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A Pandemic's grip: Volatility spillovers in Asia-Pacific equity markets during the onset of Covid-19

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ABSTRACT

The emergence of Covid-19 in late 2019 rapidly shattered the Asia-Pacific region (APR), a bastion of economic dynamism, and it became the epicenter of the global health crisis. This unprecedented pandemic not only triggered a public health catastrophe but also unleashed a financial storm, exposing vulnerability within the region's interconnected economies. This study identifies the factors driving volatility spillovers within Asian-Pacific financial markets during the initial wave of the Covid-19 pandemic (January 2020–February 2021). We analyze the interplay of pandemic transmission dynamics, government interventions, central bank policies, and socioeconomic variables. Our findings reveal a robust and persistent association between the rising number of Covid-19 cases per million and volatility spillovers. We introduce three novel determinants—the number of intensive care unit beds, population density, and the proportion of the elderly population—which significantly impact volatility transmission in response to new cases. Stringent government measures, such as travel bans and lockdowns, mitigate volatility spillovers. Conversely, central bank policies increase volatility spillovers. These insights contribute to a deeper understanding of financial market dynamics in the context of global health emergencies. This knowledge equips policy makers in the APR with valuable tools for navigating future crises.

1. Introduction

Covid-19, a highly contagious disease, emerged in China on December 31, 2019. By July 20, 2020, the disease had impacted more than 14 million people and resulted in the death of over 600,000 individuals across 216 countries or territories (WHO, 2020a; 2020b). The Asia-Pacific region (APR), as the origin of Covid-19 and a hotspot for the first reported cases outside China, rapidly became the epicenter of a global health crisis. In the wake of this health emergency, the World Health Organization (WHO) escalated its response by declaring Covid-19 a global pandemic on March 11, 2020. This declaration was a call to action, leading countries around the world to implement diverse measures aimed at mitigating the virus's spread, which, in turn, precipitated widespread social and economic challenges (Akhtaruzzaman, Abdel-Qader, Hammami, & Shams, 2021; Gunay and Gokberk, 2022).

The financial markets reacted to Covid-19 with negative returns (Ashraf, 2020), highlighting the intertwined nature of global economies. In this context, the APR's role becomes even more pronounced. The region, which includes countries in East Asia, South Asia, Southeast Asia, and Oceania, has substantial strategic and economic significance globally. Over the past five decades, the region has outperformed expectations in various aspects, such as economic growth, structural transformation, poverty reduction, and improvements in health and education (Nakao, 2020). In addition to these strides, the strong economic interconnectedness among its countries, facilitated by various trading blocs, such as The Association of Southeast Asian Nations (ASEAN), South Asian Association for Regional Cooperation (SAARC), and Shanghai Cooperation Organisation (SCO), has made the region a key engine of the global economy.

However, this economic integration has its drawbacks. It leads to integration in financial structures, which consequently has volatility spillover effects. In other words, changes in volatility in one country's financial market can be affected by volatility in other markets (Ezzati,

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2013). This result of financial globalization or interdependence is regarded as one of the primary causes of the 2007–2009 global financial crisis (Mendoza and Vincenzo, 2010). Despite the abundant literature on volatility transmission between countries, the volatility spillover effects within the APR, especially during a major pandemic, remain understudied.

Given the significance of the Asia-Pacific markets and their global relevance, many studies have examined the volatility spillover effects within the region. Notable works by Ahmed and Huo (2019), Budd (2018), Dewandaru, Masih, and Masih (2016), Da Fonseca and Gottschalk (2018), and (Mitra and Vishwanathan, 2017) have explored the concept of volatility spillover effects across selected countries of the APR. Although these studies contribute substantially to the literature, their scope is limited to four countries. However, the study by (Mitra and Vishwanathan, 2017) stands out for its broader coverage, encompassing 11 countries. In our analysis, we expand the scope to 18 countries in the region, an area largely unexplored in the existing literature.

Another crucial aspect of spillover effect studies is understanding the triggers, that is, what causes the stock markets of different countries to move synchronously. To the best of our knowledge, this aspect, particularly in the context of Asian-Pacific markets, has been largely underinvestigated. Our research fills this knowledge gap.

This study delves into the intricate web of volatility transmission across 18 Asian-Pacific stock markets during the first year of Covid-19. Our research encompasses a broader range of countries than prior studies, providing a more comprehensive picture of regional market dynamics. The primary objective of our study is to investigate the determinants of the interconnections and spillover effects across the stock markets in the APR during the first wave of Covid-19 (January 2020 to February 2021) by leveraging the volatility spillover frameworks developed by (Diebold and Kamil, 2012); cited as DY12) and Barunik and Krehlik (2018; cited as BK18). Unlike previous studies, which primarily employ wavelet analysis in a bivariate context, our analysis uses a multivariate setting. The DY12 model has been extensively applied in recent studies, such as those by Ahmad, Mishra, and Daly (2018), Antonakakis, Cunado, Filis, Gabauer, and Gracia (2018), (Awartani and Aktham, 2013), Chow (2017), Kang, Maitra, Dash, and Brooks (2019), Lee and Lee (2019),(Prasad et al., 2014), Singh and Singh (2016), and Zhou, Zhang, and Zhang (2012). Furthermore, following the introduction of the BK18 model, numerous studies, including Ferrer, Shahzad, López, and Jareño (2018) and Hoon, Kumar, Tiberiu, and Yoon (2019), have used it to measure financial interconnectedness. Some studies, such as those by Kumar, Cunado, Gupta, and Wohar (2018), Trabelsi (2019), and Wohar, Samia, Kumar, and Cu (2020), have even applied both methodologies to achieve deeper understanding.

Our research focuses on the effects of specific yet underexamined variables—namely, the nature of Covid-19-related news on stock market dynamics. We specifically examine how "positive news"—for example, statistics showing higher recovery or reductions in the number of new cases—and "negative news"—such as increases in the number of cases—impact volatility spillovers in selected equity markets. Prior studies have begun to shed light on the influence of Covid-19 news on financial markets. For instance, Long and Zhao (2022) assess the impact of Covid-19 news on risk spillovers in various sectors of the Chinese stock market. Shahzad, Naeem, Peng, and Bouri (2021) analyze asymmetric volatility spillovers in sectors of the Chinese stock market during the pandemic. Cepoi (2020) explores the link between Covid-19 news (including misinformation, media coverage, and the spread of the virus) and stock market performance in the six most affected countries. Lastly, Bakry, Kavalmthara, Saverimuttu, Liu, and Cyril (2022) delve into the response of stock market volatility to Covid-19 announcements and government measures in developed and emerging markets. Our study extends this research by offering a nuanced analysis of the differential impacts of "positive" and "negative" Covid-19 news on market volatility across selected equity markets.

