

การส่งผ่านความผันผวนและความเชื่อมโยงเชิงพลวัตระหว่างตลาดหลักทรัพย์นานาชาติประเทศ: ผลการศึกษาเชิงประจักษ์ช่วงวิกฤตโควิด-19 ในตลาดหลักทรัพย์จีน

ซงลี่ เว่ย^{1*} และ ยุทธนา เศรษฐปราโมทย์²

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บทคัดย่อ

การแพร่ระบาดของไวรัสโควิด-19 นำมาสู่ภาวะความผันผวนรุนแรงในตลาดการเงินโลก การศึกษานี้วิเคราะห์การแพร่กระจายความผันผวนระหว่างตลาดหลักทรัพย์จีนและตลาดหลักทรัพย์นานาชาติโดยใช้ดัชนีความเชื่อมโยงเชิงพลวัต ผลการศึกษาเชิงประจักษ์พบว่าระดับการแพร่กระจายความผันผวนของตลาดหลักทรัพย์นานาชาติประเทศเพิ่มขึ้นในช่วงที่เกิดวิกฤตจากการแพร่ระบาดของไวรัสโควิด-19 โดยตลาดหลักทรัพย์จีนได้รับผลกระทบจากการส่งผ่านความผันผวนในระดับที่ต่ำกว่าตลาดหลักทรัพย์ในประเทศที่พัฒนาแล้ว เช่น สหรัฐฯ สหภาพยุโรป และประเทศพัฒนาแล้วในเอเชีย เมื่อวิเคราะห์ปัจจัยที่มีผลต่อการส่งผ่านความผันผวน พบว่า ดัชนีความผันผวนของตลาดสหรัฐฯ (VIX) เป็นปัจจัยสำคัญในการกำหนดระดับของการส่งผ่านความผันผวนในแต่ละช่วงเวลา จำนวนผู้ติดเชื้อและระดับการรับวัคซีนมีผลต่อระดับการรับความผันผวนในภาพรวม แต่จำนวนผู้ติดเชื้อไม่มีผลต่อระดับการรับความผันผวนในกรณีประเทศจีน ซึ่งแสดงให้เห็นถึงการควบคุมการติดเชื้อที่มีประสิทธิภาพและการแพร่กระจายวัคซีนที่รวดเร็ว ซึ่งช่วยลดผลกระทบในช่วงวิกฤตจากความเสี่ยงจากภายนอกได้

คำสำคัญ: การแพร่ระบาดของโควิด-19, การส่งผ่านความผันผวน, ความเชื่อมโยงเชิงพลวัต, ตลาดหลักทรัพย์จีน

¹ นักศึกษาปริญญาโท หลักสูตรเศรษฐศาสตรมหาบัณฑิต, คณะพัฒนาการเศรษฐกิจ, สถาบันบัณฑิตพัฒนบริหารศาสตร์
(ผู้รับผิดชอบบทความ, Email: songli.wei@stu.nida.ac.th)

² รองศาสตราจารย์, คณะพัฒนาการเศรษฐกิจ, สถาบันบัณฑิตพัฒนบริหารศาสตร์

Spillover Effects and Dynamic Connectedness in International Stock Markets: Evidence from the COVID-19 Pandemic in China

Songli Wei^{1*} and Yuthana Sethapramote²

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Abstract

The Covid-19 outbreak triggered extreme volatility in global financial markets. This paper examines the spillover effects between China's stock market and international stock markets, using the dynamic connectedness index to measure these effects. Empirical results show that connectivity among international stock markets increased during the pandemic, with China's stock market experiencing less spillover than European and advanced Asian markets. Additionally, we investigate the factors driving spillovers during this period, identifying the volatility index (VIX) as a key indicator, underscoring the role of global risk factors before, during, and after the pandemic. The case and vaccination rates also significantly influenced spillovers in international markets during the pandemic, though the impact of case rates on spillovers into China's stock market was not significant. This reflects China's robust pandemic response and economic policies, which effectively buffered its financial markets from global shocks.

Keyword: Covid-19 Pandemic, Dynamic Connectedness, Spillover effects, Stock Market in China

JEL classification: C22, F65, G15, I18

¹ Master student in economics program, School of Development Economics, National Institute of Development Administration (Corresponding authors, Email: songli.wei@stu.nida.ac.th)

² Associate Professor, School of Development Economics, National Institute of Development Administration

Introduction

The spillover effect occurs when a shock (e.g., a financial crisis, economic downturn, or policy change) in one market or country impacts other markets or countries. During global crises, spillovers become more pronounced due to heightened interconnectedness in financial systems, and investor sentiment. The Covid-19 pandemic, which originated from global public health crisis and lockdowns, has had a deep impact on the global macroeconomy and financial markets. During the pandemic, market panic and uncertainty caused unprecedented volatility in financial markets. Volatility is spreading rapidly due to global uncertainty and investor panic. Risky asset prices plummeted, market volatility soared, and borrowing costs increased, causing a sharp increase in financial conditions. This unique financial environment provided an opportunity to investigate two key questions: 1) How did volatility spillovers and contagion in financial markets behave during the pandemic? 2) How did international economics, financial markets' risk factors and COVID-19-related variables impact these spillovers?

In current global context, studying dynamic connectivity of China's stock market during COVID-19 is both academically and practically valuable. As the initial site of the outbreak, China's financial market response offers key insights into global market volatility. Additionally, with China's stock market growing in importance within the global economy, its connectivity with other international markets has major implications for global investors and policymakers (Zhang et al., 2020).

The research objectives of this study are outlined as follows. First, we aim to examine the spillover effects and dynamic connectivity patterns of international stock markets during COVID-19, with a focus on China's stock market. By analyzing spillover effects before, during, and after the pandemic. Second, this study seeks to understand the evolution of financial market connectivity and the influence of economic, global risk and pandemic-related factors.

Following the framework of Diebold and Yilmaz (2012), this study used a spillover index to capture the time-varying connectedness between Chinese and global stock markets. Empirical findings reveal notable differences in spillover effects across pandemic phases. Spillover effects are relatively stable in the pre-pandemic period, then increase sharply during the pandemic due to heightened market uncertainty and synchronized economic shocks. In the later stages, spillovers show signs of normalizing but continue to be influenced by pandemic-related uncertainty and policy responses. This study provides contributions to the existing literature by thoroughly analyzing spillover dynamics within the context of a global pandemic. It highlights the essential role of macroeconomic and pandemic-specific variables in shaping financial market behavior, offering helpful insights for policymakers and investors on managing risk and fostering market stability during crises.

This study provides the contribution to filling the research gap in existing literature in two aspects. First, we use dynamic connectedness as a proxy of spillovers in international stock markets, while most of existing studies applied stock returns as variables to investigate spillovers effect. This approach can quantify the level of spillovers across each country and global markets. The index is also moving over time, providing the dynamic of connectedness in the international stock markets. Second, we use the data on Covid-19 pandemic, i.e. case rate, death rate and vaccination to explain spillover patterns.

The paper is structured as follows: Section 2 reviews literature on the dynamic relationships between stock markets and the impact of COVID-19. Section 3 describes the data and summarizes the econometric methodology. Section 4 reports empirical results, while Section 5 concludes and discusses the implications of the findings.

Literature Review

Spillovers in international stock markets is one of the crucial issues in international financial management. Forbes and Rigobon (2002) explained differences between "contagion" (increased cross-market linkages during crises) and "interdependence" (normal market co-movements). During the Global Financial Crisis, the international stock markets simultaneously encounter high volatility. Bekaert and Harvey (1995) explores how changes in risk perception affect international market integration. They develop a conditional regime-switching model that allows the degree of integration to vary based on observable economic and financial variables. This model shows that integration is higher during periods of high global uncertainty or when global risk factors dominate local factors. Recently, the volatility index (VIX) and economic policy uncertainty index (EPU) are usually mentioned as proxy for global risk factors. Later, oil prices are mentioned as a crucial global economic variable influencing inflation and economic growth. Kilian (2009) mentions that large fluctuations in oil prices often lead to uncertainty, impacting investor sentiment and triggering spillovers, especially in economies reliant on oil imports (e.g. China).

Subsequently, many empirical studies investigated determinants factors of this dynamic interconnectedness pattern using the global risk perception indicators e.g. VIX index, economic policy uncertainty index and commodities prices. For example, Manopimoke et al. (2018) investigated the spillover effects of international stock markets and show that financial spillover indicators are highly correlated with global and national level commodity prices (such as oil and gold) and financial risk factors (like VIX and TED spreads).

During the Covid-19 pandemic, the global economy and financial markets faced a severe crisis. The outbreak sparks intense research interest in understanding the spillovers of crisis' patterns. Altig et al. (2020) examine how economic uncertainty evolved before and after the pandemic, highlighting its influence on market volatility and policy uncertainty. Ullah (2023) provides an in-depth analysis of how the COVID-19 pandemic has affected financial markets worldwide, particularly focusing on the interconnections between markets and the mechanisms through which volatility was transmitted during the pandemic. The study examines both the direct and indirect effects of the pandemic on global financial systems, highlighting how different financial markets responded to the same shock and how those responses were interconnected. Ashraf (2020) found that government-imposed social distancing policies negatively affected stock market returns directly but had an indirect positive effect by reducing confirmed COVID-19 cases.

