-based risk spillovers transmitted by country *i* to others, with a standard deviation of 1.829 and a mean of 3.922. *NRS* denotes “NET” mean-based risk spillovers of country *i* that are the differences between transmitted to and received from others, with a standard deviation of 1.006 and a mean of −0.005. For country *i*, *NRS* is positive if it transmits more risk spillovers to than receives from other countries. Our primary focus is on COVID-19 vaccination-related variables: *vaccinated*, *vaccinated_one*, and *vaccinated_100*. It should be noted that the number of doses required for COVID-19 vaccination in each country is different (ranging from 1 to 3 doses), and therefore the number of doses per hundred people may be a better proxy in terms of comparing vaccination coverage across different countries. According to our descriptive analyses of data by country (available upon request), Singapore had the highest level of vaccination among all countries considered in this study, with the proportion of full vaccination and one-shot vaccination reaching 86.4% and 88.6%, respectively. As shown in Table 5, the average levels of these two indicators for the total sample were only 31.6% and 38.9%, respectively. This implies that the general vaccination rate in the Asia-Pacific region is not high and that there are distinct differences across different countries.

4.1.2. Correlation coefficients

Table 6 reports the correlation matrix of variables presented in Table 5. It is noted that the COVID-19 vaccination is inversely associated with the *TRS* and the finding is robust across three quantitative measures. Besides, two variables, *From* and *AsiaNet*, are also negatively correlated with the vaccination. However, the relationship between the vaccination and the *NRS* is not clear and requires further examination. Although these correlations suggest that the increasing COVID-19 vaccination may be associated with the decreasing risk spillovers, panel regressions are needed to further test for their associations, especially involving *NRS*.

4.2. COVID-19 vaccinations and standard risk spillovers

4.2.1. COVID-19 vaccinations and “TO” risk spillovers

Table 7 reports the regression results for the impact of COVID-19 vaccinations on “TO” mean-based (i.e. standard) risk spillovers (denoted as *TRS*). We gradually add control variables, country, and country-month fixed effects. A significant and negative relationship between COVID-19 vaccinations and *TRS* is robust across alternative measures,⁴ *Vaccinated* (see columns 1–3), *Vaccinated_one* (see columns 4–6), and *Vaccinated_100* (see columns 7–9). Coefficient estimates for all vaccination-related variables in regression models are significantly negative at the 1% statistical level. Besides, we use two-way clustering robust standard errors (reported in parentheses). These results have economic implications. For a one-standard-deviation increase in COVID-19 vaccinations, in terms of *Vaccinated*, *Vaccinated_one*, and *Vaccinated_100*, *TRS* will decrease by approximately 27.75% ($1.6110 \times 0.315 / 1.829$), 20.19% ($1.1297 \times 0.327 / 1.829$) and 41.13% ($0.0106 \times 70.968 / 1.829$) after utilizing the standard deviations of *TRS*, *Vaccinated*, *Vaccinated_one* and *Vaccinated_100* reported in Table 5 to normalize the coefficients, respectively. Given that different types of COVID-19 vaccines require different numbers of doses, the standard deviation of *Vaccinated_100* (doses per hundred people) is large. Even so, the negative impact of COVID-19 vaccination on *TRS* remains robust. Therefore, increasing the coverage of the COVID-19 vaccination in country *i* can help to reduce the risk of spillovers transmitted by it to other countries.

4.2.2. COVID-19 vaccinations and “NET” risk spillovers

Table 8 reports the regression results regarding the effect of COVID-19 vaccinations on “NET” mean-based (i.e. standard) risk spillovers (denoted as *NRS*). Again, we can observe that the primary explanatory variables yield coefficient estimates which are significantly negative at the 1% statistical level. After the coefficient normalization, the results indicate that a one-standard-deviation increase in *Vaccinated*, *Vaccinated_one*, and *Vaccinated_100* is associated with an approximate decrease in *NRS* by 48.50% ($1.5490 \times 0.315 / 1.006$), 34.30% ($1.0551 \times 0.327 / 1.006$) and 71.25% ($0.0101 \times 70.968 / 1.006$). Comparing the normalized coefficients for Table 8 with those for Table 7, we find that the COVID-19 vaccination has a stronger impact on the *NRS* than the *TRS*. In sum, we obtain empirical evidence that an increasing penetration rate of COVID-19 vaccines in a country has a significant effect on reducing its cyber risk spillovers to others, especially net spillovers.

4.3. Heterogeneity of social attention and market uncertainty

It is observed that the COVID-19 pandemic causes a lot of uncertainty in economic environment and such kind of economic

⁴ We also conduct univariate regressions, and obtain results consistent with main findings presented in Table 7.

Table 6
Correlation among variables.

	<i>TRS</i>	<i>NRS</i>	<i>Vaccinated</i>	<i>Vaccinated_one</i>	<i>Vaccinated_100</i>	<i>From</i>	<i>AsiaNet</i>	<i>Vol</i>	<i>VIX_Gold</i>	<i>VIX_Oil</i>	<i>VIX_SPX</i>	<i>VIX_Emerging</i>
<i>TRS</i>	1.000											
<i>NRS</i>	0.827***	1.000										
<i>Vaccinated</i>	−0.118***	0.027	1.000									
<i>Vaccinated_one</i>	−0.086***	0.082***	0.958***	1.000								
<i>Vaccinated_100</i>	−0.122***	0.028*	0.967***	0.964***	1.000							
<i>From</i>	0.851***	0.423***	−0.204***	−0.203***	−0.208***	1.000						
<i>AsiaNet</i>	0.290***	−0.010	−0.773***	−0.822***	−0.783***	0.484***	1.000					
<i>Vol</i>	−0.083***	−0.021	0.347***	0.305***	0.418***	−0.084***	−0.192***	1.000				
<i>VIX_Gold</i>	0.119***	−0.021	−0.185***	−0.270***	−0.159***	0.242***	0.486***	0.477***	1.000			
<i>VIX_Oil</i>	−0.071***	−0.017	0.334***	0.279***	0.369***	−0.071***	−0.162***	0.686***	0.454***	1.000		
<i>VIX_SPX</i>	0.036**	−0.013	0.097***	0.010	0.129***	0.087***	0.169***	0.625***	0.720***	0.643***	1.000	
<i>VIX_Emerging</i>	0.029*	−0.014	0.039**	−0.021	0.074***	0.076***	0.147***	0.552***	0.690***	0.600***	0.802***	1.000