Aside from the impact of good and bad news on stock market volatility, the policies by countries in response to Covid-19, a health crisis at its core, might also play a crucial role in mitigating its repercussions. Specific aspects of the health sector, such as the availability of beds in hospital intensive care units and demographic factors, such as the proportion of individuals over age 65, who proved to be more susceptible to the disease (Aronson, 2020)—may define the pandemic's transmission. Moreover, the virus is more likely to proliferate in densely populated countries because of its highly contagious nature. Government measures to combat the pandemic influence not only the country's ability to contain the virus but also its overall economic conditions. Implementing stringent policies, such as strict lockdowns, halting business activities, restricting mobility, and adopting fiscal and monetary measures, may have aided in curbing the virus's spread but also led to significant economic setbacks. As a result, we incorporate data from the Stringency Index, which measures the various actions taken by governments over time to control the Covid-19 outbreak. These potential determinants of volatility spillover, though unexplored in existing literature, have significant relevance in the Covid-19 era.

In undertaking this research, we enhance the existing body of knowledge on volatility spillover effects in several significant ways. First, this work broadens the scope of investigation to encompass volatility transmissions in 18 APR countries. Second, by exploring the various determinants of these volatility transmissions across the entire region, our study is pioneering. Third, this research examines a diverse set of determinants responsible for volatility transmission, such as the impact of both good and bad news, health-care infrastructure (availability of ICU beds), demographic factors (the proportion of the elderly population), and stringent government policies. Last, to our knowledge, prior research has not investigated the volatility spillover effects across the entire APR during a highly infectious pandemic. Conducting a study on this pandemic is both timely and highly relevant because this is the first time in history that a significant health crisis has triggered a financial emergency.

Our findings shed light on the complex interplay between Covid-19, news sentiment, health-care capacity, demographics, and government policies and how these factors influence volatility spillovers across the APR. Our findings indicate that the number of new cases per million contributes significantly to volatility transmission. Furthermore, we find evidence of the influence of other determining factors on transmission, such as health-care facilities (i.e., the number of ICU beds), population density, and the proportion of individuals over age 65. Because of their high relevance, these variables notably affect the impact of new cases on volatility transmission, especially during a pandemic.

The remainder of this study is organized as follows: Section 2 presents a literature review, Section 3 describes the dataset and methodology used, Section 4 presents our findings, and Section 5 offers our conclusions.

2. Literature review

Financial globalization—characterized by the integration of global financial markets—has long been viewed as a catalyst for promoting greater financial stability. However, in light of the global financial crisis, the validity of this view has been called into question, particularly when a financial crisis in one region precipitates a global financial emergency (Stiglitz, 2010). Various studies focus on the integration of global financial markets. For example, Diamandis (2009) investigates the stock markets in four Latin American countries (Argentina, Brazil, Chile, and Mexico) in conjunction with the US stock market and conclude that they are partially integrated. In a separate study, Click and Plummer (2005) evaluate the level of integration of the ASEAN countries' stock markets after the Asian financial crisis, revealing a high degree of integration among these markets. Narayan and Smyth (2004) examine the Australian equity market's integration with those in the G7 economies. They find evidence of pairwise integration between the Australian equity market and those of Canada and the UK. Furthermore, some evidence is found of integration between Australian stock price indexes and those of Canada, Japan, and Italy.

Narayan, Smyth, and Nandha (2004) explore the dynamic linkage among the stock markets in Bangladesh, India, Pakistan, and Sri Lanka. One of their significant findings is the existence of a long-term relationship among stock prices in these four countries. Looking at stock markets in 120 countries, Narayan, Mishra, and Narayan (2011) perform the first comprehensive study on stock market convergence. Their research confirms the existence of market convergence beyond economic growth and productivity parameters, as shown in the macroeconomic literature.

Global financial markets are increasingly intertwined, leading to volatility spillover effects from one market to another. Several studies use the DY12 framework to measure these spillover effects between specific countries. Zhou et al. (2012) conduct a pioneering exploration of volatility spillovers between the Chinese and global equity markets from 1996 to 2009, covering 11 world markets, the Chinese, Greater Chinese, and Asian markets, as well as major individual markets, such as those in the US, the UK, Japan, India, Hong Kong, and Taiwan. They conclude that, until 2005, China appeared unaffected by volatility spillovers from other markets, but after 2005, China became a significant transmitter of volatility to other markets. (Awartani and Aktham, 2013) highlight that oil markets significantly influence equity markets in the Gulf countries from 2004 to 2012. They note that these impacts are particularly pronounced after the global financial crisis, with intensification in oil market volatility contributions after crisis. Further, Singh and Singh (2016) examine the pairwise volatility spillover effects among the US-BRIC (Brazil, Russia, India, and China) equity markets. They find evidence of bidirectional volatility spillover effects, highlighting the influence of overall US financial market conditions on these spillovers. Chow (2017) investigates the partial opening of China's financial markets to foreign participation and its effect on volatility transmissions to Asian markets between 1999 and 2016, finding that volatility transmissions rise noticeably during this period, and these increases are not merely temporary side effects of the global financial crisis but, rather, persist well beyond it.

Li (2021) employs various techniques, such as the Diebold-Yilmaz spillover index, network analysis, and asymmetric spillover index, to estimate time-varying volatility and asymmetry in these spillovers across the stock markets in the US, Japan, Germany, the UK, France, Italy, Canada, China, India, and Brazil. The study confirms the existence of volatility spillovers across global markets and shows that these spillovers are highly asymmetric and crisis sensitive. Ahmad et al. (2018) explore financial connectedness among the BRICS (Brazil, Russia, India, China, and South Africa) countries and three global bond market indexes (the US, the European Monetary Union, and Japan). They observe that Russia and South Africa are the primary transmitters of shock among the BRICS countries, implying that risks from these two markets are likely to spill over to other BRICS countries. Choi (2022) studies the dynamic connectedness among the stock markets in three Northeast Asian countries (South Korea, Japan, China) and the US using the DY-12 index. They also compare the dynamic connectedness during the pandemic and the global financial crisis (GFC) and find that interdependence is stronger during the GFC than during the pandemic. Antonakakis et al. (2018) examine the volatility spillovers and comovements among oil prices and the stock prices of major oil and gas corporations. Their findings confirm the presence of significant volatility spillover effects among these markets. Similarly,(Prasad et al., 2014) study the volatility spillovers across the stock markets in 16 countries during the GFC. Their research reveals that spillovers increase substantially during the crisis and the subsequent European sovereign debt crisis. They also find that larger stock markets, particularly those in the US, are dominant in transmitting volatility to other markets. Kang et al. (2019) estimate the total and net directional spillovers between various financial assets and assess the strength of spillovers between these assets. They conclude that emerging economies are mainly recipients of shocks, whereas developed markets are primarily transmitters. Lastly, Lee and Lee (2019) delve into interconnectedness between the financial markets in the Northeast Asian region. Their findings suggest that although regional market connectedness is relatively weak, spillovers from the US markets to this region are significant.