The pandemic's impact on businesses varied widely across industries. Chen (2020) noted that non-state-owned companies with limited foreign trade or assets were especially vulnerable to pandemic-related disruptions. Fang et al. (2020) analyzed the pandemic's role in risk transmission across money, stock,

and exchange markets, finding that risk spillovers increased significantly within 3–5 days of major pandemic-related events.

Zhang et al. (2021), estimate the time-varying parameter vector autoregression model (TVP-VAR) and spillover index of Diebold and Yilmaz (2009, 2012), evaluated spillover effects in energy and stock markets, showing a notable rise during the pandemic. Similarly, Youssef et al. (2021) used a TVP-VAR model to assess dynamic correlations between stock indices and prices, finding strong associations in early 2020, especially among European markets (excluding Italy) and Northeast Asian markets. They identified the U.S. as a major transmitter of volatility shocks across these markets.

For the Chinese stock market, Liu et al. (2021) conducted one of the first studies on the pandemic's impact. They found that although China's stock market initially saw sharp declines, it began recovering sooner than Western markets due to China's swift policy responses. He et al. (2020) examined market volatility in China during the pandemic, noting significant risk increases, especially in sectors linked to global supply chains. The healthcare and technology sectors in China performed well, reflecting a shift in demand and government support for those industries. Zhang et al. (2020) studied market risk transmission during COVID-19 and found that while China's stock markets were influenced by global investor sentiment, domestic factors played a larger role in their recovery. This study highlighted the importance of government intervention and containment measures in stabilizing China's market conditions.

The literature review shows that COVID-19 had a substantial impact on global and China's stock markets, with spillovers and dynamic correlations between markets shifting considerably during the pandemic. Models like VAR and GARCH are essential for analyzing volatility transmission across markets. This literature provides theoretical foundation and empirical evidence for the current study, guiding its research direction and methodology. By comparing and synthesizing findings from various studies, this study aims to strengthen the understanding dynamics of stock markets during COVID-19 and offer valuable insights for policy formulation.

Data and Methodology

Data

This paper investigated spillover effects across major stock markets with significant financial and trade linkages to China. These markets were affected by the pandemic, underscoring their relevance to this study. Table 1 summarized the list of international stock markets. The data spans from January 1, 2018, to February 29, 2024, covering daily stock index values, macroeconomic indicators, global risk factors, COVID-19 case counts, and vaccination data, sourced from the World Health Organization (WHO), Johns Hopkins University Coronavirus Resource Center, CEIC database, and Investing.com. All datasets underwent rigorous preprocessing and validation to ensure data reliability.

The sample period is divided into three phases: Pre-pandemic (January 1, 2018, to January 29, 2020), Pandemic (January 30, 2020, to February 28, 2022), and Post-pandemic (March 1, 2022, to February 29, 2024). Daily stock market returns are calculated as the logarithmic difference of daily price indices. To examine spillover patterns between China and other countries during the pandemic, we use explanatory

variables. Table 2 summarizes the key determinant factors using in Section 3.2.2. Our analysis also incorporates oil prices, economic policy uncertainty indices (EPU), and volatility indices (VIX). These factors are applied in empirical research about the determinant factors of spillovers in international stock markets (Manopimoke et al., 2018). The CEIC database provides oil prices, the Chicago Board Options Exchange (CBOE) provides the VIX index, and policyuncertainty.com website provides the EPU data.

The VIX serves as a standardized measure of market volatility and investor sentiment, offering real-time insights into market dynamics. It is widely used in financial research and has become essential in analyzing market spillovers due to its significant influence on global markets (Bollerslev et al., 2009; Diebold & Yilmaz, 2009; Whaley, 2009). The EPU index reflects economic policy uncertainty, which can increase market volatility and influence investor behavior, especially during crises (Baker et al., 2016, 2020; Pástor & Veronesi, 2013). Oil prices are also crucial, as their volatility impacts global economic conditions, affecting production costs, inflation rates, and stock market performance (Hamilton, 1983, 2009; Kilian, 2009). Including these variables provides a more comprehensive view of short-term market responses and long-term economic uncertainty, which are essential for understanding how policy uncertainties and economic conditions impact the stock markets in China and other developed economies in our study. The covid-related variables consist of case rate, death rate and vaccination rate. Prukumpai et al (2003) showed that these variables could represent the impact of Covid-19 pandemic to stock markets in the ASEAN countries during the crisis.

Table 1 List of International Stock Markets

Abbreviation	Stock Market	Stock market index
CHI	People's Republic of China	Shanghai Stock Exchange: Index: SSE Composite
SGP	Singapore	Straits Times Indices: Straits Times Index
KOR	South Korea	KRX: Index: Korea Composite
HKG	Hong Kong	Hong Kong Hang Seng Index (HIS)
JPN	Japan	Tokyo: Index: Nikkei225 (NKY)
IND	India	Bombay Stock Exchange: Index: SENSEX
AUS	Australia	ASX: Index: All Ordinaries
US	The United States	S&P500
UK	The United Kingdom	FTSE 30 Index (UKX)
FRA	France	Euronext Paris: Index: CAC40
GER	Germany	German Stock Index DAX (Deutsche Boerse AG)

Table 2 Lists of Explanatory Variables

Abbreviation	Variables	Definition
Case_rate	The ratio of the case	Rate of infections per 1 million people
Death rate	The ratio of the death	Rate of deaths per 1 million people
CFR	Case fatality rate	(Deaths / Cases) * 100
Vacc_rate	Vaccination rate	Vaccination rate per 100,000 population
VIX	The VIX index	Chicago Board of Exchange volatility index

Abbreviation	Variables	Definition
EPU	Economic policy Uncertainty	Index of Economic Policy Uncertainty US
EPU_CHI	Chinese Economic policy Uncertainty	Index of Economic Policy Uncertainty CHI
OIL	Crude oil price	WTI Oil Futures closing price

Research methodology

In this study, we use two main research methods. First, we apply the spillover index model developed by Diebold and Yilmaz (2009, 2012) to measure the dynamic connectedness patterns in international stock markets before, during, and after the pandemic. Second, we perform time-series and panel data regressions to identify the factors driving these spillover patterns. Details of each method are summarized below.

1) Spillover index approach

We employ the methodology proposed by Diebold and Yilmaz (2009, 2012) to construct a spillover index using a generalized variance-based approach within a vector autoregressive (VAR) model framework. To make the spillover index more interpretable, we present a model with p lags within a covariance stationary N variable VAR framework. The VAR model aims to capture linear relationships between multiple time series. Specifically, the VAR model with p lags (VAR(p)) for a system of N variables is expressed as follows:

$$\mathbf{X}_t = \Phi_1 \mathbf{X}_{t-1} + \dots + \Phi_p \mathbf{X}_{t-p} + \mathbf{B}\mathbf{c} + \boldsymbol{\varepsilon}_t \quad (1)$$

In this equation, $\mathbf{X}_t = \{X_{1,t}, X_{2,t}, \dots, X_{N,t}\}$ represents the matrix of endogenous variables (In this study, $\mathbf{X}$ includes returns on eleven stock markets), $\boldsymbol{\varepsilon}_t \sim (0, \Sigma)$ denotes the variance matrix of the error term. We assume that these error terms are contemporaneously correlated and independently distributed in time.

An alternative interpretation of the moving average representation in the VAR system is that the variances in the system change jointly. This is then given by:

$$\mathbf{X}_t = \sum_{i=0}^{\infty} \mathbf{A}_i \boldsymbol{\varepsilon}_{t-i} \quad (2)$$

where $\mathbf{A}_i$ is an $N \times N$ matrix of coefficients obeying the recurrence relation $\mathbf{A}_i = \Phi_1 \mathbf{A}_{i-1} + \Phi_2 \mathbf{A}_{i-2} + \dots + \Phi_p \mathbf{A}_{i-p}$. From there, the decomposition of the H -ahead prediction error variance can be derived, based on the generalized VAR framework, as :

$$\theta_{ij}(H) = \frac{\sigma_{jj} \sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{A}_h \Sigma \mathbf{e}_i)^2}{\sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{A}_h \Sigma \mathbf{A}_h' \mathbf{e}_i)} \quad (3)$$

where σ_{ij} is the error term of i -th equity with standard deviation, $\mathbf{e}_i$ is an $N \times 1$ optima vector with 1 being the i -th element and 0 elsewhere. It can thus be interpreted $\theta_{ij}(H)$ as the contributor to the predicted $\mathbf{X}_i$ of H -step error variance, derived from each $i, j = 1, 2, \dots, N$ of standard error shocks of $\mathbf{X}_j$ where $\forall i \neq j$. To conclude, Diebold and Yilmaz (2012) standardized each item of the covariance breakdown matrix by row, as follows:

$$\tilde{\theta}_{i,j}(H) = \frac{\theta_{i,j}(H)}{\sum_{j=1}^N \theta_{i,j}(H)} \quad (4)$$

Therefore, $\sum_{j=1}^N \tilde{\theta}_{i,j}(H) = 1, \sum_{j=1}^N \tilde{\theta}_{i,j}(H) = N,$

Thus, the total spillover index, which assesses the impact of spillover between N variables on the variance of the total prediction error, is calculated as:

$$TS(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{i,j}(H)}{\sum_{i,j=1}^N \tilde{\theta}_{i,j}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{i,j}(H)}{N} \times 100 \quad (5)$$

Orientation premium: which measures the volume spillover effect which I receives from all other markets j ($DS_{i \rightarrow \cdot}(H)$):

$$DS_{i \rightarrow \cdot}(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{i,j}(H)}{\sum_{i,j=1}^N \tilde{\theta}_{i,j}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{i,j}(H)}{N} \times 100 \quad (6)$$

In this study, we construct a spillover index of structural variance decomposition to measure spillover effects in stock markets, focusing on China and various developed countries. This approach can capture dynamic patterns of spillovers, allowing researchers to track how spillovers evolve over time. In addition, the index can be shown at the overall levels and break down at a country level showing how specific markets contribute to or are affected by global volatility. The total spillover effect serves as an indicator of global financial conditions, reflecting the interconnectedness of global markets. Additionally, we examine the directional spillover effect, which helps us understand the determinants and dynamics of one-way spillovers between China and other developed economies.