Note: This table reports Pearson correlation coefficients. The total directional spillover transmitted by market *i* to all other markets, namely “TO” risk spillovers (denoted as *TRS*). The net directional volatility spillovers received from or transmitted to other markets, namely “NET” risk spillovers (denoted as *NRS*). Vaccination status are proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people. The control variables include the level of spillovers received by country *i* from other countries on trading day *t* in the risk network (*From*), the overall level of risk spillovers among the Asia-Pacific market (*AsiaNet*), MSCI European Monetary Economic Union Index (*Vol*), Gold ETF Volatility Index (*VIX_Gold*), Crude Oil ETF Volatility Index (*VIX_Oil*), S&P 500 Volatility Index (*VIX_SPX*), and the emerging market volatility index (*VIX_Emerging*). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7
COVID-19 vaccinations and “TO” risk spillovers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	<i>TRS</i>	<i>TRS</i>	<i>TRS</i>	<i>TRS</i>	<i>TRS</i>	<i>TRS</i>	<i>TRS</i>	<i>TRS</i>	<i>TRS</i>
<i>Vaccinated</i>	−0.8477*** (0.1341)	−1.0561*** (0.1016)	−1.6110*** (0.0890)						
<i>Vaccinated_one</i>				−0.5220*** (0.1864)	−0.9720*** (0.1374)	−1.1297*** (0.0936)			
<i>Vaccinated_100</i>							−0.0044*** (0.0008)	−0.0071*** (0.0006)	−0.0106*** (0.0005)
<i>From</i>	1.5318*** (0.0204)	0.9966*** (0.0669)	1.0044*** (0.0760)	1.5183*** (0.0178)	0.9864*** (0.0668)	1.0025*** (0.0765)	1.5405*** (0.0181)	0.9719*** (0.0654)	0.9608*** (0.0748)
<i>AsiaNet</i>	−0.0812*** (0.0074)	−0.0447*** (0.0085)	−0.1188*** (0.0395)	−0.0687*** (0.0101)	−0.0430*** (0.0098)	−0.1173*** (0.0398)	−0.0869*** (0.0096)	−0.0629*** (0.0088)	−0.1176*** (0.0380)
<i>Vol</i>	−0.8108 (0.6682)	−0.6884 (0.4281)	−0.3993 (0.6697)	−0.7973 (0.6498)	−0.5756 (0.4164)	−0.2235 (0.6842)	−0.2416 (0.5497)	0.2923 (0.3805)	−0.0020 (0.6486)
<i>VIX_Gold</i>	−0.0114 (0.0194)	−0.0058 (0.0128)	0.0166 (0.0156)	−0.0201 (0.0203)	−0.0126 (0.0128)	0.0143 (0.0158)	−0.0107 (0.0181)	0.0011 (0.0124)	0.0147 (0.0153)
<i>VIX_Oil</i>	−0.0017 (0.0035)	−0.0007 (0.0023)	0.0033 (0.0027)	−0.0033 (0.0035)	−0.0018 (0.0023)	0.0037 (0.0028)	−0.0020 (0.0033)	−0.0001 (0.0022)	0.0033 (0.0026)
<i>VIX_SPX</i>	0.0234* (0.0121)	0.0256*** (0.0071)	0.0019 (0.0055)	0.0160 (0.0121)	0.0187*** (0.0070)	0.0009 (0.0056)	0.0233* (0.0121)	0.0295*** (0.0068)	0.0019 (0.0053)
<i>VIX_Emerging</i>	−0.0055** (0.0026)	−0.0082** (0.0042)	−0.0001 (0.0046)	−0.0003 (0.0022)	−0.0044 (0.0043)	0.0007 (0.0048)	−0.0054** (0.0025)	−0.0115*** (0.0042)	0.0007 (0.0046)
<i>_cons</i>	2.0278*** (0.6687)	2.3405*** (0.3540)	6.7168*** (1.9689)	1.6652** (0.8280)	2.5389*** (0.4605)	6.6431*** (1.9856)	2.2416*** (0.7420)	3.2084*** (0.3748)	6.8280*** (1.8859)
<i>Country FE</i>	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
<i>Month FE</i>	No	No	Yes	No	No	Yes	No	No	Yes
adj. R^2	0.752	0.534	0.569	0.747	0.523	0.545	0.753	0.557	0.596
<i>N</i>	3588	3588	3588	3588	3588	3588	3588	3588	3588