Recent studies have adopted the BK18 approach to investigate volatility spillover. The BK18 framework is an extended version of the DY12 framework. Unique to the BK18 approach is its accommodation of spillovers across assets in the frequency domain, which enables examination of investment horizons at various ranges. For example, Ferrer et al. (2018) investigate the time and frequency dynamics of connectedness among stock prices of US clean energy companies, crude oil prices, and other key financial variables. Their results indicate that the majority of return and volatility connectedness is generated in the very short term, and movements of up to five days are especially influential. Conversely, they find that long-term movements play a minor role. Interestingly, they report that crude oil prices are net recipients of financial shocks, not transmitters, as might be expected. Furthermore, significant short-term pairwise connectedness is found between clean energy and technology stock prices. This suggests that investors often view these two types of stocks as similar. Hoon et al. (2019) explore frequency-domain connectedness among international crude oil and agricultural commodities from 1990 to 2017. Their research suggests that the degree of connectedness increases at higher frequencies. Additionally, they find that the entity that acts as the net transmitter of volatility spillovers across the markets depends on which frequency is considered.

Several studies have used DY12 and BK18 frameworks to deepen their understanding of financial connectedness. Trabelsi (2019), for instance, investigates the connectedness between Islamic stock markets and five regional financial systems (the US, the UK, the European Union, the Gulf Cooperation Council [GCC], and Asia-Pacific countries) and various asset classes (bonds, gold, and crude oil). The study's findings indicate that the nature of connectedness over the past decade is primarily dominated by long-term components. Dominant regions are the largest contributors to the spillover index, whereas the GCC market contributes the least. The study also observes a slightly higher volatility spillover index for Islamic equity indexes than conventional ones. Interestingly, the system encompassing commodities and Islamic financial instruments generates much lower volatility spillovers than its conventional counterpart. Wohar et al. (2020) study connectedness between oil prices and the stock returns of clean energy and technology companies. Their results demonstrate that volatility is transmitted from technology companies to oil and clean energy markets at all frequencies and over the full study period. Kumar et al. (2018) analyze volatility spillovers across four global asset classes (stocks, sovereign bonds, credit default swaps [CDS], and currency) from September 2009 to September 2016. They employ both time-domain and frequency-domain frameworks. Using the DY12 methodology, they observe a low level of connection among the four markets, with stock and CDS markets as net transmitters of volatility and foreign exchange and bond markets as net receivers of spillovers. But their results using the BK18 framework indicate an increase in the degree of connectedness at higher frequencies. Like Hoon et al. (2019), they note that the net transmitter of volatility spillovers across the markets depends on the frequency under consideration.

A wide range of studies related to our research have delved into financial interconnectedness among Asian-Pacific markets, examining their degree of financial integration both regionally and globally. The existing literature presents diverse findings on the extent of this integration. Traditionally, Asian markets have minimal exposure to global economic factors, indicating a lower level of integration with Western economies. Nonetheless, over the past few decades, national stock markets in this region have shown an increasing trend of correlation, attributed to the effects of trade integration on stock market connectivity (Narayan, Sriananthakumar, & Islam, 2014). Further, some papers, including Chakrabarti (2011), suggest that the GFC played a significant role in amplifying this correlation.

Numerous investigations have explored financial connectedness among the Asia-Pacific markets. Dewandaru et al. (2016) investigate contagion among the equity markets in Japan, Hong Kong, and Australia during 12 major global crises. Their findings suggest that shocks were transmitted primarily through excessive linkage, and the Asian financial crisis had the most notable impact. Furthermore, they posit that the subprime crisis revealed fundamentals-based contagion due to strengthening fundamental linkages, in which the Japanese market was dominant. Mitra and Iyer (2017) examine the transmission of volatility across 11 international stock markets in the APR over a 20-year period, encompassing periods with and without a (contagious) crisis. They seek identify whether the volatility formed any discernible patterns, concluding that volatility transmission among the Asia-Pacific markets occurs continuously, not only due to financial crises. Moreover, they find that, in most instances, the transmissions are predictable and follow a specific pattern.

Da Fonseca and Gottschalk (2018) study the comovement of CDS, equity, and volatility markets in four Asia-Pacific countries at both the firm and index levels from 2007 to 2010. Their results suggest that realized volatility (at the firm level) and implied volatility (at the index level) were the primary transmitters of cross-market volatility spillovers. Budd (2018) examines the spillover effects of cluster volatility between equity markets in the US and four Asia-Pacific countries within the context of significant US financial market crises. His study looks at whether increased volatility in US equity markets increased volatility in the Asia-Pacific equity markets under examination. His findings support the existence of a dynamic conditional correlation between these markets. Ahmed and Huo (2019) explore the price and volatility dynamics between China and major stock markets in the APR, with a focus on the effects of the Chinese stock market crash in 2015–2016. Their results indicate that spillovers from China to other Asia-Pacific markets were considerable. Moreover, they find that shocks to Asia-Pacific stock markets spilled over to China during the crisis, implying that it has become increasingly integrated with the regional stock markets. Although these studies focus on volatility transmissions among Asia-Pacific markets, to the best of our knowledge, no prior study has investigated the causes of these volatility transmissions among financial markets in that region.

Numerous studies have delved into the factors that contribute to greater integration among financial markets. For example, Jiang, Konstantinidi, and Skiadopoulos (2012) find that news announcements can transmit volatility across financial markets. Although they conclude that news announcements might not be solely responsible for transmitting volatility, they influence the magnitude of its transmission. Vrugt (2009) identify announcements of international macroeconomic news as a significant determinant of stock market volatility, and those by the US have the most profound impact. Ferreira and Gama (2007) suggest that a downgrade in a specific stock market rating could also determine stock market volatility. Nishimura, Tsutsui, and Hirayama (2018) argue that greater openness by a stock market could cause volatility transmission, which could also be influenced by the behavior of international stock market investors. Balli, Uddin, Mudassar, and Yoon (2017) claim that trade and having a common language are strong determinants of pairwise spillover effects. Su (2020) concludes that shocks generating long-term uncertainty are the primary cause of volatility spillovers. Each of these studies contributes to our understanding of the complex interplay of factors that drive integration and volatility in financial markets.