This analysis aims to offer a comprehensive view of how external economic shocks and market movements impact domestic stock market fluctuations and vice versa, providing valuable insights into the global financial ecosystem.

2) Determinants of Spillover Effects in China's and International Stock Markets

In the previous section, we examined the patterns of linkages and spillovers among stock markets across 11 countries. The data analysis highlighted a complex interplay of factors influencing spillover patterns between China and developed countries. Building on this foundation, this section introduces macroeconomic factors and COVID-19-related variables to further investigate these dynamics. We propose the following hypothetical equation to analyze the determinants of spillover effects.

$$Spill_{i,t} = a_i + \gamma_1 Case_{i,t} + \gamma_2 Death_{i,t} + \gamma_3 Vacc_{i,t} + \beta_1 VIX_t + \beta_2 EPU_t + \beta_3 OIL_t + \epsilon_{i,t} \quad (7)$$

The Spillover Index, our dependent variable, measures the strength and direction of market spillover effects. The COVID-19-related factors, include new case counts (Case), death rates (Death), and vaccination progress (Vacc), each significantly impacting market behavior during the pandemic. We include the following control variables, the oil price (oil), the CBOE VIX index (VIX) and the global economic policy

uncertainty index (EPU), which are crucial for a comprehensive understanding of market fluctuations. The residual effects are captured by $\epsilon_{i,t}$.

We estimate equation (7) using time series for the overall index. Furthermore, we estimate the panel data model with fixed effects using spillover effect that each country received from the other markets. These equations allow us to quantify and analyze the factors driving spillover effects, providing a deeper understanding of the interconnected nature of global financial markets, especially considering the pandemic and its economic impacts. The regressions are estimated by the panel data for the case of individual stock market analysis and time series regressions in the case of overall spillover and China spillover.

Research results

In this section, we display the empirical investigation. First, we examine the movements of international stock markets. Figure 1 illustrates the increasing trends in the level for most of the stock markets included in this study. However, in case of Singapore, stock market exhibits a decreasing trend.

Market movements display notable volatility. Before the COVID-19 pandemic, most indices followed an upward trend, signaling economic growth and optimism. However, sharp declines across all indices in early 2020 reflect the immediate, widespread market response to the outbreak, marking a period of peak panic and mass selloffs. Recovery trends varied across markets afterward; for example, the U.S. and India showed strong recovery and growth post-2020, while markets like Hong Kong experienced slower, more modest rebounds. These differences highlight the varied impacts of the pandemic on national economies and the resilience of different financial systems, shaped by unique economic policies and conditions.

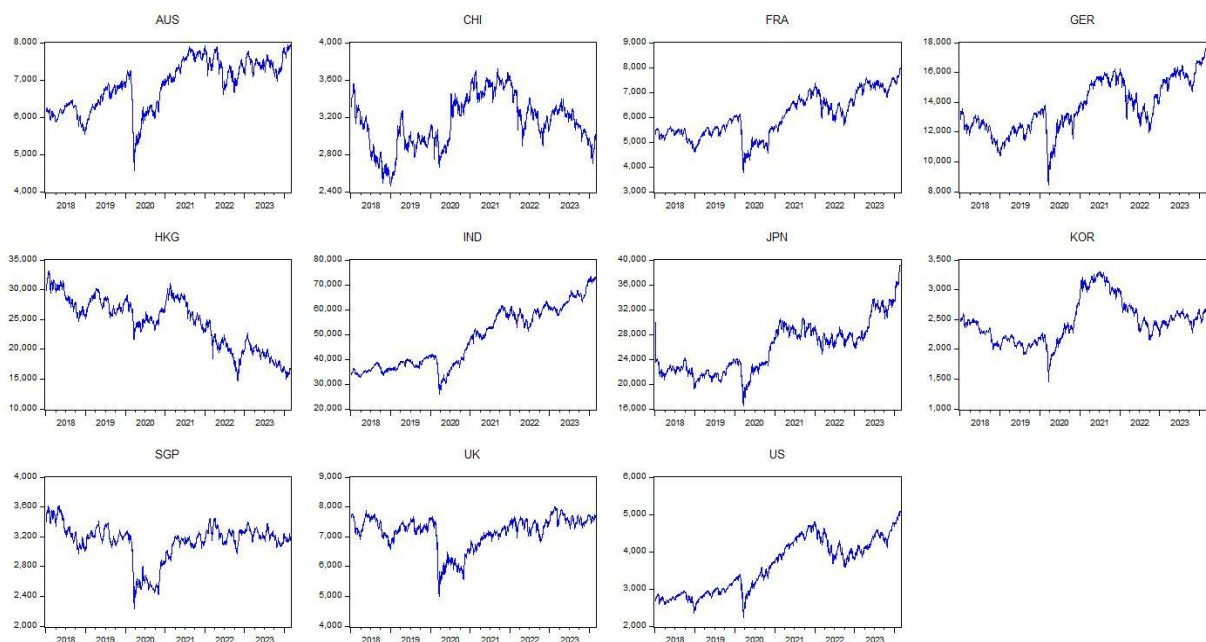


Figure 1 Daily Stock Market Price Indices.

Note: CHI refers to China, PDR, SGP refers to Singapore. KOR refers to South Korea, HKG refers to Hong Kong, JPN refers to Japan, IND refers to India, AUS refers to Australia, US refers to the United States, UK refers to the United Kingdom, FRA refers to France and GER refers to Germany.

Source: Data were retrieved from Investing.com; the data cover the period from January 1, 2018, to February 29, 2024.

Spillover Index Results

To quantify market spillovers, we apply the Diebold and Yilmaz (2009, 2012) methodology, first estimating a vector autoregressive (VAR) model based on stock market indices from the selected countries. We then perform forecast error variance decomposition to gauge how much of each market's forecast error stems from shocks in other markets. From this, we calculate a spillover index, which reflects the extent of market interconnections. The total spillover index is determined by aggregating the impacts received from other markets and dividing them by the number of markets, indicating overall market interaction. The results are displayed in Table 3.

Subsequently, we compute dynamic connectedness indices. Using the Generalized Rolling Spillover Index, Figure 2 plots the dynamic connectivity among major global stock markets from January 2018 to February 2024. This Spillover Index, calculated with a 200-day rolling window and a 10-day projection horizon, measures the degree of market interconnectivity and risk transmission over time.

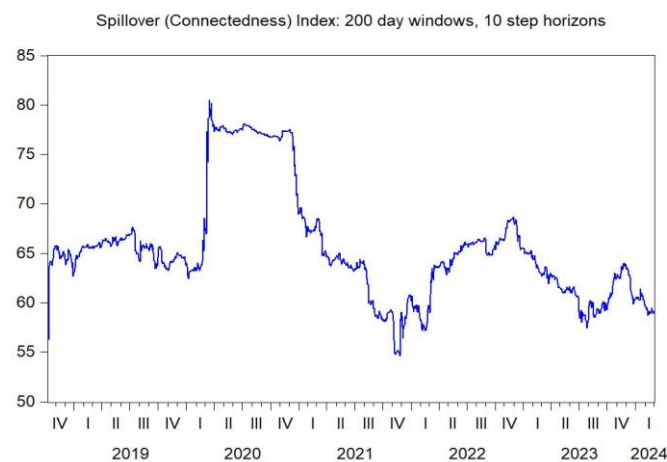


Figure 2 Spillover Index Sequence Diagram

Source: Data were compiled from the CBOE database and CEIC database; the data cover the period from January 1, 2018, to February 29, 2024.

The COVID-19 outbreak in early 2020 marked a significant shift in global markets. As shown in Figure 2, the spillover index rose sharply, peaking at 80.5% on March 16, and stayed elevated between 75% and 80% from March to November 2020. This surge corresponded with the global spread of the virus, causing unprecedented economic disruptions, market panic, and increased uncertainty. In response, governments worldwide introduced economic policies to mitigate these effects, further shaping market behavior.