Note: This table reports the regression results for the impact of COVID-19 vaccinations on “TO” risk spillovers (denoted as *TRS*). The independent variable is vaccination status. It is proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people. The control variables include *From*, *AsiaNet*, *Vol*, *VIX_Gold*, *VIX_Oil*, *VIX_SPX*, and *VIX_Emerging*. Country-time two-way clustering robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8
COVID-19 vaccinations and “NET” risk spillovers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	<i>NRS</i>	<i>NRS</i>	<i>NRS</i>	<i>NRS</i>	<i>NRS</i>	<i>NRS</i>	<i>NRS</i>	<i>NRS</i>	<i>NRS</i>
<i>Vaccinated</i>	−0.7463*** (0.0655)	−0.9021*** (0.0600)	−1.5490*** (0.0786)						
<i>Vaccinated_one</i>				−0.3825*** (0.0934)	−0.7435*** (0.0717)	−1.0551*** (0.0822)			
<i>Vaccinated_100</i>							−0.0038*** (0.0004)	−0.0060*** (0.0003)	−0.0101*** (0.0004)
<i>From</i>	0.5357*** (0.0172)	0.0765** (0.0390)	0.0641 (0.0419)	0.5183*** (0.0166)	0.0707* (0.0394)	0.0636 (0.0430)	0.5419*** (0.0165)	0.0560 (0.0385)	0.0232 (0.0407)
<i>AsiaNet</i>	−0.0757*** (0.0035)	−0.0434*** (0.0051)	−0.0535*** (0.0185)	−0.0610*** (0.0046)	−0.0386*** (0.0056)	−0.0520*** (0.0187)	−0.0796*** (0.0043)	−0.0583*** (0.0053)	−0.0523*** (0.0176)
<i>Vol</i>	−0.3399 (0.2357)	−0.2388 (0.3216)	−0.5161 (0.6253)	−0.3503 (0.2301)	−0.1691 (0.3227)	−0.3420 (0.6400)	0.1431 (0.2043)	0.5844* (0.3080)	−0.1346 (0.6058)
<i>VIX_Gold</i>	0.0054 (0.0067)	0.0098 (0.0101)	0.0091 (0.0139)	−0.0032 (0.0071)	0.0029 (0.0101)	0.0070 (0.0141)	0.0056 (0.0059)	0.0154 (0.0101)	0.0073 (0.0136)
<i>VIX_Oil</i>	0.0011 (0.0013)	0.0019 (0.0019)	0.0017 (0.0024)	−0.0004 (0.0013)	0.0007 (0.0019)	0.0020 (0.0025)	0.0008 (0.0011)	0.0024 (0.0018)	0.0017 (0.0023)
<i>VIX_SPX</i>	0.0145*** (0.0040)	0.0160*** (0.0050)	0.0014 (0.0054)	0.0074* (0.0042)	0.0095* (0.0051)	0.0004 (0.0056)	0.0141*** (0.0039)	0.0191*** (0.0048)	0.0013 (0.0052)
<i>VIX_Emerging</i>	−0.0077*** (0.0020)	−0.0098*** (0.0038)	−0.0014 (0.0040)	−0.0026** (0.0012)	−0.0058 (0.0039)	−0.0007 (0.0042)	−0.0074*** (0.0021)	−0.0125*** (0.0038)	−0.0007 (0.0040)
<i>_cons</i>	1.4897*** (0.2225)	1.7196*** (0.1706)	2.7360*** (0.9265)	1.0147*** (0.3098)	1.7141*** (0.2141)	2.6601*** (0.9354)	1.6361*** (0.2508)	2.4287*** (0.1730)	2.8385*** (0.8835)
<i>Country FE</i>	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
<i>Month FE</i>	No	No	Yes	No	No	Yes	No	No	Yes
adj. R^2	0.255	0.064	0.104	0.243	0.037	0.049	0.257	0.102	0.160
<i>N</i>	3588	3588	3588	3588	3588	3588	3588	3588	3588

Note: This table reports the regression results for the impact of COVID-19 vaccinations on “NET” risk spillovers (denoted as *NRS*). The independent variable is vaccination status. It is proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people. The control variables include *From*, *AsiaNet*, *Vol*, *VIX_Gold*, *VIX_Oil*, *VIX_SPX*, and *VIX_Emerging*. Country-time two-way clustering robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

uncertainty is widely discussed on social media which provokes public attention (Altig et al., 2020). It is also apparent that uncertainty about financial markets (typically, equity market) is induced by COVID-19 pandemic (Caggiano et al., 2020).

In this section, we further explore whether the negative effect of the COVID-19 vaccination on standard risk spillovers is heterogeneous due to social attention (driven by economic uncertainty) and market uncertainty. As mentioned in the section 2.1, We use Twitter-based measures developed by Baker et al. (2021) as proxies. It is noted that the Twitter Market Uncertainty index focuses on equity market. Baker et al. (2021) provided four quantitative methods: proportional index, weighted index, English tweets index, and USA index. We employ the natural logarithm of the average of above-mentioned four categories of indices.

Table 9 reports the subsample regression results based on social attention. Here we only present the regression results of the country-month fixed-effects model, including control variables. The regression results of other models are similar to those reported in

Table 9
Heterogeneity analysis of social attention: COVID-19 vaccinations and risk spillovers.

Panel A:	Completely Vaccinated			
	High		Low	
	(1)	(2)	(3)	(4)
	TRS	NRS	TRS	NRS
<i>Vaccinated</i>	−1.7867*** (0.1706)	−1.6913*** (0.1402)	−1.3749*** (0.0999)	−1.3689*** (0.1000)
<i>From</i>	1.0136*** (0.1370)	1.1172* (0.0703)	1.0446*** (0.0460)	0.0404 (0.0460)
<i>AsiaNet</i>	−0.1332*** −1.7867***	−0.0626*** −1.6913***	−0.0356* −1.3749***	−0.0357* −1.3689***
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Country FE</i>	Yes	Yes	Yes	Yes
<i>Month FE</i>	Yes	Yes	Yes	Yes
adj. R^2	0.580	0.115	0.515	0.080
N	1656	1656	1932	1932
χ^2	TRS	1.78	NRS	1.59
P -value		0.1825		0.2079
Panel B:	Vaccinated at least once			
	(5)	(6)	(7)	(8)
	TRS	NRS	TRS	NRS
<i>Vaccinated_one</i>	−1.6200*** (0.1776)	−1.5100*** (0.1456)	−0.4883*** (0.1201)	−0.4760*** (0.1202)
<i>From</i>	1.0156*** (0.1378)	0.1202* (0.0712)	1.0650*** (0.0490)	0.0612 (0.0490)
<i>AsiaNet</i>	−0.1322*** 1.0156***	−0.0617** 0.1202*	−0.0171 1.0650***	−0.0171 0.0612
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Country FE</i>	Yes	Yes	Yes	Yes
<i>Month FE</i>	Yes	Yes	Yes	Yes
adj. R^2	0.570	0.089	0.473	0.011
N	1656	1656	1932	1932
χ^2	TRS	9.49***	NRS	10.94***
P -value		0.0021		0.0009
Panel C:	Vaccination per hundred people			
	(9)	(10)	(11)	(12)
	TRS	NRS	TRS	NRS
<i>Vaccinated_100</i>	−0.0114*** (0.0010)	−0.0107*** (0.0007)	−0.0099*** (0.0006)	−0.0099*** (0.0006)
<i>From</i>	1.0072*** (0.1339)	0.1123* (0.0672)	0.9518*** (0.0459)	−0.0528 (0.0458)
<i>AsiaNet</i>	−0.1343*** (0.0483)	−0.0637*** (0.0226)	−0.0481** (0.0211)	−0.0484** (0.0211)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Country FE</i>	Yes	Yes	Yes	Yes
<i>Month FE</i>	Yes	Yes	Yes	Yes
adj. R^2	0.610	0.182	0.541	0.130
N	1656	1656	1932	1932
χ^2	TRS	0.56	NRS	0.20
P -value		0.4560		0.6577