The outbreak of the Covid-19 pandemic led to a surge in research focused on the dynamics of financial markets during periods of crisis. Sahadudheen and Kumar (2023) analyze returns and volatility spillovers among four Indian markets—oil, gold, foreign exchange, and equity—during both the GFC and the Covid-19 pandemic. Significantly, the research highlights that, during crisis periods, volatility spillovers were more pronounced than return spillovers, with a marked increase during the Covid-19 era. Further contributing to the discourse, Elgammal, Ahmed, and Alshami (2021) find bidirectional spillovers between equity and gold markets, as well as unidirectional spillovers from energy to equity and gold markets during the same period. This highlights the widespread impact of Covid-19 across different market segments.

Abuzayed, Bouri, Al-Fayoumi, and Jalk (2021) demonstrate the bivariate contagion effects between the global stock market and individual country markets, which intensified amid the pandemic. This notion of increased interconnectedness during Covid-19 is further supported by Ajmi, Arfaoui, and Saci (2021), who observed stronger links among stocks, gold, and crude oil markets. Giang, Manh, and Anh (2022) evaluate volatility transmission between the US and Chinese stock markets, finding that the pandemic facilitated positive volatility transmission between these major economies. Jebabli, Kouaissah, and Arouri (2022) compare volatility transmission during the GFC and Covid-19, noting that greater volatility transmission occurred in the latter period. (Samitas et al., 2022) focus on the role of lockdowns and the virus's spread in triggering immediate market contagion across 51 stock markets in advanced and developing countries.

Aslam, Ferreira, Mughal, and Bashir (2021) examine complex market behavior in European financial markets during Covid-19. Their study uses the methodology by Diebold and Yilmaz, revealing that nearly 80 percent of intraday volatility forecast error variance across 12 European markets originates from spillovers, highlighting the extensive influence of the pandemic on market volatility. (Yousaf et al., 2022) and Malik, Sharma, and Kaur (2022) provide insights into the GCC and BRICS member countries, respectively, observing that the pandemic had more significant volatility spillovers and a larger impact than the GFC. Lastly, (Saqib et al., 2021) investigate intersectoral volatility linkages within the US market, confirming that volatility connectedness reached its peak during Covid-19.

To the best of our knowledge, no prior studies have determined the factors that contribute to the transmission of volatility within the APR. However, some papers have explored the determinants of spillover effects from developed markets to less developed markets within the APR. For instance, Balli, Hajhoj, Syed, and Hassan (2015) conclude that bilateral factors, such as trade volume, portfolio investment, and geographic distance, significantly influence spillover effects. Asia et al. (2015) provide further insight, showing that regional factors were predominantly responsible for explaining spillover effects before the Asian financial crisis. They note that global factors are the primary determinants in the post-crisis period. However, (Prasad et al., 2014) find little evidence that the Asian markets significantly influence volatility spillovers among one another. They suggest that spillovers from European and American markets, rather than local market shocks, dominate volatility in the Asian markets. This indicates that foreign markets could also be significant sources of volatility spillovers to Asian markets.

In summary, the existing literature is replete with studies on volatility spillover among global financial markets, including those specifically about the APR, focused on identifying the determinants of volatility. Despite this extensive work, few papers address the determinants of spillover within the APR, specifically during a pandemic, or analyze diverse determinants, such as the impact of good and bad news, health-care infrastructure (e.g., ICU bed availability), demographic conditions (e.g., the proportion of the elderly population), and stringent government policy. Consequently, our research contributes to the literature by addressing these unexplored areas. We analyze volatility transmission across stock markets within the APR during the pandemic, employing the DY12 and BK18 methodologies. Additionally, we investigate these diverse determinants, which are relevant to the pandemic. Examining health-related variables seems particularly pertinent, because this is the first time in history that a pandemic has precipitated a global financial emergency.

3. Empirical methodology

3.1. Vector autoregression (spillover index)

This study employs the DY12 spillover index approach, which identifies the direction of transmission among the equity indexes in APR stock markets, enabling us to distinguish whether they are net transmitters or net recipients of shocks. The spillover index is calculated using forecast error variance decomposition (FEVD) with a generalized vector autoregressive (VAR) framework, a methodology developed by Koop, Hashem Pesaran, and Potter (1996) and Pesaran and Shin (1998).[1] In contrast to orthogonalized FEVD, generalized FEVD does not depend on the order of variables in the VAR (Kinkyo, 2020). By introducing a shock to one variable in the model, we estimate the response of the other variable(s) to this shock. The net spillover index, which indicates whether an asset is a net transmitter (positive value) or net receiver (negative value) of shocks, is calculated as the difference between the "To" and "From" spillover values.

Following DY12, we model stock market volatility as an N-variable VAR. The shares of forecast error covariance for each stock market i that is due to shocks in another stock market j (where all $j \neq i$) are added up. To obtain the spillover index, we aggregate the spillover contributions to the total forecast error variance across all 18 markets ($i = 1, \ldots, N$, $N = 18$). This sum represents the sum of all nondiagonal elements in the forecast error variance matrix. A major advantage of the FEVD method is that it is invariant to the order of the variables, as the shocks to each variable are not orthogonalized. Assuming stationary covariance in 18 variables, VAR(p) is as follows:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-1} + \varepsilon_t, \tag{1}$$

where x_t is the 18×1 vector of market volatility, Φ is a 18×18 autoregressive parameter matrix, and ε_t is the vector of error terms, presumed to be serially uncorrelated.

If the VAR system has stationary covariance, its moving average (MA) is represented by $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-1}$, where the 18×18 coefficient matrix A_i follows a recursion of the form $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} \cdots + \Phi_p A_{i-p}$ where A_0 is the $N \times N$ identity matrix, and $A_i = 0$ for $i < 0$. MA is then used to forecast the future H-steps ahead of the vector of independent variables.