As the pandemic continued into late 2021, the spillover index dropped below 60%, nearing pre-pandemic levels. This decline in market connectedness can be attributed to rising global vaccination rates,

gradual economic recovery, and markets adjusting to the "new normal." Between 2022 and 2024, Figure 2 shows the spillover index fluctuating between 55% and 70%, indicating stabilization in market connectedness despite ongoing fluctuations. This suggests that, even as the pandemic's impact waned, market interdependence remained influenced by factors like inflation and geopolitical risks.

To examine connectivity among international stock markets in detail, we calculated the spillover index, analyzing connectivity levels for the full sample (entire period) shown in Table 3. We also divided the data into three sub-samples: Pre-Pandemic (January 1, 2018–January 29, 2020), Pandemic (January 30, 2020–February 28, 2022), and Post-Pandemic (March 1, 2022–February 29, 2024), with sub-sample results displayed in Tables 4, 5, and 6, respectively.

As shown in Table 3, the overall spillover index for the entire period stands at 62.1%, indicating strong interconnections among the selected countries' stock markets. A comparison of pre-pandemic and pandemic indices reveals an increase from 58.9% to 67.9% during the outbreak (Tables 4 and 5). In the post-pandemic period, as seen in Table 6, the spillover index decreased slightly to 61.6%.

Table 3 International Stock Market Returns Spillover Table–Whole Period (January 1, 2018, to February 29, 2024)

To	From											Contribution from others
	AUS	CHI	FRA	GER	HKG	IND	JPN	KOR	SGP	UK	US	
AUS	34.1	1.3	9.7	9.3	2.9	4.8	4.4	6	5.5	9.1	12.8	65.9
CHI	2.3	53.6	3	2.6	17.8	1.9	2.2	5.8	5.1	2.6	3.1	46.4
FRA	3.2	0.8	28.1	23.5	2.3	4.4	1.3	2.6	3.9	19.6	10.2	71.9
GER	2.7	0.8	24.7	29.5	2.1	4.2	1.2	2.3	3.8	18.1	10.6	70.5
HKG	3.4	12.9	5.6	4.8	39.5	3.8	2.6	9	8.5	5	5	60.5
IND	6	1.4	8.1	7.5	4.3	44.9	2.5	5.2	6	6.7	7.4	55.1
JPN	5.8	1.7	7.8	7.8	2.9	2.7	44.4	7.6	3	5.7	10.6	55.6
KOR	6.3	3.7	7.4	6.9	8	4.4	5.9	35.5	7.3	6.1	8.4	64.5
SGP	5.7	3.1	9.2	8.2	7.4	5	2.4	7.3	35.6	8.3	7.9	64.4
UK	4.2	1.1	21.4	18.8	2.7	4	1.7	2.8	4.3	30.6	8.5	69.4
US	5.7	0.8	13.9	13.6	1.8	4.9	2.1	2.6	2.9	10.5	41.2	58.8
Contribution to others	45.4	27.6	110.5	102.9	52.3	40.1	26.5	51.1	50.3	91.8	84.5	682.9
Contribution from own	79.5	81.2	138.7	132.4	91.8	85	70.9	86.5	85.9	122.3	125.7	Spillover index 62.1%

Note: The variance decomposition is derived from an order two daily generalized VAR model that was chosen using the AIC criterion. The anticipated contribution of innovations in the country *j*'s stock returns to the variance of the nation *i*'s 10-day ahead stock return forecast error is represented by the value at position (*i,j*). Table 1 provides definitions for the utilized abbreviations.

Table 4 International Stock Market Returns Spillover Table–Pre-Pandemic Period (January 1, 2018, to January 29, 2020)

To	From											Contribution from others
	AUS	CHI	FRA	GER	HKG	IND	JPN	KOR	SGP	UK	US	
AUS	37.1	1.3	13.5	11.5	1.5	1	1.5	2.2	3.1	9.3	18.0	62.9
CHI	1.1	44.5	6.0	5.2	16.2	1.4	1.5	6.9	7.6	5.0	4.8	55.5
FRA	0.8	2.3	29.8	23.6	3.8	1.7	0.5	3.4	3.9	18.9	11.3	70.2
GER	0.5	2.4	25.1	31.8	3.6	1.6	0.4	3.0	3.4	17.4	10.8	68.2
HKG	1.0	12.2	6.9	5.7	33.5	3.4	1.8	11.3	12.8	5.2	6.2	66.5
IND	0.7	2.2	4.1	3.6	6.3	64.9	1.1	6.1	4.6	3.1	3.3	35.1
JPN	2.5	2.2	5.6	5	2.7	1.2	58.9	7.2	2.0	3.6	9.1	41.1
KOR	2.2	5.3	7.5	6.1	11.7	3.3	4.2	36.7	10	4.8	8.3	63.3
SGP	2.4	5.5	9.3	7.3	12.9	2.2	1.1	9.8	34.4	6.1	9.1	65.6
UK	1.3	2.1	21.9	18.7	3.7	1.7	0.8	2.6	3.2	34.4	9.7	65.6
US	0.7	1.3	15.6	13.9	3.3	1.2	0.7	3.5	3.1	10.2	46.6	53.4
Contribution to others	13.0	36.7	115.5	100.5	65.6	18.5	13.5	56.1	53.6	83.7	90.6	647.4
Contribution from own	50.2	81.2	145.4	132.3	99.1	83.4	72.4	92.8	88	118	137.2	Spillover index 58.90%

Note: The variance decomposition is derived from an order two daily generalized VAR model that was chosen using the AIC criterion. The anticipated contribution of innovations in the country *j*'s stock returns to the variance of the nation *i*'s 10-day ahead stock return forecast error is represented by the value at position (*i,j*). Table 1 provides definitions for the utilized abbreviations.

Table 5 International Stock Market Returns Spillover Table–Pandemic Period (January 30, 2020, to February 28, 2022)

To	From											Contribution from others
	AUS	CHI	FRA	GER	HKG	IND	JPN	KOR	SGP	UK	US	
AUS	30.4	2.2	8.0	7.8	4.4	7.8	7.5	6.7	7.1	8.2	9.9	69.6
CHI	4.4	49.4	2.1	1.7	16.4	3.8	4.5	6.5	5.5	2.0	3.7	50.6
FRA	5.0	0.9	24.4	20.6	3.4	5.5	3.5	3.2	5.1	18.8	9.6	75.6
GER	4.4	0.8	21.7	25.6	3.1	5.5	3.3	2.8	5.4	17.5	10.0	74.4
HKG	5.3	10.8	5.6	4.9	34.5	5.8	5.5	9.4	8.6	5.5	4.2	65.5
IND	8.6	2.3	8.8	8.2	5.7	34.4	4.0	5.3	7.0	7.5	8.2	65.6
JPN	8.4	2.6	8.5	8.1	5.2	3.9	33.4	9.3	4.4	7.0	9.2	66.6
KOR	7.4	4.0	6.7	6.1	8.8	5.3	8.9	31.9	7.3	6.4	7.1	68.1
SGP	7.6	2.7	9.4	8.6	7.4	6.4	4.1	7.3	30.6	8.9	6.9	69.4
UK	5.6	1.1	20	17.6	3.8	5.2	3.7	3.6	5.2	25.8	8.4	74.2

To	From											Contribution from others
	AUS	CHI	FRA	GER	HKG	IND	JPN	KOR	SGP	UK	US	
US	9.2	1.6	12.8	11.9	2.7	8.0	4.2	2.6	4.1	10.8	32.2	67.8
Contribution to others	65.9	29	103.6	95.4	60.8	57.2	49.3	56.6	59.7	92.5	77.4	747.4
Contribution from own	96.3	78.4	128	121	95.3	91.6	82.7	88.5	90.3	118.3	109.6	Spillover index 67.90%

Note: The variance decomposition is derived from an order two daily generalized VAR model that was chosen using the AIC criterion. The anticipated contribution of innovations in the country j's stock returns to the variance of the nation i's 10-day ahead stock return forecast error is represented by the value at position (i,j). Table 1 provides definitions for the utilized abbreviations.

Table 6 International Stock Market Returns Spillover Table–Post Period (March 1, 2022 to February 29, 2024)

To	From											Contribution from others
	AUS	CHI	FRA	GER	HKG	IND	JPN	KOR	SGP	UK	US	
AUS	22.8	0.8	14.1	13.5	2.1	2.8	2.5	4.6	3.3	11.9	21.5	77.2
CHI	1.5	58	3.5	3.0	21.9	0.8	0.4	3.6	2.1	3.2	2.2	42.0
FRA	3.0	0.6	30.6	26.3	1.5	4.4	1.0	1.3	2.2	19.3	9.9	69.4
GER	2.8	0.5	26.6	30.9	1.4	4.5	1.2	1.3	2.1	17.8	10.8	69.1
HKG	2.9	15.4	6.7	6.2	41.3	2.1	1.1	5.2	6.4	6.2	6.5	58.7
IND	3.7	0.8	9.5	10.3	2.2	46.4	3.0	3.5	3.5	7.1	9.9	53.6
JPN	4.3	0.6	12.2	13.1	1.6	3.2	33.5	4.5	2.2	7.4	17.2	66.5
KOR	7.1	2.1	9.4	9.9	4.7	3.1	4.4	35.2	5.8	7.2	11.0	64.8
SGP	5.2	1.6	9.1	9.6	5.4	3.7	1.9	4.8	39.3	8.4	10.9	60.7
UK	3.1	1.3	22	20.1	2.1	3.9	1.2	1.2	3.2	34.6	7.3	65.4
US	1.5	0.5	14.7	16.3	1.0	2.9	1.3	1.4	1.3	8.8	50.3	49.7
Contribution to others	35.1	24.3	127.9	128.4	44.0	31.3	17.9	31.5	32.1	97.5	107.1	677.1
Contribution from own	57.9	82.3	158.5	159.4	85.4	77.6	51.4	66.7	71.3	132.1	157.4	Spillover index 61.60%

Note: The variance decomposition is derived from an order two daily generalized VAR model that was chosen using the AIC criterion. The anticipated contribution of innovations in the country j's stock returns to the variance of the nation i's 10-day ahead stock return forecast error is represented by the value at position (i,j). Table 1 provides definitions for the utilized abbreviations.