Note: This table reports the subsample regression results based on Twitter economic uncertainty. The dependent variables are “TO” risk spillovers (denoted as TRS) and “NET” risk spillovers (denoted as NRS). The independent variable is vaccination status. It is proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people. The control variables include *From*, *AsiaNet*, *Vol*, *VIX_Gold*, *VIX_Oil*, *VIX_SPX*, and *VIX_Emerging*. Country-time two-way clustering robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9, which are kept for request. When the Twitter-based Economic Uncertainty is greater than the median of each period, we define it as high attention and low otherwise. Two measures, *TRS* and *NRS*, of standard risk spillovers are discussed as dependent variables as in Section 4.2. Panels A-C demonstrate the results of subsampled regressions based on alternative indicators of COVID-19 vaccinations, respectively. All the vaccination-related variables yield significantly negative results at the 1% statistical level.

To further check whether the coefficient estimations between the subsamples are significantly different, we use seemingly uncorrelated regression (SUR) and chi-square tests. We find that the chi-squares are 9.49 and 10.49, with corresponding *p*-values of 0.0021 and 0.0009 in panel B (vaccinated at least once). This finding implies that the negative effect of COVID-19 vaccinations on risk spillovers is more pronounced when social attention is severe. However, the checking of panel A (completely vaccinated) and panel C (vaccinated per hundred people) does not reach similar conclusions. Owing to the lack of robustness across panels, we prefer not to

Table 10

Heterogeneity analysis of market uncertainty: COVID-19 vaccinations and risk spillovers.

Panel A:	Completely Vaccinated			
	High		Low	
	(1)	(2)	(3)	(4)
	<i>TRS</i>	<i>NRS</i>	<i>TRS</i>	<i>NRS</i>
<i>Vaccinated</i>	−1.6157*** (0.1617)	−1.5269*** (0.1368)	−1.6082*** (0.0939)	−1.6022*** (0.0941)
<i>From</i>	1.0092*** (0.1379)	0.1175* (0.0694)	0.9559*** (0.0446)	−0.0487 (0.0450)
<i>AsiaNet</i>	−0.1317*** (0.0494)	−0.0622*** (0.0231)	−0.0332* (0.0195)	−0.0330* (0.0196)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Country FE</i>	Yes	Yes	Yes	Yes
<i>Month FE</i>	Yes	Yes	Yes	Yes
adj. <i>R</i> ²	0.545	0.095	0.607	0.112
<i>N</i>	1572	1572	2016	2016
χ^2	<i>TRS</i>	0.00	<i>NRS</i>	0.10
<i>P</i> -value		0.9796		0.7572
Panel B:	Vaccinated at least once			
	(5)	(6)	(7)	(8)
	<i>TRS</i>	<i>NRS</i>	<i>TRS</i>	<i>NRS</i>
<i>Vaccinated_one</i>	−1.4104*** (0.1758)	−1.3022*** (0.1486)	−0.9084*** (0.1032)	−0.9056*** (0.1038)
<i>From</i>	1.0077*** (0.1387)	0.1176* (0.0703)	0.9428*** (0.0488)	1.0077*** (0.1387)
<i>AsiaNet</i>	−0.1305*** (0.0497)	−0.0613*** (0.0234)	−0.0179 (0.0209)	−0.1305*** (0.0497)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Country FE</i>	Yes	Yes	Yes	Yes
<i>Month FE</i>	Yes	Yes	Yes	Yes
adj. <i>R</i> ²	0.535	0.069	0.568	0.024
<i>N</i>	1572	1572	2016	2016
χ^2	<i>TRS</i>	2.03	<i>NRS</i>	1.84
<i>P</i> -value		0.1538		0.1754
Panel C:	Vaccination per hundred people			
	(9)	(10)	(11)	(12)
	<i>TRS</i>	<i>NRS</i>	<i>TRS</i>	<i>NRS</i>
<i>Vaccinated_100</i>	−0.0115*** (0.0010)	−0.0107*** (0.0007)	−0.0101*** (0.0005)	−0.0101*** (0.0005)
<i>From</i>	0.9921*** (0.1351)	0.1022 (0.0663)	0.8718*** (0.0456)	−0.1328*** (0.0459)
<i>AsiaNet</i>	−0.1321*** (0.0478)	−0.0627*** (0.0219)	−0.0410** (0.0196)	−0.0409** (0.0197)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Country FE</i>	Yes	Yes	Yes	Yes
<i>Month FE</i>	Yes	Yes	Yes	Yes
adj. <i>R</i> ²	0.580	0.171	0.624	0.150
<i>N</i>	1572	1572	2016	2016
χ^2	<i>TRS</i>	0.48	<i>NRS</i>	0.16
<i>P</i> -value		0.4871		0.6873

Note: This table reports the subsample regression results based on the Twitter market uncertainty. The dependent variables are “TO” risk spillovers (denoted as *TRS*) and “NET” risk spillovers (denoted as *NRS*). The independent variable is vaccination status. It is proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people. The control variables include *From*, *AsiaNet*, *Vol*, *VIX_Gold*, *VIX_Oil*, *VIX_SPX*, and *VIX_Emerging*. Country-time two-way clustering robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

declare the heterogeneity of the impact of COVID-19 vaccination on risk spillovers between high and low levels of attention. In other words, the effect of increasing COVID-19 vaccinations on reducing cyber risk spillovers does not seem to be affected by economic uncertainty-related social attention.