Koop et al. (1996) and Pesaran and Shin (1998) propose the following H-step-ahead FEVD based on the generalized impulse responses as follows:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h P e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{2}$$

where $\theta_{ij}(H)$ is the contribution of a one-standard-deviation shock to x_j to the variance in the H-step-ahead forecast error of x_i, σ_{jj} is the standard deviation of the error term for the j th equation, $\sum$ is the variance matrix of the vector errors ε, and e_i is an $N \times 1$ selection vector with 1 as the i th element and 0 otherwise. The spillover index yields an $N\times N$ matrix $\theta(H) = \left[\theta_{ij}(H)\right]$, in which each entry reveals the contribution of variable j to the forecast error variance of variable i. Own-variable and cross-variable contributions are in the main diagonal and off-diagonal elements, respectively, of the $\theta(H)$ matrix. Each entry in the $\theta(H)$ matrix is normalized by the row sum to ensure that it equals 1. Using the normalized FEVD, $\widetilde{\theta}_{ij}(H)$, we construct the total spillover index, directional spillover index, and net spillover index.

The total spillover index (TSI) measures the contribution of spillovers across all 18 stock markets to the total forecast error variance and is calculated as follows:

$$TSI(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\theta}_{ij}(H)}{N} \times 100 \tag{3}$$

where TSI is the sum of the off-diagonal elements of the matrix obtained from a standard variance decomposition exercise in any VAR system relative to the number of variables. The sum of the diagonal elements relative to the number of variables, conversely, quantifies how much of the forecast error variance is due to its own shocks.

The directional spillover index (DSI) gauges the spillovers received by market i from all other markets j as follows. Conversely, it also accounts for the directional spillovers transmitted by market i to all other markets. Essentially, DSI enables a breakdown of TSI to identify spillovers emanating from or directed to a specific stock market. The "From" directional spillover can be calculated as:

$$DSI_{i\bullet}(H) = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{\theta}_{ij}(H)}{N} \times 100 \tag{4}$$

Subsequently, the "To" DSI is measured using a similar approach:

$$DSI_{\bullet i}(H) = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\theta}_{ji}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ji}(H)} \times 100 = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{\theta}_{ji}(H)}{N} \times 100 \tag{5}$$

The net spillover index (NSI) quantifies the net contribution to all other markets by market i. It is determined as the difference between the "To" and "From" directional spillover indexes:

$$NSI_i(H) = DSI_{\bullet i}(H) - DSI_{i\bullet}(H) \tag{6}$$

In order to account for the time-varying nature of the spillover index, $NSI_{it}(H)$, we employ a rolling-window methodology.

Lastly, we incorporate the BK18 method, advances the DY12 framework by assessing interconnectedness within the time-frequency domain.[2]

3.2. Volatility calculation

This study uses the absolute value of returns as a proxy for volatility in examining volatility spillovers. Returns are calculated as the daily percentage change in their respective stock indexes.

We follow, among others, (Forsberg and Eric, 2007) and Antonakakis and Kizys (2015), opting for the absolute value of returns to measure volatility, that is, $V_t = |P_t - P_{t-1}|$, where P_t is the daily closing value of the market index on day t. As per (Forsberg and Eric, 2007), absolute returns predict future volatility more accurately than other measures.

3.3. Net spillover determinants

We divide the potential determinants of net directional connectedness into three groups: country-specific Covid-19 cases, country-specific Covid-19 transmission variables, and a stringency variable that represents governments' pandemic containment policies.

$$NSI_{it}(H) = \alpha + \sum_{h=1}^{q} \gamma_h COVIDC_{it} + \sum_{h=1}^{p} \beta_h COVIDT_i + \delta STRINGENCY_{it} + \varepsilon_{it} \tag{7}$$

[1] The optimal lag length in the VAR models is selected with the Akaike information criterion (AIC).

[2] For a detailed description of the techniques, see DY12 and BK18.

Country-specific Covid (COVIDC) is represented by the daily new documented Covid-19 cases per million people. COVIDT variables are factors that have received more attention in the media about the transmission of the virus. More specifically, the Covid-19 pandemic exposed that almost all countries have a shortage of ICU beds and ventilators, and health-care systems worldwide need to address this shortage. We use the dataset released by Ma and Vervoort (2020), showing the number of ICU beds per 100,000 people. Because the pandemic mostly affected the elderly, we also include the share of the population above age 65. The third Covid-19 transmission variable includes population density, which was found to be a catalyst for the spread of the virus (Rocklöv & Sjödin, 2020). We include Stringency Index data by country over time to capture the range of measures that governments took to contain the spread of the virus. The Stringency Index includes policy measures such as school closures and travel bans and financial indicators such as fiscal and monetary measures. In addition, we interact the variables for the Stringency Index, population density, age 65 and over, ICU beds, and central bank policy rate with the number of new cases to assess whether the increase in new cases amplifies or mitigates the influence of those variables on net connectedness. The variables for age over 65, population density, Covid cases, and Stringency Index come from the Our World in Data Covid-19 dataset. Our regression analysis employes a fixed effects model with time effects.

Our dataset comprises a total of 18 equity indexes from the following Asia-Pacific countries: Australia, Bangladesh, Chile, China, Hong Kong, India, Indonesia, Japan, Malaysia, New Zealand, Philippines, Peru, Russia, Singapore, South Korea, Sri Lanka, Thailand, and Vietnam. The stock market data come from Refinitiv Eikon. The sample captures the first year of the pandemic, from January 6, 2020, to February 23, 2021. This period encompasses the pandemic's onset and immediate aftermath, a time when the world was largely unprepared for such a global health crisis. The first year of the pandemic, marked by the highest levels of uncertainty and constant evolution in knowledge and strategies to combat the spread of the virus, is a unique and valuable study period. Analyzing this period offers insights into the initial reactions of the markets and the impact of government measures during the early stages of the crisis.

4. Empirical findings

4.1. Net spillover analyses

Table 1 displays the net directional spillover for each stock market index, evaluated against the other 17 Asia-Pacific stock market indexes in the study. The calculation employs the DY12 methodology for the time domain and the BK18 approach for the frequency domain.

The spillover analysis reveals that equity indexes in China, Japan, Sri Lanka, Malaysia, Bangladesh, New Zealand, and Vietnam significantly contribute to volatility spillovers. This means that volatility in one country's stock market significantly affects the stock markets in the other Asia-Pacific countries. However, among the countries studied, Russia, Peru, Australia, Indonesia, the Philippines, and Thailand are the primary net receivers of spillovers, thus their market volatility is influenced mostly by external shocks from other Asia-Pacific markets.

The frequency decomposition of spillovers, as proposed by Barunik and Krehlik (2018), supplements the net spillover analysis performed with the DY12 model. We divide the frequency bands into movements of as many as 5 days (high frequency), from 5 to 22 days (medium frequency), and for more than 22 days (low frequency). These subdivisions facilitate evaluation of each equity index's connectedness to the others over varying time horizons. Applying the BK18 method enables us to identify the full spectrum of information transmission within each group across these horizons.