These findings demonstrate that spillover effects between individual stock markets reached unprecedented levels during the pandemic, with increased interconnectedness across global markets. Our results align with those of Harjoto et al. (2021), Liu et al. (2024), and Prukumpai et al. (2023).

Examining the spillover indices of the 11 selected countries in Table 3, France exhibited the highest spillover effect from other markets (71.9%), followed by Germany (70.5%) and the United Kingdom (69.4%). In contrast, China displayed the lowest spillover effect, with a spillover index of 46.4%. During the pandemic, as shown in Table 5, France (75.6%), Germany (74.4%), and the United Kingdom (74.2%) experienced the largest spillover effects among Asian markets. This suggests that spillover effects are more pronounced in developed economies, consistent with findings from Gunay and Can (2022), who observed stronger shock propagation in developed markets compared to emerging ones. China's spillover index declined from 55.5% pre-pandemic (Table 4) to 50.6% during the pandemic (Table 5), possibly due to its lower case and death rates achieved through strict outbreak control measures, leading to lower spillover effects.

Overall, the analysis of the four tables provides a comprehensive view of dynamic spillovers among global stock markets, underscoring the role of regional integration and the impact of global events like the pandemic. The increasing self-contribution of the Chinese market and the steady influence of Hong Kong highlight the strong economic ties within East Asia. This supports Zhou et al. (2022), who suggest that Hong Kong acts as a conduit for pricing information exchange among the Chinese, Japanese, and Korean stock markets. Consistent findings were also reported by Zhao and Park (2024).

Determinants of the Overall Spillover Level in the International Stock Markets

For the regression analysis, we first explore the relationship between the spillover index and its determining factors in the overall market level. Starting with general financial risk factors and the level of dynamic correlation in the international stock market during COVID-19, we analyze rolling estimates of overall connectivity throughout the pandemic. Using time-series data, we employ the dynamic spillover index as the dependent variable in a time-series regression model, assessing key international economic and financial risk factors like the Volatility Index (VIX), Economic Policy Uncertainty Index (EPU), and Crude Oil Prices (OIL). The whole sample covers the data from January 1, 2018, to February 29, 2024. Results are presented in Table 7.

In Model 1 of Table 7, we estimate the regression using the whole sample period, we include traditional international market risk factors (VIX, EPU, and OIL) along with lagged dependent variables to control for serial correlation. Results indicate that VIX and EPU significantly explain global stock market dynamics, while OIL has an insignificant effect.

Model 2 introduces COVID-19-specific variables identified earlier, including the rate of new infections (CASE_RATE), daily death rate (DEATH_RATE), and new vaccine doses (VACC_RATE). Results suggest that VIX and EPU continue to be primary factors in explaining global stock market correlations, and the COVID-19 case rate has a significant effect on the spillover index. During the pandemic period (Models 4 and 5), an increase in the diagnosis rate aligns with heightened market panic and volatility. Across the full sample period (Model 2), the significance of the case rate underscores its continued impact on the market throughout the outbreak.

To further examine the correlation between financial risk factors and international stock market dynamics during the vaccination period, we segment the sample into three phases. The first phase, pre-

vaccination, spans from January 2018 to January 2020. The second phase, covering the vaccination period, extends from January 2020 to February 2022. Results from Models 4 and 5 in Table 7 indicate that the Economic Policy Uncertainty (EPU) index and the case rate remain key determinants of stock market spillovers.

This aligns with findings from other researchers. Prukumpai et al. (2023) suggest that infection rates, mortality, and vaccination levels significantly influence stock markets, with asymmetric effects observed in the early and late stages of COVID-19. Similarly, Bissoondoyal-Bheenick et al. (2021) found that the correlation between returns and volatility in developed markets (G20 countries) increased, primarily due to rising global confirmed cases and deaths. Sharif et al. (2020) indicate that unexpected changes in COVID-19 case numbers had a significant impact on the U.S. stock market. In contrast, Scherf et al. (2022) argue that while changes in COVID-19 cases prompted the implementation or relaxation of stringent measures, they did not significantly affect stock market returns.

Overall, these results imply that COVID-19 influenced the dynamic correlations among international stock markets between 2020 and 2022, with the case rate being a key indicator affecting spillover levels in our sample.

Determinants of the Country-Level Spillover Indices

This section uses country-level data on spillover indices to analyze how each country is affected by others. The results show the importance of the country-level characteristics affecting the level of spillovers that each country received during the crisis. We use similar model set up to those of the overall level of spillover discussed in last section. Empirical results are shown in Table 8. This includes a full sample data panel regression (Models 1 and 2) and subsamples from before the onset of COVID-19 in January 2020 (Model 3), as well as during the pandemic (Models 4 and 5). Models 4 and 5 specifically explore the linear and quadratic effects of vaccination rates on spillover levels, while Model 6 focuses on the post-pandemic period.

From Table 8, we find that the VIX significantly increased spillover effects during the pandemic. The economic policy uncertainty index (EPU) consistently shows a significant negative impact across most models. According to Sen and Wesselbaum (2023), the effects of EPU on spillovers are mixed. Their study suggests that markets experiencing high uncertainty anticipate policy intervention, leading to reduced spillovers. Additionally, the impact of changes in crude oil prices on spillovers varies across models. Notably, during the pandemic (Models 4 and 5 in Table 8), falling crude oil prices significantly increased spillover effects.

Table 7 Spillover Determinant Factors: Time Regression for the Total Dynamic Spillover Index

Variable	Model 1: Full Sample 1	Model 2: Full Sample 2	Model 3: Pre- Pandemic	Model 4: Pandemic Period 1	Model 5: Pandemic Period 2	Model 6: Post- Pandemic	Model 7: Full Sample 3	Model 8: Pandemic Period 3
Sample Period	1/01/2018– 02/29/2024	1/01/2018– 02/29/2024	01/01/2018– 01/29/2020	01/30/2020– 02/28/2022	01/30/2020– 02/28/2022	03/01/2022– 02/29/2024	1/01/2018– 02/29/2024	01/30/2020– 02/28/2022
C	0.2965 (0.2342)	0.2172 (0.2435)	14.6775*** (1.5731)	1.7273 (1.2045)	0.5298 (0.9674)	9.4115 (15.4163)	1.0493 (0.3227)	2.5008 (1.0111)
LOG(VIX)	0.3007*** (0.0531)	0.2886*** (0.0538)	0.4042*** (0.1098)	0.1052 (0.3737)	0.4895*** (0.1394)	0.2230*** (0.0820)	0.4483*** (0.0652)	0.5481*** (0.1362)
LOG(EPU)	-0.0830** (0.0287)	-0.0714** (0.0294)	-0.0672 (0.0501)	-0.1239* (0.0748)	-0.1888** (0.0747)	0.0210 (0.0283)	-0.0431 (0.0335)	-0.1851*** (0.0715)
OIL	-0.0007 (0.0008)	0.0007 (0.0011)	0.0256*** (0.0043)	-0.0128 (0.0102)	-0.0043 (0.0047)	0.0048** (0.0021)	-0.0001 (0.0012)	-0.0059 (0.0043)
Ccse_rate		0.6991* (0.3763)		1.9012*** (0.6568)	1.4518** (0.6612)	0.1556 (1.2374)		
Death rate		-0.0636 (0.0686)		-0.1284 (0.0922)	-0.1217 (0.0899)	255.1753 (526.5788)		
CFR							-0.0274 (0.3509)	1.7119 (2.0606)
Vacc_rate		-3.37×10^{-7} (2.23×10^{-7})		1.75×10^{-6} (1.09×10^{-6})	1.27×10^{-6} (2.38×10^{-6})	-1.01×10^{-4} (1.60×10^{-4})	-0.0051*** (1.30×10^{-7})	-0.0039* (2.30×10^{-6})
Vacc_rate^2					-5.80×10^{-12} (1.49×10^{-11})	2.70×10^{-10} (4.02×10^{-10})	2.06×10^{-5} *** (5.44×10^{-6})	1.28×10^{-5} (1.30×10^{-5})
SPILLINDEX(-1)	0.9884*** (0.0034)	0.9882*** (0.0034)	0.7350*** (0.0233)	0.9865*** (0.0077)	0.9861*** (0.0083)	0.9801*** (0.0080)	0.9683*** (0.0057)	0.9570*** (0.0113)
R-squared	0.9908	0.9908	0.7710	0.9935	0.9936	0.9879	0.9927	0.9925
Adjusted R-squared	0.9908	0.9908	0.7683	0.9934	0.9936	0.9877	0.9926	0.9924
Durbin-Watson stat	1.8656	1.8651	1.1983	2.0684	2.0992	1.9586	2.0598	2.1171

Note: The computed coefficients are shown in the first line, and the standard errors are given in parenthesis. In the regression model, autocorrelation is addressed by adding the lagged dependent variable. The null hypothesis is rejected when the symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Global case rates also had a significant positive impact on spillover effects in both the overall and pandemic periods. The coefficients for vaccination progress and their squared terms are significant in both the full sample period (Model 2) and the late pandemic period (Model 6), indicating that higher vaccination rates significantly influence spillover effects and suggest a nonlinear relationship. The results from the country-level spillover index underscore the notable impact of vaccination progress, a trend not observed globally. Specifically, the findings highlight COVID-19 vaccination's crucial role in explaining variations in financial stability across different countries. Countries with higher vaccination rates tend to experience lower

spillovers from global markets, emphasizing the importance of vaccination speed. However, this impact is most pronounced in the early stages and diminishes over time.