Table 10 reports the subsample regression results based on market uncertainty. The low and high levels of Twitter-based Market Uncertainty are also distinguished by the median. The coefficient estimates of all vaccination-related variables are significantly negative at the 1% statistical level. Furthermore, the results of the chi-square test all show that the coefficient estimates of explanatory variables in the subsamples are not significantly different. This suggests that the impact of COVID-19 vaccination on risk spillovers is unshakeable from market uncertainty. In sum, we find that the external conditions (investor sentiment or market uncertainty) do not have a significant effect on the relation between COVID-19 vaccinations and risk spillovers.

4.4. COVID-19 vaccinations and extreme risk spillovers

To estimate risk spillovers under extreme shocks, we follow Bouri et al. (2020) and employ connectedness measures based on the quantile VAR process. The “TO” and “NET” spillover indices are also constructed from the extreme downside and upside risk spillovers.

Table 11
COVID-19 vaccinations and extreme downside risk spillovers.

Panel A:		Completely Vaccinated			
		(1)	(2)	(3)	(4)
		<i>TRS_L</i>	<i>TRS_L</i>	<i>NRS_L</i>	<i>NRS_L</i>
<i>Vaccinated</i>		−0.77228*** (0.2631)	−2.94397*** (0.6664)	−0.72484*** (0.2368)	−2.87881*** (0.5521)
<i>From</i>		4.45221*** (0.0470)	3.99118*** (0.0935)	3.45897*** (0.0417)	3.02076*** (0.0792)
<i>AsiaNet</i>		−3.28268*** (0.0853)	−3.47614*** (0.3274)	−3.27941*** (0.0817)	−3.36571*** (0.2727)
<i>Controls</i>	Yes		Yes	Yes	Yes
<i>Country FE</i>	No		Yes	No	Yes
<i>Month FE</i>	No		Yes	No	Yes
adj. R^2		0.876	0.727	0.825	0.631
<i>N</i>		3588	3588	3588	3588
Panel B:		Vaccinated at least once			
		(5)	(6)	(7)	(8)
		<i>TRS_L</i>	<i>TRS_L</i>	<i>NRS_L</i>	<i>NRS_L</i>
<i>Vaccinated_one</i>		−0.45725 (0.2825)	−1.84439** (0.7674)	−0.40676 (0.2521)	−1.84597*** (0.6255)
<i>From</i>		4.44820*** (0.0484)	4.00224*** (0.0939)	3.45457*** (0.0428)	3.03159*** (0.0798)
<i>AsiaNet</i>		−3.32768*** (0.0838)	−3.50701*** (0.3278)	−3.32305*** (0.0806)	−3.39526*** (0.2731)
<i>Controls</i>	Yes		Yes	Yes	Yes
<i>Country FE</i>	No		Yes	No	Yes
<i>Month FE</i>	No		Yes	No	Yes
adj. R^2		0.875	0.726	0.825	0.628
<i>N</i>		3588	3588	3588	3588
Panel C:		Vaccination per hundred people			
		(9)	(10)	(11)	(12)
		<i>TRS_L</i>	<i>TRS_L</i>	<i>NRS_L</i>	<i>NRS_L</i>
<i>Vaccinated_100</i>		−0.00440*** (0.0012)	−0.01684*** (0.0028)	−0.00393*** (0.0011)	−0.01547*** (0.0025)
<i>From</i>		4.45959*** (0.0464)	4.00070*** (0.0928)	3.46478*** (0.0413)	3.03011*** (0.0787)
<i>AsiaNet</i>		−3.29040*** (0.0859)	−3.47779*** (0.3266)	−3.28966*** (0.0822)	−3.37071*** (0.2726)
<i>Controls</i>	Yes		Yes	Yes	Yes
<i>Country FE</i>	No		Yes	No	Yes
<i>Month FE</i>	No		Yes	No	Yes
adj. R^2		0.876	0.728	0.825	0.631
<i>N</i>		3588	3588	3588	3588

Note: This table reports the regression results regarding the effect of COVID-19 vaccination on extreme tail-downside risk spillovers. The dependent variables are extreme tail-downside “TO” risk spillovers (*TRS_L*) and extreme tail-downside “NET” risk spillovers (*NRS_L*). The independent variable is vaccination status. It is proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people. The control variables include *From*, *AsiaNet*, *Vol*, *VIX_Gold*, *VIX_Oil*, *VIX_SPX*, and *VIX_Emerging*. Country-time two-way clustering robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TRS_L and TRS_H denote extreme lower- and upper-tail “TO” risk spillovers, while NRS_L and NRS_H denote extreme lower- and upper-tail “NET” risk spillovers. We then replace standard spillovers with extreme spillovers in the regressions. Table 11 presents the regression results regarding vaccination effects on extreme downside-tail risk spillovers. We focus on the estimation results of the pooled OLS regressions with control variables. Our discussions mainly focus on COVID-19 vaccination-related variables, while the dependent variables are changed to extreme lower-tail “TO” risk spillovers (TRS_L) and extreme lower-tail “NET” risk spillovers (NRS_L). TRS_L and NRS_L are obtained from risk spillovers at an extremely low quantile of 0.05. Most of the estimates for vaccination-related variables are significantly negative, at least at the 5% level. Exceptions are only shown in columns (5) and (7) for *Vaccinated_One*, without introducing the country-month fixed effect. These results highlight the benefit of universal vaccination in alleviating the extreme risk spillovers associated with negative shocks. Downside risk propagation is useful for regulators and policymakers who care about the soundness and resilience of financial systems (Basel III). International investors are also nervous about the transmission of negative shocks, which affect the diversification of portfolio management (Ayub et al., 2015).