Table 1
Net volatility spillovers: DY12 and BK18 results.

Country	DY12	High Frequency	Medium Frequency	Low Frequency
Australia	−0.67	−0.28	−0.21	−0.18
Bangladesh	0.70	0.46	0.13	0.11
China	0.46	0.20	0.12	0.14
Chile	−0.39	0.05	−0.28	−0.16
Hong Kong	−0.16	−0.25	0.04	0.05
India	0.00	−0.05	0.02	0.03
Indonesia	−0.49	−0.28	−0.04	−0.17
Japan	0.68	0.32	0.25	0.12
South Korea	−0.13	−0.32	0.05	0.14
Malaysia	0.71	−0.10	0.41	0.39
New Zealand	0.62	0.05	0.32	0.25
Peru	−1.04	−0.16	−0.42	−0.47
Philippines	−0.46	−0.04	−0.21	−0.21
Russia	−1.06	−0.22	−0.45	−0.38
Singapore	−0.24	−0.46	0.07	0.14
Sri Lanka	1.20	0.88	0.19	0.13
Thailand	−0.49	−0.20	−0.14	−0.15
Vietnam	0.50	0.27	0.13	0.10

Notes: This table summarizes the results obtained from the application of DY12 and BK18 methodologies. It presents the net spillovers for equity indexes in the studied countries. The sum of all values from different bands produced by BK18 (frequencies of volatility spillovers up to 5 days, from 5 to 22 days, and above 22 days, respectively) should equal the DY12 value. A positive value suggests that the equity index of the corresponding country acts as a net exporter of shocks, while a negative value designates it as a net importer of shocks. The sample period considered runs from January 27, 2020, to February 23, 2021.

4.2. Determinants of net volatility spillovers

This section analyzes the factors that drive these dynamics in net directional connectedness. The Covid-19 crisis, which was fundamentally a health crisis, is rooted in various sociodemographic variables. The ability of countries to manage the pandemic was largely contingent on the availability of ICU beds, acting as the first line of defense. Moreover, because the elderly are more likely to suffer severely from infection by the virus, the proportion of the population age 65 and above is also factored into our model as a potential determinant. Lastly, considering the higher exposure risk in densely populated areas, we include a country's population density as another explanatory variable. These three variables are considered collectively as the variable for being "Covid-19 transmission related" and, to our knowledge, we introduce them for the first time in financial spillover literature. In addition to these variables related to transmission of the virus, we incorporate daily new Covid-19 cases per 1 million people to quantify the effect of Covid-19 case numbers on net spillover.

The Stringency Index reflects the range of government measures implemented to contain the Covid-19 outbreak. Alterations in central bank policy rates, such as significant reductions, demonstrate the response of central banks to the Covid crisis, which were expected to reduce borrowing costs for both governments and the private sector. Table 2 lists the descriptive statistics, and Table 3 presents the correlation matrix.

Table 4 presents the results for the determinants of volatility spillovers. The second column represents overall volatility spillover as the dependent variable, while the dependent variables in the third, fourth, and fifth columns denote the frequency of volatility spillovers for as many as 5 days, from 5 to 22 days, and more than 22 days, respectively.

The results indicate that rising numbers of new Covid-19 cases per million consistently drive up the volatility spillover index. Stringency measures, however, generally have a negative correlation with the index, except for the high-frequency scenario (up to 5 days, Model 2). Population density also has a positive association with volatility spillovers. Notably, a higher proportion of people over age 65 is linked to greater volatility spillovers. Although an increase in ICU bed availability

Table 2
Descriptive statistics.

Variable	Abbreviation	Mean	Min	Max	S.D.	Skew.	Kurt.
Net Spillover	NET	−0.39	−749.73	448.32	110.58	−0.42	2.15
Net Spillover 1	NET1	0.34	−224.18	241.72	52.52	0.57	1.79
Net Spillover 2	NET2	0.00	−190.35	123.34	41.51	−0.32	1.68
Net Spillover 3	NET3	−0.73	−571.76	341.94	46.27	−1.25	14.57
New cases	CAS	23.38	−0.42	538.07	48.64	3.49	16.19
Age 65 and over	AGE	10.95	4.80	27.05	5.46	1.31	1.95
ICU Beds	BED	3.78	0.00	13.05	3.71	1.59	1.21
Stringency Index	STR	59.68	0.00	100.00	21.92	−0.61	−0.14
Population density	POP	5.00	1.16	8.98	1.91	−0.07	−0.15
Central bank policy rate	POL	0.24	−4.68	2.03	1.31	−0.58	−0.72
Trade openness	TRA	4.20	3.57	5.87	0.65	1.20	0.37
Equity market	STO	4.22	2.93	7.20	0.65	0.76	3.86
Crude oil	OIL	3.69	2.21	4.25	0.34	−1.41	2.03
Volatility index	VIX	3.26	2.20	4.67	0.42	1.03	1.27

Notes: NET1 = frequency spillover up to 5 days; NET2 = from 5 to 22 days; NET3 = more than 22 days; POL, POP, TRA, STO, OIL, and VIX are converted into logarithm. Net spillover indexes are multiplied by 100.

mitigates volatility spillovers in Models 1 (overall) and 2 (up to 5 days), it becomes insignificant in Models 3 (5–22 days) and 4 (above 22 days). Lastly, a higher central bank policy rate contributes to an increase in volatility spillovers.

As for the interaction terms, the stricter stringency measures generally mitigate the positive effect of new cases on volatility spillovers, with the exception of Model 2, in which the interaction is insignificant. The amplifying effect of new cases on volatility spillovers is further intensified in more densely populated areas, although this effect is weaker in Model 2.

Although the impact of new cases on volatility spillovers does not significantly differ for populations with higher proportions of older individuals in Models 1 and 3, Model 2 has a negative effect, and Model 4 a positive effect. This suggests potential context-specific nuances in the relationship between older populations and volatility spillovers.

The positive effect of new cases on volatility spillovers is attenuated by greater ICU bed availability, highlighting the importance of health-care infrastructure in buffering against spillovers. However, no significant interaction is observed between new cases and the central bank policy rate in relation to volatility spillovers.

To enhance the robustness of our findings, in Table 5, we introduce additional control variables into our model, namely, trade openness, equity market, crude oil, and the volatility index. These variables capture important aspects of global economic and financial conditions that might influence volatility spillovers. Our results are generally consistent, thus confirming the robustness of our initial findings.