Next, we consider the role of global economic policy uncertainty that affect the level of spillover, Antonakakis et al. (2013) found that, in some economies, spillovers between markets actually increase when economic policy uncertainty rises, which contrasts with our findings that higher EPU reduces spillovers. However, Baker et al. (2016) suggest that increasing economic policy uncertainty correlates with greater market volatility and caution among investors, typically leading to reduced spillovers. Several other studies (e.g., Arouri et al., 2016; Liang et al., 2020; Škrinjaric & Orlovic, 2020) support these conclusions.

Determinants of the Spillover Index in China

This section focuses on the Chinese stock market, utilizing the spillover index established in earlier sections. We specifically use the spillover index for China in time series regression estimation. The results from Table 9 analyzes the determinants of spillovers in the Chinese stock market over time. Our primary finding is that, while economic policy uncertainty (EPU) generally reduces spillovers, the volatility index (VIX) significantly boosts them in most periods. Notably, changes in oil prices have a significant impact on spillovers during pandemic, and an increase in case rates enhances spillovers during these times.

We observe that the EPU has a negative correlation with the spillover effect on the Chinese market during the pandemic period, while the VIX shows a significant positive correlation. The coefficient for VIX is significantly positive in most models, especially during the pandemic, indicating that higher volatility significantly increases spillover effects on the Chinese market. However, in the later stages of the pandemic (Model 6 in Table 9), the effect of VIX on spillovers is no longer significant. The negative coefficients for EPU across the full sample period (Models 1 and 2 in Table 9) suggest that increased economic policy uncertainty reduces spillovers, although this effect is not significant during the pandemic (Models 4 and 5 in Table 9). This aligns with findings presented in Tables 7 and 8.

The coefficient for changes in oil prices is significantly negative in most models, particularly during the pandemic, indicating that a decrease in oil prices substantially reduces spillovers. In both the pre-pandemic (Model 3 in Table 9) and post-pandemic (Model 6 in Table 9) periods, the effect of oil prices on spillover effects is not significant.

Table 8 Panel Regression (Spillover 'Received From' Other Indices) in the International Stock Markets:
Determinant Factors of Spillover

Variable	Model 1: Full Sample 1	Model 2: Full Sample 2	Model 3: Pre-Pandem ic	Model 4: Pandemic Period 1	Model 5: Pandemic Period 2	Model 6: Post- Pandemic	Model 7: Full Sample 3	Model 8: Pandemic Period 3
Sample Period	1/01/2018– 02/29/2024	1/01/2018– 02/29/2024	01/01/2018– 01/29/2020	01/30/2020– 02/28/2022	01/30/20200 2/28/2022	03/01/2022– 02/29/2024	1/01/2018– 02/29/2024	01/30/2020– 02/28/2022
C	0.2965 (0.2342)	0.1838 (0.0866)	1.4970*** (0.3020)	-0.0659 (0.1972)	0.0393 (0.2246)	1.4968*** (0.5307)	0.2119 (0.0950)	0.5509 (0.1691)
LOG(VIX)	0.3007*** (0.0531)	0.2527*** (0.0292)	0.3038*** (0.0712)	0.4503*** (0.0695)	0.4321*** (0.0719)	0.1327*** (0.0288)	0.2955*** (0.0246)	0.4330*** (0.0491)
LOG(EPU)	-0.0830** (0.0287)	-0.0803*** (0.0155)	-0.0950*** (0.0328)	-0.1457*** (0.0397)	-0.1484*** (0.0398)	0.0183 (0.0134)	-0.0504*** (0.0136)	-0.1289*** (0.0261)

Variable	Model 1: Full Sample 1	Model 2: Full Sample 2	Model 3: Pre-Pandemic	Model 4: Pandemic Period 1	Model 5: Pandemic Period 2	Model 6: Post- Pandemic	Model 7: Full Sample 3	Model 8: Pandemic Period 3
OIL	-0.0007 (0.0008)	-1.6567*** (0.2049)	-0.7009 (0.7139)	-1.8613*** (0.3141)	-1.8796*** (0.3146)	-0.2419 (0.2537)	-3.1288*** (0.2050)	-4.3301*** (0.3044)
Ccse_rate		0.4776*** (0.1463)		0.7786*** (0.2492)	0.7605*** (0.2499)	-0.0593 (0.5984)		
Death_rate		-0.0008 (0.0023)		-0.0009 (0.0031)	-0.0009 (0.0031)	-167.8374 (141.0652)		
CFR							-5.18×10^{-5} (0.0002)	-1.36×10^{-5} (0.0002)
Vacc_rate		-1.04×10^{-6} *** (3.46×10^{-7})		-1.80×10^{-7} (2.83×10^{-7})	-1.16×10^{-6} (1.04×10^{-6})	-1.08×10^{-12} 12*** (4.02×10^{-6})	-1.76×10^{-6} 6*** (3.01×10^{-7})	-2.60×10^{-6} *** (6.60×10^{-7})
Vacc_rate^2		3.72×10^{-12} *** (1.38×10^{-12})			5.29×10^{-12} (5.41×10^{-12})	1.91×10^{-11} ** (8.04×10^{-12})	6.27×10^{-12} (1.11×10^{-12})	7.88×10^{-12} ** (3.37×10^{-12})
SPILLINDEX(-1)	0.9884*** (0.0034)	0.9917*** (0.0009)	0.9708*** (0.0031)	0.9905*** (0.0017)	0.9901*** (0.0018)	0.9917*** (0.0014)	0.9874*** (0.0012)	0.9824*** (0.0022)
R-squared	0.9908	0.9936	0.9910	0.9927	0.9927	0.9975	0.9957	0.9938
Adjusted R-squared	0.9908	0.9936	0.9909	0.9927	0.9927	0.9975	0.9957	0.9938
Durbin-Watson stat	1.8656	1.8396	1.2295	2.0305	2.0305	2.0122	2.0640	2.0987

Note: The computed coefficients are shown in the first line, and the standard errors are given in parenthesis. In the regression model, autocorrelation is addressed by adding the lagged dependent variable. The null hypothesis is rejected when the symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Additionally, case and death rates in China play important roles as determinants. During the pandemic (Models 4 and 5 in Table 9), we find that the spillover impact increases with the case rate. The negative coefficient for vaccination rates is significant throughout the sample period (Model 2 in Table 9), suggesting that higher vaccination rates reduce spillovers, although this effect is not observed in other models. The effect of mortality on spillovers is insignificant across all models, likely due to the very low mortality rate resulting from the Chinese government's effective pandemic control. This situation may reflect differing market responses to the outbreak's severity and government interventions.

The findings of this study closely align with our expectations, particularly highlighting the VIX index as a significant influence. Notably, the analysis indicates that the impact of oil prices on other markets diminishes after vaccination efforts are implemented. This contrasts with Sharif's analysis, which found that oil prices had a substantial effect on the US market during the COVID-19 pandemic, as determined by Granger causality tests. Furthermore, Sharif et al. (2020) noted that the pandemic directly affected employment, job security, corporate operations, and key services. In response to COVID-19, investors generally adopted a pessimistic outlook, leading to strategic adjustments to cope with the challenges

presented by the pandemic. The research conducted by Mazur (2021) and Zhang et al. (2021) supports the conclusion that COVID-19 had a significant negative impact on the stock and energy markets.

The analysis of spillovers in the Chinese stock market during various periods, particularly throughout the COVID-19 pandemic, reveals important insights into the dynamic interactions among various financial risk factors. The findings suggest that the volatility index (VIX) significantly increases spillovers during the pandemic, aligning with the results of Diebold and Yilmaz (2009, 2012). Additionally, economic policy uncertainty (EPU) generally reduces spillovers, corroborating earlier studies by Antonakakis et al. (2013) and Baker et al. (2016). Importantly, the oil price index also had a significant impact on spillovers during the pandemic, consistent with the observations made by Filis et al. (2011).