Further, to examine whether there is an asymmetric impact of COVID-19 vaccinations on the lower and upper tails of risk spillovers, we apply the same regression methods to the upper tail of risk spillovers. Table 12 presents the regression results regarding the vaccination effects on the extreme upside-tail risk spillovers at the quantile equal to 0.95, in terms of “TO” risk spillovers (TRS_H) and “NET” risk spillovers (NRS_H). We find that the coefficient estimates of all vaccination-related variables are not statistically significant. Compared with the results for the lower tail of risk spillovers (see Table 11), no evidence shows that the upper tail of risk spillovers is significantly impacted by mass vaccination. This comparison reveals that an asymmetric effect exists, with COVID-19 vaccination affecting the risk spillover during periods of extreme market depreciation rather than periods of extreme market appreciation. Therefore, the understanding of the function of vaccinations in stabilizing financial markets is enriched.

4.5. The channel of the COVID-19 vaccination effect

It is observed in previous sections that the increase in COVID-19 vaccine coverage in a country helps to reduce the stock market risk spillovers transmitted by it to other countries. In this section, we further explore the channel through which vaccinations have an influence on stock market risk spillovers. Standard “TO” and “NET” risk spillovers are considered. Recent studies provide empirical evidences that the global pandemic provokes investor sentiment, particularly a rise in fear and anxiety, which negatively impacts stock prices (e.g. Huynh and Xia, 2021; Sun et al., 2021; etc.). Hence, we are encouraged to construct an index to reflect the level of panic sentiment and further explore whether panic sentiment mediates the impact of COVID-19 vaccinations on risk spillovers by a two-stage regression. The results are reported in Table 13.

From Table 13, we first notice that the increase in COVID-19 vaccine coverages is significantly associated with the decrease in the level of panic sentiment (see Panel A). The results are robust across different measures of COVID-19 vaccinations. It is suggested that the successful launch of COVID-19 vaccines alleviate the public anxiety induced by COVID-19 pandemic. This finding is consistent with previous studies on public emotional responses to the approval and coverage of COVID-19 vaccines (e.g. Nguyen, 2021; Wu et al., 2022; etc.). Next, we examine the impact of vaccination-driving panic sentiment on “TO” and “NET” mean-based risk spillovers (denoted by TRS and NRS , respectively). As reported in Panel B & C, the coefficients of all channel estimators are positive significant at 1% level. Results are robustness across different specifications. It is implied that risk spillovers across stock markets are contributed by investor panic. And the overall findings of two-stage regression point out that increasing COVID-19 vaccination ratios helps to alleviate panic sentiment alongside COVID-19 pandemic, which lowers risk spillovers among Asia-Pacific stock markets.

5. Conclusions

This study presents the first attempt to investigate the effect of COVID-19 vaccinations on volatility (risk) spillovers among major stock markets in the Asia-Pacific region. This study estimates both mean-based and quantile-based spillovers within the framework of Diebold and Yilmaz (2012, 2014). The quantile-based approach allows us to differentiate between the risk spillovers at the extreme lower and upper tails. To identify the vaccination effect, we not only examine the network of risk spillovers before and after the presence of COVID-19 vaccines but also conduct a series of regression analyses.

Both static and dynamic analyses of spillover network indicate that there are fewer system-wide volatility (risk) spillovers among regional stock markets after the launch of COVID-19 vaccines, with extreme spillovers always stronger than the standard (i.e., mean-based) ones. The regression results indicate that increasing vaccinations in each country helps stabilize the Asia-Pacific equity markets by reducing risk spillovers (both total and net terms) transmitted by it to others. Specifically, there is a significant and negative association between the levels of standard spillovers and the rates of COVID-19 vaccination. This finding is robust across different vaccination-related and control variables. Besides, we find asymmetry in the impact of vaccinations that extreme downside-tail spillovers are significantly affected by mass vaccination, while extreme upside-tail spillovers are not. Further, we employ a two-stage regression to investigate the mechanism behind the COVID-19 vaccination effect on stock market risk spillovers. Panic sentiment is identified as a potential channel. Increasing vaccination in each country helps to reduce its stock market risk transmission to others by decreasing local panic sentiment.

Our findings suggest that policymakers and investors should be aware of the benefits of mass COVID-19 vaccination in financial markets. Progress in vaccination programs differs across countries, and transnational regulators should enhance the assessment of financial risks in countries that lag in vaccinating the majority of their populations. Investors need to pay attention to the development of countries' vaccination policies. In particular, within the Asia-Pacific region, several major contributors to volatility spillovers are highlighted during the post-vaccination period in this study. When managing a portfolio with a focus on regional stocks, investors

Table 12
COVID-19 vaccinations and extreme upside risk spillovers.