Increased trade openness leads to higher spillover effects, whereas equity market performance tends to have the opposite effect (except for a higher scale beyond 22 days, which is insignificant). The dynamics of international crude oil markets positively influence spillovers, except for the horizon for 5–22 days, when the relationship is insignificant. The volatility index has an inverse relationship with spillovers in the first two models, but this correlation becomes insignificant at frequencies of more than 5 days.

In conclusion, when the variable for new cases interacts with the three Covid transmission–related variables, the number of ICU beds and population density have a significant indirect impact on spillovers but the results on the elderly population are inconclusive.

As previously noted, various factors that influence spillover effects are identified in earlier studies, such as trade and common language (Balli et al., 2017), significant market events and market uncertainty (Su, 2020), the increased openness of a stock market (Nishimura et al., 2018), a downgraded rating of a stock market (Ferreira & Gama, 2007), and news announcements (Jiang et al., 2012). We provide evidence that the number of new Covid-19 cases per million is a significant factor in transmitting volatility. Moreover, we identify an additional set of determinants of transmission: health-care facilities (measured by the number of ICU beds), population density, and the proportion of people over age 65. Because of their high relevance, these variables significantly affect the impact of new cases on the transmission of volatility, especially during the pandemic.

5. Conclusion

This study delves into the factors that influence volatility spillovers within the Asian-Pacific financial markets during the first phase of the Covid-19 pandemic, a period of unprecedented global uncertainty. We focus on aspects related to transmission of the virus, government measures, central bank policies, and various socioeconomic variables. Our analysis raises several crucial insights into their complex interplay, significantly advancing our understanding of financial market dynamics in times of crisis.

Our findings conclusively demonstrate the substantial impact of the rising number of Covid-19 cases per million on volatility spillovers. This highlights the profound influence of the pandemic on global financial markets, confirming that health crises can trigger significant economic instability. Our research reveals three previously overlooked variables related to the transmission of volatility spillovers due to Covid-19: the availability of ICU beds, population density, and the percentage of people over age 65. These factors highlight the crucial role played by health-care infrastructure and demographic composition in the propagation of financial market volatility during a pandemic. Stringent government measures such as travel bans, lockdowns, and trade disruption were generally found to have a negative influence on volatility spillovers. But our results indicate that central bank policies significantly increase volatility spillovers. The robustness of our findings, confirmed by including additional control variables such as trade openness, equity market performance, crude oil prices, and the volatility index, reinforces the credibility of our conclusions.

This research significantly enhances the existing literature by emphasizing the importance of Covid-19 transmission–related variables in shaping financial market volatility. It offers several key insights that can inform policy formulation and adjustment in times of global health crises, particularly in the context of financial market stability within the APR. First, the robust association between increases in the number of Covid-19 cases and increased volatility spillovers highlights the importance of effective public health interventions. Rapid and decisive actions to contain outbreaks can mitigate not only the public health impact but also the associated financial market volatility. This suggests that policy makers should prioritize health crisis management strategies, such as enhancing testing, tracing, and vaccination campaigns, to reduce the uncertainty that fuels market volatility. Second, our findings highlight the significant role of health-care infrastructure, as evidenced by the impact of ICU bed availability on dampening volatility spillovers. This

Table 3
Correlation matrix.

Correlation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) NET	1.00	0.68	0.88	0.82	−0.19**	0.05*	0.04*	−0.12**	0.23	0.22	0.01**	−0.11**	0.02*	−0.02**
(2) NET1	0.68	1.00	0.34	0.19	−0.08**	−0.01**	0.01**	0.01**	0.08	0.35	−0.19**	−0.36**	0.01**	−0.02**
(3) NET2	0.88	0.34	1.0	0.83	−0.24**	0.07	0.05*	−0.19**	0.26	0.09	0.10	0.06	0.01**	−0.01**
(4) NET3	0.82	0.19	0.83	1.0	−0.15**	0.05	0.05*	−0.13**	0.22	0.03*	0.13	0.09	0.03*	−0.03**
(5) CAS	−0.19**	−0.08**	−0.24**	−0.15**	1.00	−0.07**	−0.06**	0.26	−0.25**	−0.16**	−0.09**	−0.11**	0.10	−0.12**
(6) AGE	0.05*	0.01**	0.07	0.05	−0.07**	1.00	0.77	−0.41**	−0.13**	−0.55**	−0.08**	0.35	0.01*	−0.01**
(7) BED	0.04*	0.01**	0.05*	0.05*	−0.06**	0.77	1.00	−0.31**	−0.04**	−0.06**	−0.17**	0.08	0.02*	−0.02**
(8) STR	−0.12**	0.01**	−0.19**	−0.13**	0.26	−0.41**	−0.31**	1.00	−0.03**	0.09	−0.14**	−0.16**	−0.34**	0.12
(9) POP	0.23	0.08	0.26	0.22	−0.25**	−0.13**	−0.04**	−0.03**	1.00	0.13	0.44	0.26	0.01*	−0.01**
(10) POL	0.22	0.35	0.09	0.03*	−0.16**	−0.55**	−0.06**	0.09	0.13	1.00	−0.36**	−0.53**	−0.05**	0.08
(11) TRA	0.01**	−0.19**	0.10	0.13	−0.09**	−0.08**	−0.17**	−0.14**	0.44	−0.36**	1.00	0.54	0.02*	−0.02**
(12) STO	−0.11**	−0.36**	0.06	0.09	−0.11**	0.35	0.08	−0.16**	0.26	−0.53**	0.54	1.00	0.02*	−0.02**
(13) OIL	0.02*	0.01**	0.01**	0.03*	0.10	0.01*	0.02*	−0.34**	0.01*	−0.05**	0.02*	0.02*	1.00	−0.65**
(14) VIX	−0.02**	−0.02**	−0.01**	−0.03**	−0.12**	−0.01**	−0.02**	0.12	−0.01**	0.08	−0.02**	−0.02**	−0.65**	1.00

Table 4
Determinants of net volatility spillovers.