Overall, case rates and vaccination rates in China had a weaker effect on stock market spillovers compared to international cases, being significant only in certain instances. The study indicates that the case rate in China significantly increased the spillover effect during the pandemic period, suggesting a direct link between the pandemic's severity and market volatility. Conversely, vaccination rates significantly reduced spillover effects throughout the sample period; however, this effect was not significant in other models, possibly reflecting different phases in the market's response to vaccination efforts. Additionally, mortality rates did not significantly affect spillovers, likely due to the Chinese government's effective control measures, which resulted in lower mortality rates and mitigated their impact on the market. These findings underscore the effectiveness of vaccination and pandemic containment strategies in China.

Table 9 China's Spillover Determinant Factors: Time Regression Analysis for the Overall Dynamic Spillover Index (EPU_US)

Variable	Model 1: Full Sample 1	Model 2: Full Sample 2	Model 3: Pre- Pandemic	Model 4: Pandemic Period 1	Model 5: Pandemic Period 2	Model 6: Post- Pandemic	Model 7: Full Sample 3	Model 8: Pandemic Period 3
Sample Period	10/15/201– 2/29/2024	10/15/2018– 2/29/2024	10/15/2018– 1/29/2020	1/30/2020– 2/28/2022	1/30/2020– 2/28/2022	3/01/2022– 2/29/2024	1/01/2018– 02/29/2024	01/30/2020– 02/28/2022
C	0.0275 (0.2457)	0.4069 (0.3258)	1.0392 (0.6495)	-0.3639 (0.6455)	-0.4930 (0.6756)	46.9464 (74.5233)	0.4479 (0.4177)	-0.1269 (0.6464)
LOG(VIX)	0.2086*** (0.0761)	0.2948*** (0.0862)	0.3178* (0.1702)	0.4949** (0.1954)	0.5465** (0.2110)	-0.0017 (0.1816)	0.2500*** (0.0965)	0.5877*** (0.2099)
LOG (EPU_US)	-0.0762* (0.0415)	-0.1032** (0.0428)	-0.0511 (0.0649)	-0.0919 (0.1121)	-0.0768 (0.1146)	-0.0856 (0.0559)	-0.0833 (0.0573)	-0.0866 (0.1154)
DLOG(OIL)	-1.9935*** (0.7169)	-1.9343*** (0.7167)	0.3059 (1.3271)	-3.6034*** (1.2476)	-3.4998*** (1.2584)	0.7067 (1.0582)	-2.3891*** (0.8351)	-3.3994*** (1.2598)
Ccse rate chi		-3.72×10 ⁻⁷ (4.16×10 ⁻⁶)		0.0083* (0.0049)	0.0089* (0.0050)	-3.48×10 ⁻⁶ (3.91×10 ⁻⁶)		
Death_rat e_chi		0.0026 (0.0039)		-0.1102 (0.1027)	-0.1317 (0.1079)	0.0034 (0.0034)		

Variable	Model 1: Full Sample 1	Model 2: Full Sample 2	Model 3: Pre- Pandemic	Model 4: Pandemic Period 1	Model 5: Pandemic Period 2	Model 6: Post- Pandemic	Model 7: Full Sample 3	Model 8: Pandemic Period 3
Sample Period	10/15/201– 2/29/2024	10/15/2018– 2/29/2024	10/15/2018– 1/29/2020	1/30/2020– 2/28/2022	1/30/2020– 2/28/2022	3/01/2022– 2/29/2024	1/01/2018– 02/29/2024	01/30/2020– 02/28/2022
CFR_chi							-0.1261 (3.6478)	-4.2937 (7.4856)
Vacc_rate _chi		-1.02×10 ^{-7***} (3.75×10 ⁻⁸)		-1.61×10 ⁻⁷ (9.97×10 ⁻⁸)	2.42×10 ⁻⁸ (3.01×10 ⁻⁷)	-3.75×10 ⁻⁵ (6.31×10 ⁻⁵)	-2.20×10 ⁻⁶ (1.90×10 ⁻⁶)	-3.65×10 ⁻⁷ (2.82×10 ⁻⁶)
Vacc_rate _chi^2					-9.84×10 ⁻¹⁴ (1.51×10 ⁻¹³)	7.73×10 ⁻¹² (1.34×10 ⁻¹¹)	7.18×10 ⁻¹² (9.04×10 ⁻¹²)	-6.50×10 ⁻¹² (1.47×10 ⁻¹¹)
FROM_CHI (-1)	0.9328*** (0.0266)	0.9275*** (0.0266)	0.9750*** (0.0552)	0.9003*** (0.0428)	0.8987*** (0.0428)	0.9353*** (0.0440)	0.9228*** (0.0303)	0.9042*** (0.0428)
FROM_CHI (-2)	-0.0114 (0.0362)	-0.0123 (0.0361)	0.0334 (0.0721)	-0.0199 (0.0577)	-0.0196 (0.0578)	-0.0484 (0.0603)	-0.0201 (0.0413)	-0.0179 (0.0579)
FROM_CHI (-3)	0.0729*** (0.0264)	0.0706*** (0.0264)	-0.0377 (0.0491)	0.1027** (0.0433)	0.1022** (0.0433)	0.0879* (0.0442)	0.0827*** (0.0305)	0.0935** (0.0431)
R-squared	0.9875	0.9875	0.9683	0.9835	0.9836	0.9538	0.9823	0.9835
Adjusted R-squared	0.9874	0.9875	0.9677	0.9833	0.9833	0.9529	0.9821	0.9832
Durbin- Watson stat	2.0150	2.0147	1.9708	2.0413	2.0392	1.9924	2.0177	2.0354

Note: The computed coefficients are shown in the first line, and the standard errors are given in parenthesis. In the regression model, autocorrelation is addressed by adding the lagged dependent variable. The null hypothesis is rejected when the symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Conclusion and implications

Discussion on empirical results

This research examines spillovers and dynamic connectedness between the China's stock market and other global markets, building on the theoretical framework established by Diebold and Yilmaz (2009, 2012). The findings indicate a substantial increase in spillover effects from other markets to each country due to the COVID-19 outbreak. In advanced economies such as France, the United Kingdom, and Germany, the integration of stock markets intensified, reflecting their roles as central nodes in the global financial network. These countries have major stock exchanges and multinational corporations, making them particularly sensitive to shifts in global investor sentiment and capital flows.

Next, we address the variables associated with general financial risk factors and the level of dynamic correlation in the Chinese stock market, utilizing a time series index derived from rolling estimates of overall connectivity. The results highlight several important insights into the dynamics of spillovers in financial markets, particularly in the context of the COVID-19 pandemic. The prominence of the Volatility Index (VIX) as a critical indicator of spillovers highlights the pivotal role of global risk perception in driving market dynamics. The VIX, often referred to as the "fear gauge," captures investor sentiment and expectations of future volatility. Its persistent influence across the pre-pandemic, pandemic, and post-pandemic phases reflects the interconnected nature of global financial markets and the spillover effects of external shocks. The findings suggest that the Chinese stock market, despite being partially insulated due to domestic policies and market structure, remains susceptible to global financial turbulence. The correlation dynamics during the pandemic also reveal heightened connectivity and synchronization with global markets, signaling a shift in China's financial integration over time. This is particularly relevant as China's economy and stock markets continue to play an increasingly prominent role in the global economy.

Next, the regression results sheds light on the role of COVID-related variables—case rates and vaccination rates—in influencing financial market stability. The findings reveal contrasting dynamics in China compared to other countries, primarily driven by the country's robust pandemic control measures. While rising case rates generally exacerbate financial instability due to heightened uncertainty and reduced economic activity, the evidence from China suggests a weaker relationship between case rates and market disruptions. This can be attributed to China's swift and stringent public health measures, such as widespread testing, strict lockdowns, and centralized pandemic management, which minimized the economic and financial fallout. The findings indicate that the degree of financial disruption caused by the pandemic is not only dependent on the severity of case rates but also significantly influenced by the effectiveness of government actions in controlling the outbreak.

Moreover, vaccination progress appears to be a critical determinant of financial stability. Rapid vaccination campaigns not only limit the spread of the virus but also bolster investor confidence by reducing uncertainty about the future economic outlook. The findings suggest that higher vaccination progress is associated with lower spillover effects across markets, as effective vaccination efforts enhance public health, economic resilience, and financial market recovery.

Compared to other countries, China exhibits a unique pattern of spillover effects, with COVID-19 having a comparatively slight impact on financial market spillovers. Although clear impacts are observed, they are significant only in specific cases. This distinctive pattern may reflect China's robust outbreak response and economic policies, which effectively shielded its financial markets from global shocks. The nuanced responses seen in China suggest that market dynamics were influenced by a combination of stringent public health measures and timely economic interventions.

In summary, the results underscore the importance of considering both global and country-specific factors when assessing financial market vulnerabilities and formulating policy responses. In the face of the global crisis, policymakers should draw on lessons learned from the varied impacts observed in different regions to develop strategies for mitigating spillover risks and enhancing economic resilience.

Policy Implication

In this section, several implications are derived from empirical results.