Panel A:	Completely Vaccinated			
	(1)	(2)	(3)	(4)
	<i>TRS_H</i>	<i>TRS_H</i>	<i>NRS_H</i>	<i>NRS_H</i>
<i>Vaccinated</i>	1.70763 (1.1732)	-1.45452 (2.7193)	1.88669 (1.1696)	-1.37851 (2.7165)
<i>From</i>	-6.43747*** (0.1275)	-6.39300*** (0.1269)	-7.47220*** (0.1249)	-7.42612*** (0.1243)
<i>AsiaNet</i>	6.90716*** (0.3664)	6.93379*** (0.4149)	6.87870*** (0.3652)	6.90082*** (0.4133)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Country FE</i>	No	Yes	No	Yes
<i>Month FE</i>	No	Yes	No	Yes
adj. R^2	0.648	0.636	0.714	0.703
<i>N</i>	3588	3588	3588	3588
Panel B:	Vaccinated at least once			
	(5)	(6)	(7)	(8)
	<i>TRS_H</i>	<i>TRS_H</i>	<i>NRS_H</i>	<i>NRS_H</i>
<i>Vaccinated_one</i>	3.46702 (2.2596)	7.51072 (4.6904)	3.62542 (2.2070)	7.43871 (4.6516)
<i>From</i>	-6.42592*** (0.1876)	-6.36206*** (0.2584)	-7.46048*** (0.1765)	-7.39566*** (0.2467)
<i>AsiaNet</i>	6.78905*** (0.6323)	6.87312*** (0.6524)	6.76043*** (0.6110)	6.84111*** (0.6537)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Country FE</i>	No	Yes	No	Yes
<i>Month FE</i>	No	Yes	No	Yes
adj. R^2	0.649	0.637	0.714	0.704
<i>N</i>	3588	3588	3588	3588
Panel C:	Vaccination per hundred people			
	(9)	(10)	(11)	(12)
	<i>TRS_H</i>	<i>TRS_H</i>	<i>NRS_H</i>	<i>NRS_H</i>
<i>Vaccinated_100</i>	0.01319 (0.0100)	0.01487 (0.0123)	0.01397 (0.0097)	0.01464 (0.0124)
<i>From</i>	-6.43057*** (0.1877)	-6.38164*** (0.1281)	-7.46517*** (0.1766)	-7.41510*** (0.1255)
<i>AsiaNet</i>	6.84242*** (0.6337)	6.90976*** (0.4124)	6.81418*** (0.6133)	6.87750*** (0.4109)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Country FE</i>	No	Yes	No	Yes
<i>Month FE</i>	No	Yes	No	Yes
adj. R^2	0.649	0.636	0.714	0.703
<i>N</i>	3588	3588	3588	3588

Note: This table reports the regression results regarding the effect of COVID-19 vaccination on extreme tail-downside risk spillovers. The dependent variables are extreme tail-upside risk spillovers at the extreme high quantile equal to 0.95, including “TO” risk spillovers (*TRS_H*) and “NET” risk spillovers (*NRS_H*). The independent variable is vaccination status. It is proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people. The control variables include *From*, *AsiaNet*, *Vol*, *VIX_Gold*, *VIX_Oil*, *VIX_SPX*, and *VIX_Emerging*. Country-time two-way clustering robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

should consider the spillover effects of volatility risk that vary with vaccination progress. Future studies could explore the impact of vaccination on risk spillovers among other asset classes or other factors potentially relevant to the vaccination effect in heterogeneous tests.

Credit authorship contribution statement

Yanshuang Li: Conceptualization, Writing - original draft, Writing - review & editing, Software, Visualization, Methodology.

Yongdong Shi: Funding acquisition, Supervision, Writing - review & editing.

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Weiping Zhang: Funding acquisition, Writing - original draft.

Table 13
COVID-19 vaccinations, panic sentiment and risk spillovers.

Panel A:	First Stage: COVID-19 vaccine and panic sentiment		
	(1)	(2)	(3)
	<i>PanicSent</i>	<i>PanicSent</i>	<i>PanicSent</i>
<i>Vaccinated</i>	−1.44810*** (0.3899)		
<i>Vaccinated_one</i>		−2.24437*** (0.4043)	
<i>Vaccinated_100</i>			−0.00614*** (0.0022)
<i>Controls</i>	Yes	Yes	Yes
<i>Country FE</i>	Yes	No	Yes
<i>Month FE</i>	Yes	No	Yes
adj. R^2	0.350	0.353	0.349
<i>N</i>	3572	3572	3572
Panel B:	Second Stage: COVID-19 vaccine-driven panic sentiment and “TO” risk spillovers		
	(4)	(5)	(6)
	<i>TRS</i>	<i>TRS</i>	<i>TRS</i>
$\widehat{PanicSent}$	1.12179*** (0.0614)		
$\widehat{PanicSent_one}$		0.51004*** (0.0418)	
$\widehat{PanicSent_100}$			1.74239*** (0.0875)
<i>Controls</i>	Yes	Yes	Yes
<i>Country FE</i>	Yes	Yes	Yes
<i>Month FE</i>	Yes	Yes	Yes
adj. R^2	0.545	0.596	0.106
<i>N</i>	3572	3572	3572
Panel C:	Second Stage: COVID-19 vaccine-driven panic sentiment and “NET” risk spillovers		
	(7)	(8)	(9)
	<i>NRS</i>	<i>NRS</i>	<i>NRS</i>
$\widehat{PanicSent}$	1.07819*** (0.0543)		
$\widehat{PanicSent_one}$		0.47623*** (0.0367)	
$\widehat{PanicSent_100}$			1.65426*** (0.0708)
<i>Controls</i>	Yes	Yes	Yes
<i>Country FE</i>	Yes	Yes	Yes
<i>Month FE</i>	Yes	Yes	Yes
adj. R^2	0.106	0.050	0.162
<i>N</i>	3572	3572	3572

Note: This table reports the two-stage regression results that examine the impact of COVID-19 vaccination on risk spillovers through panic sentiment. Panel A presents the results of regressing COVID-19-related panic sentiment (i.e. channel variable) onto vaccination ratios. Vaccination status is proxied by three alternative measures: (1) *Vaccinated* represents the percentage of the population fully vaccinated; (2) *Vaccinated_one* is defined as the share of people who complete at least one dose of vaccination in the population; and (3) *Vaccinated_100* is calculated by vaccination doses per hundred people. Panel B and Panel C present the results of regressing risk spillovers onto channel estimators obtained by three types of vaccination ratios. The dependent variables are “TO” risk spillovers (denoted as *TRS*) and “NET” risk spillovers (denoted as *NRS*). The control variables include *From*, *AsiaNet*, *Vol*, *VIX_Gold*, *VIX_Oil*, *VIX_SPX*, and *VIX_Emerging*. Country-time two-way clustering robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Declaration of Competing Interest

The authors declare no conflict of interest.

Acknowledgments

This work is supported by Liaoning Provincial Social Science Foundation of China (L22CJY014); Basic Research Project of Liaoning Provincial Department of Education (LJKQR20222505); General Program of China Postdoctoral Fund (2021M702005); National Natural Science Foundation of China (71971046; 71973085; 72172029); and Major Project of the National Social Science Foundation of China (19ZDA094). All coauthors have made equal contribution to the paper.