Variable	Model 1	Model 2	Model 3	Model 4
New cases	2.547***	0.531***	1.016***	1.000***
	(0.346)	(0.164)	(0.126)	(0.154)
Stringency Index	−0.293***	0.062*	−0.217***	−0.138***
	(0.078)	(0.037)	(0.028)	(0.035)
Population density	7.913***	2.838***	1.954***	3.121***
	(0.938)	(0.444)	(0.341)	(0.417)
Age 65 and over	7.016***	4.602***	1.143***	1.270***
	(0.766)	(0.363)	(0.279)	(0.340)
ICU beds	−3.174***	−3.222***	−0.349	0.397
	(0.700)	(0.332)	(0.255)	(0.311)
Central bank policy rate	31.065***	21.851***	5.472***	3.742***
	(1.806)	(0.856)	(0.657)	(0.803)
New cases × Stringency Index	−0.029***	0.002	−0.016***	−0.016***
	(0.004)	(0.002)	(0.001)	(0.002)
New cases × Population Density	0.074***	−0.089***	0.091***	0.072***
	(0.024)	(0.012)	(0.009)	(0.011)
New cases × age 65 and over	−0.012	−0.021***	−0.004	0.014*
	(0.017)	(0.008)	(0.006)	(0.008)
New cases × ICU beds	−0.241***	−0.057***	−0.090***	−0.094**
	(0.032)	(0.015)	(0.012)	(0.014)
New cases × Central bank policy rate	−0.064	−0.029	−0.018	−0.017
	(0.042)	(0.020)	(0.015)	(0.019)
Constant	−90.096***	−59.256***	−7.988*	−22.852***
	(11.610)	(5.501)	(4.225)	(5.161)
Observations	4458	4458	4458	4458
R^2	0.156	0.198	0.193	0.111
Adjusted R^2	0.153	0.196	0.191	0.109
F statistic (df = 11; 4446)	74.430***	99.535***	96.908***	50.475***

Notes: In Model 1, the dependent variable represents the overall net volatility spillover. In Models 2–4, the dependent variable represents the frequencies of volatility spillovers up to 5 days, from 5 to 22 days, and over 22 days, respectively. Standard errors are reported in parentheses. In the regression analysis, fixed effects model with time effects is employed. *, **, and *** represent significance of 10%, 5%, and 1%, respectively.

indicates that investment in health-care capacity not only prepares countries for managing the health aspects of a crisis but also contribute to financial stability. Policy makers should consider bolstering health-care resources, including ICU beds, as a dual-purpose strategy for health crisis preparedness and economic resilience. Our analysis also shows the need for considering demographic factors, such as population density and the proportion of the elderly, in policy formulation. Densely populated areas and populations with a higher proportion of people over age 65 may require more focused interventions to mitigate volatility spillovers effectively. Tailoring policies to these demographic realities can enhance the effectiveness of crisis response measures. Lastly, the role of central bank policies in influencing volatility spillovers during the pandemic period suggests that monetary policy responses must be carefully evaluated to determine their potential impact on financial markets. Although liquidity support and interest rate adjustments are essential tools for economic stabilization, our findings call for a balanced approach that considers the timing, magnitude, and communication of these measures to minimize unintended consequences for market volatility.

With respect to directions for future research, it would be intriguing to explore how the transition to post-pandemic normalcy impacts volatility spillovers. Additionally, investigating the role of fiscal policy responses, vaccine distribution and administration, and economic recovery measures in the context of volatility transmission could provide further valuable insights. These topics could help us deepen our understanding of financial market dynamics in the face of unprecedented global events, enhancing our preparedness and resilience for future challenges.

Table 5
Determinants of net volatility spillovers, robustness check.

Variable	Model 5	Model 6	Model 7	Model 8
New cases	2.937*** (0.341)	0.760*** (0.152)	1.121*** (0.127)	1.057*** (0.156)
Stringency Index	−0.019 (0.087)	0.188*** (0.038)	−0.144*** (0.032)	−0.064 (0.040)
Population Density	7.519*** (1.097)	4.689*** (0.488)	0.893** (0.408)	1.937*** (0.501)
Age 65 and over	9.212*** (0.757)	6.329*** (0.337)	1.453*** (0.282)	1.430*** (0.346)
ICU beds	−4.706*** (0.691)	−4.698*** (0.308)	−0.441* (0.257)	0.433 (0.316)
Central bank policy rate	25.270*** (1.988)	14.256*** (0.884)	5.953*** (0.740)	5.061*** (0.908)
Trade openness	30.209*** (3.428)	14.468*** (1.525)	8.944*** (1.276)	6.797*** (1.565)
Equity market	−50.946*** (3.282)	−42.409*** (1.460)	−6.600*** (1.222)	−1.937 (1.498)
Crude oil	13.146** (6.269)	4.948* (2.789)	2.994 (2.334)	5.204* (2.863)
Volatility Index	−10.022** (4.594)	−6.808*** (2.043)	−2.189 (1.710)	−1.025 (2.097)
New cases × Stringency Index	−0.033*** (0.003)	−0.002 (0.002)	−0.017*** (0.001)	−0.017*** (0.002)
New cases × Population density	0.076*** (0.024)	−0.090*** (0.011)	0.092*** (0.009)	0.074*** (0.011)
New cases × Age 65+	−0.004 (0.017)	−0.013* (0.007)	−0.004 (0.006)	0.013* (0.008)
New cases × ICU beds	−0.313*** (0.032)	−0.108*** (0.014)	−0.104*** (0.012)	−0.101*** (0.015)
New cases × CB policy rate	0.013 (0.043)	0.043** (0.019)	−0.009 (0.016)	−0.021 (0.020)
Constant	−49.753 (40.596)	34.180* (18.057)	−24.067 (15.112)	−59.867*** (18.535)
Observations	4458	4458	4458	4458
R^2	0.204	0.334	0.205	0.116
Adjusted R^2	0.201	0.331	0.202	0.113
F statistic (df = 15; 4442)	75.947***	148.215***	76.208***	38.896***

Notes: In Model 1, the dependent variable represents the overall net volatility spillover. In Models 2–4, the dependent variable represents the frequencies of volatility spillovers up to 5 days, from 5 to 22 days, and over 22 days, respectively. In the regression analysis, a fixed effects model with time effects is employed. Standard errors are reported in parentheses. *, **, and *** represent significance of 10%, 5%, and 1%, respectively.

Author contributions statement

All authors, Kinan Salima, Mustafa Disli, Ruslan Nagayev, Abubakar Ilyas, and Ahmet F. Aysan, have similarly contributed to the work titled "Determinants of Volatility Spillovers across Asian Pacific Equity Markets during the Emergence of the COVID-19 Pandemic". Each author has played an integral role in the conception and design of the study, the acquisition of data, the analysis and interpretation of data, and the drafting and critical revision of the manuscript for important intellectual content. Furthermore, all authors have given final approval of the version to be published and agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. Their affiliations with institutions across Malaysia, the United Kingdom, Qatar, and Türkiye reflect a collaborative effort that spans significant geographical and academic boundaries, bringing diverse perspectives and expertise to the study.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT and Google Bard to improve readability.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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