- i) In emerging markets such as China, the stock markets are often more vulnerable to external shocks. Spillovers from advanced economies can destabilize emerging markets, leading to capital flight, currency volatility, and economic hardship. These findings emphasize the need for China to strengthen their economic fundamentals and develop buffers to withstand global financial turbulence.
- ii) The persistent influence of the VIX underscores the need for policymakers and regulators to monitor global market volatility. By keeping a close watch on VIX and similar indicators, decision-makers can proactively identify periods of heightened risk and take preemptive measures to stabilize markets. Moreover, given the predictive power of the VIX for spillover dynamics, it can serve as a key input for stress-testing frameworks and early warning systems. Policymakers and institutions could integrate VIX-based scenarios into their crisis management planning to better prepare for systemic risks.
- iii) The weaker impact of case rates on China's financial markets highlights the importance of effective pandemic control measures in mitigating financial disruptions. Governments should prioritize swift, coordinated, and robust public health responses during crises to limit economic and market instability. For countries with less effective pandemic management, case rates may serve as an early warning indicator of potential financial disruptions. Furthermore, vaccination rates have a direct bearing on financial stability, underscoring the critical role of public health policies in restoring investor confidence and reducing spillover effects. Governments worldwide should prioritize the speed and coverage of vaccination campaigns, particularly during the early stages of a pandemic, to stabilize markets and facilitate economic recovery.

Reference

- Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., Davis, S. J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N., Renault, T., Smietanka, P., & Thwaites, G. (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics*, 191, 104274. <https://doi.org/10.1016/j.jpubeco.2020.104274>
- Antonakakis, N., Chatziantoniou, I., & Filis, G. (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. *Economics Letters*, 120(1), 87–92. <https://doi.org/10.1016/j.econlet.2013.04.004>
- Ashraf, B. N. (2020). Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. *Journal of Behavioral and Experimental Finance*, 27, 100371. <https://doi.org/10.1016/j.jbef.2020.100371>
- Arouri, M., Estay, C., Rault, C., & Roubaud, D. (2016). Economic policy uncertainty and stock markets: Long-run evidence from the US. *Finance Research Letters*, 18, 136–141. <https://doi.org/10.1016/j.frl.2016.04.011>
- Bekaert, G., & Harvey, C. R. (1995). Time-varying world market integration. *Journal of Finance*, 50(2), 403–444. <https://doi.org/10.1111/j.1540-6261.1995.tb04790.x>
- Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593–1636. <https://doi.org/10.1093/qje/qjw024>
- Baker, S., Nicholas, B., Steven, D., & Stephen, T. (2020). *COVID-induced economic uncertainty and its consequences*. CEPR. <https://cepr.org/voxeu/columns/covid-induced-economic-uncertainty-and-its-consequences>
- Bissoondoyal-Bheenick, E., Do, H., Hu, X., & Zhong, A. (2021). Learning from SARS: Return and volatility connectedness in COVID-19. *Finance Research Letters*, 41, 101796. <https://doi.org/10.1016/j.frl.2020.101796>
- Bollerslev, T., Tauchen, G., & Zhou, H. (2009). Expected stock returns and variance risk premia. *The Review of Financial Studies*, 22(11), 4463–4492. <https://doi.org/10.1093/rfs/hhp008>
- CEIC. (n.d.). <https://www.ceicdata.com>
- Chen, F. G. (2020). The heterogeneous Impact of COVID-19 on Chinese enterprises—Empirical research based on the perspective of stock price fluctuations. *Journal of Industrial Technological Economics*, 39(10), 3–14. <http://doi.org/10.3969/j.issn.1004-910X.2020.10.001>
- Chicago Board Options Exchange. (n.d.). <https://www.cboe.com>
- Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534), 158–171. <https://doi.org/10.1111/j.1468-0297.2008.02208.x>
- Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66. <https://doi.org/10.1016/j.ijforecast.2011.02.006>

- Fang, Y., Yu, B., & Wang, W. (2020). China's financial market risk measurement and controlling under COVID-19 shock. *Journal of Central University of Finance & Economics*, 8, 116–128.
https://xbbjb.cufe.edu.cn/EN/volumn/volumn_1530.shtml
- Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis*, 20(3), 152–164. <https://doi.org/10.1016/j.irfa.2011.02.014>
- Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance*, 57(5), 2223–2261. <https://doi.org/10.1111/0022-1082.00494>
- Gunay, S., & Can, G. (2022). The source of financial contagion and spillovers: An evaluation of the covid-19 pandemic and the global financial crisis. *PLOS ONE*, 17(1), e0261835.
<https://doi.org/10.1371/journal.pone.0261835>
- Hamilton, J. D. (1983). Oil and the Macroeconomy since World War II. *Journal of Political Economy*, 91(2), 228–248. <https://doi.org/10.1086/261140>
- Hamilton, J. D. (2009). Causes and consequences of the oil shock of 2007-2008. *National Bureau of Economic Research Working Paper No. 15002*. <https://doi.org/10.3386/w15002>
- Harjoto, M. A., Rossi, F., Lee, R., & Sergi, B. S. (2021). How do equity markets react to COVID-19? Evidence from emerging and developed countries. *Journal of Economics and Business*, 115, 105966.
<https://doi.org/10.1016/j.jeconbus.2020.105966>
- He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID-19's impact on stock prices across different sectors—An event study based on the Chinese stock market. *Emerging Markets Finance and Trade*, 56(10), 2198–2212. <https://doi.org/10.1080/1540496X.2020.1785865>
- Investing.com. (n.d.). <https://www.investing.com>
- Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3), 1053–1069. <https://doi.org/10.1257/aer.99.3.1053>
- Liang, C. C., Troy, C., & Rouyer, E. (2020). U.S. uncertainty and Asian stock prices: Evidence from the asymmetric NARDL model. *The North American Journal of Economics and Finance*, 51, 101046.
<https://doi.org/10.1016/j.najef.2019.101046>
- Liu, Z., Huynh, T. L. D., & Dai, P.-F. (2021). The impact of Covid-19 on stock market crash risk in Chian. *Research in International Business and Finance*, 57, 101419.
<https://doi.org/10.1016/j.frl.2020.101838>
- Manopimoke, P., Prukumpai, S., & Sethapramote, Y. (2018). Dynamic connectedness in emerging Asian equity markets. In William, B., & Sergi, S. (Eds). *Banking and finance issues in emerging markets* (pp. 51–84). Emerald Publishing Limited. <http://doi.org/10.1108/S1571-038620180000025004>
- Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the march 2020 stock market crash: Evidence from S&P1500. *Finance Research Letters*, 38, 101690. <http://doi.org/10.1016/j.frl.2020.101690>
- Pástor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3), 520–545. <https://doi.org/10.1016/j.jfineco.2013.08.007>

- Prukumpai, S., Dacuycuy, L. B., & Sethapramote, Y. (2023). Dynamic connectedness in the ASEAN's equity markets during the COVID-19 Pandemic. *DLSU Business & Economics Review* 32(2). 1–22.
<https://doi.org/10.59588/2243-786X.1153>
- Scherf, M., Matschke, X., & Rieger, M. O. (2022). Stock market reactions to COVID-19 lockdown: A global analysis. *Finance Research Letters*, 45, 102245. <https://doi.org/10.1016/j.frl.2021.102245>
- Sen, A., & Wesselbaum, D. (2023). On the International Spillover Effects of Uncertainty. *Open Economies Review*, 34(3), 541–554. <https://doi.org/10.1007/s11079-022-09694-2>
- Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, 70, 101496. <https://doi.org/10.1016/j.irfa.2020.101496>
- Škrinjarić, T., & Orlović, Z. (2020). Economic policy uncertainty and stock market spillovers: Case of Selected CEE Markets. *Mathematics*, 8(7), Article 7. <https://doi.org/10.3390/math8071077>
- Ullah, S. (2023). Impact of COVID-19 pandemic on financial markets: A global perspective. *Journal of the Knowledge Economy*, 14(2), 982–1003. <https://doi.org/10.1007/s13132-022-00970-7>
- Whaley, R. (2009). Understanding the VIX. *Journal of Portfolio Management*, 35(3), 98–105.
<https://doi.org/10.3905/JPM.2009.35.3.098>
- Youssef, M., Mokni, K., & Ajmi, A. N. (2021). Dynamic connectedness between stock markets in the presence of the COVID-19 pandemic: Does economic policy uncertainty matter?. *Financial Innovation*, 7(1), 13. <https://doi.org/10.1186/s40854-021-00227-3>
- Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 36, 101528. <https://doi.org/10.1016/j.frl.2020.101528>
- Zhang, H., Chen, J., & Shao, L. (2021). Dynamic spillovers between energy and stock markets and their implications in the context of COVID-19. *International Review of Financial Analysis*, 77, 101828. <https://doi.org/10.1016/j.irfa.2021.101828>
- Zhao, M., & Park, H. (2024). Bidirectional risk spillovers between Chinese and Asian stock markets: A dynamic copula-EVT-CoVaR approach. *Journal of Risk and Financial Management*, 17(3), Article 3. <https://doi.org/10.3390/jrfm17030110>
- Zhou, B., Yin, Q., Wang, S., & Li, T. (2022). Research on the dynamic spillover of stock markets under COVID-19—Taking the stock markets of China, Japan, and South Korea as an example. *Frontiers in Public Health*, 10. <https://doi.org/10.3389/fpubh.2022.1008348>