Appendix A. Appendix

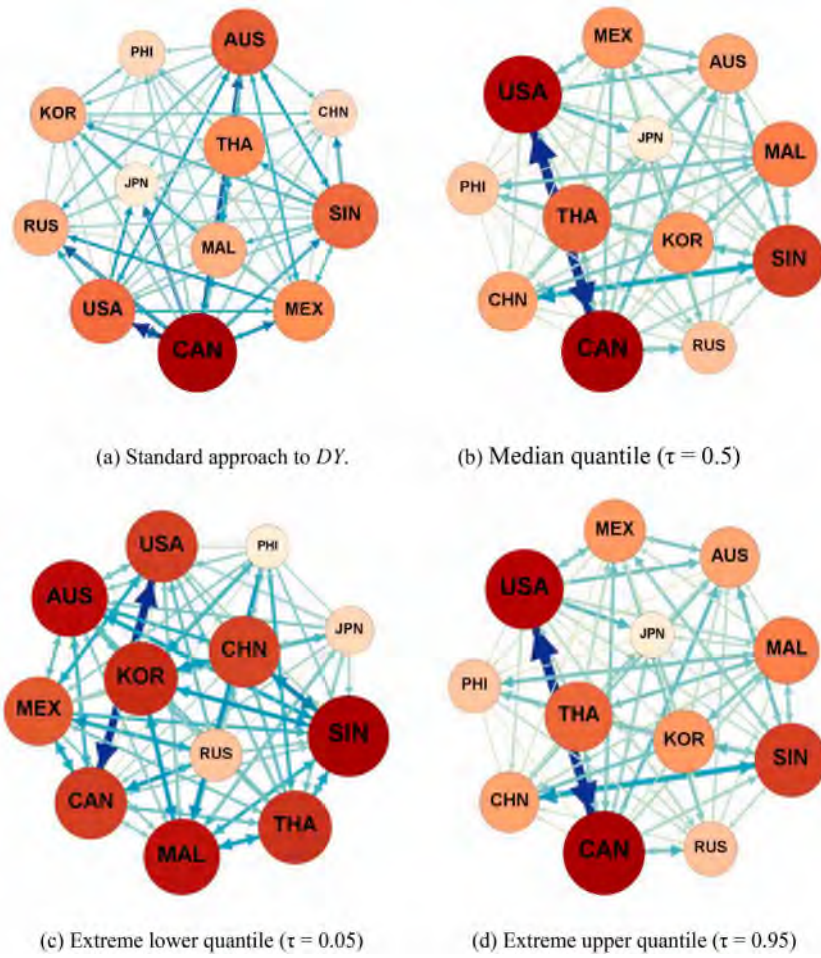


Fig. A. Pairwise directional network of volatility spillovers among the 12 stock markets before the vaccination period.

Notes: Node size reflects the overall magnitude of transmission/reception for each stock market. Edge size indicates the magnitude of pairwise volatility spillovers between the two stock markets. In addition, the magnitude is also reflected by the color types of node/edge, dark (strong), and light (weak) colors.

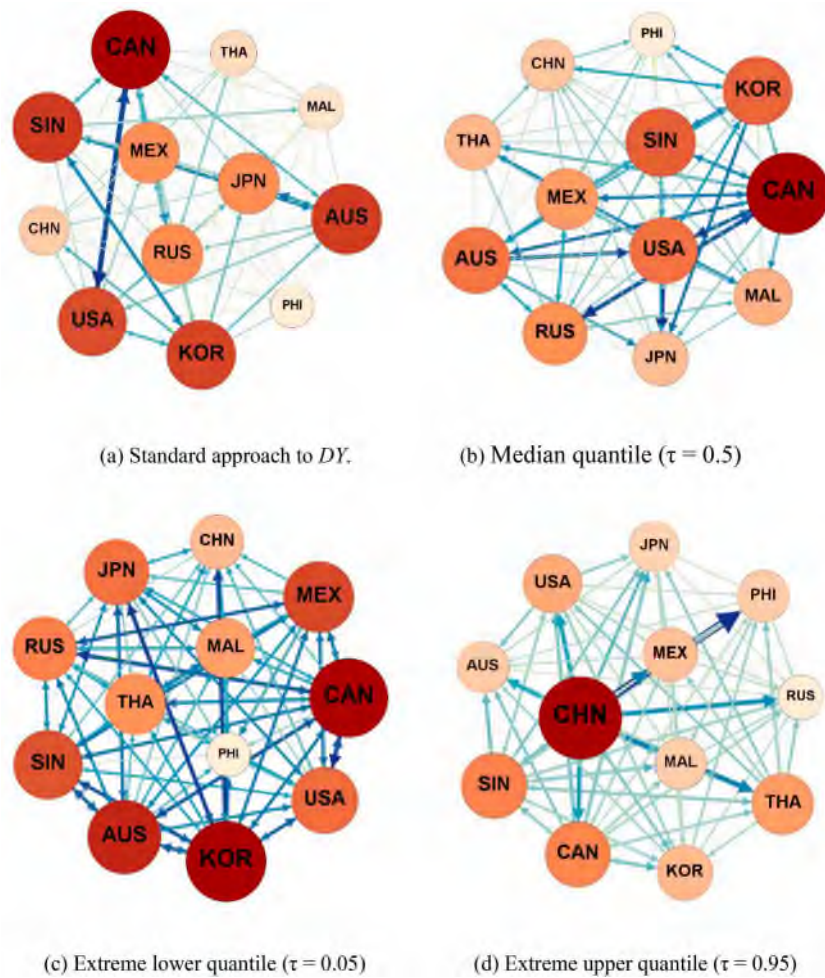


Fig. B. Pairwise directional network of volatility spillovers among the 12 stock markets during the vaccination period.

Notes: Node size reflects the overall magnitude of transmission/reception for each stock market. Edge size indicates the magnitude of pairwise volatility spillovers between the two stock markets. In addition, the magnitude is also reflected by the color types of node/edge, dark (strong), and light (weak) colors.

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