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Volatility spillovers from the Chinese stock market to the U.S. stock market: The role of the COVID-19 pandemic

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ABSTRACT

The COVID-19 pandemic, which originated in Wuhan, China, precipitated the stock market crash of March 2020. According to published global data, the U.S. has been most affected by the tragedy throughout this outbreak. Understanding the degree of integration between the financial systems of the world's two largest economies, particularly during the COVID-19 pandemic, necessitates thorough research of the risk transmission from China's stock market to the U.S. stock market. This study examines the volatility transmission from the Chinese to the U.S. stock market from January 2001 to October 2020. We employ a variant form of the EGARCH (1,1) model with long-term control over the excessive volatility breakpoints identified by the ICSS algorithm. Since 2004, empirical evidence indicates that the volatility shocks of the Chinese stock market have frequently and negatively affected the volatility of the U.S. stock market. Most importantly, we explore that the COVID-19 pandemic vigorously and positively promoted the volatility infection from the Chinese equity market to the U.S. equity market in March 2020. This precious evidence endorses the asymmetric volatility transmission from the Chinese to the U.S. stock market when COVID-19 broke out. These experimental results provide profound insight into the risk contagion between the U.S. and China stock markets. They are also essential for securities investors to minimize portfolio risk. Furthermore, this paper suggests that globalization has carefully driven the integration of China's stock market with the international equity markets.

1. Introduction

Globalization has caused capital market interdependence to increase (Baele, 2005; Chevallier et al., 2018). Many studies have shown that the rise in financial integration has led to stock market return transmission and volatility spillovers (BenSaïda et al., 2018; Maghyereh et al., 2022; Zehri, 2021; Zorgati & Garfatta, 2021). Vo and Tran (2020) illustrate that volatility spillovers between stock markets are typically associated with the variation in stock returns and investment risks in equity markets. The degree of volatility transmission indicates the extent of market integration (Nath Mukherjee & Mishra, 2010). Determining the source of volatility; the timing of volatility spillovers; and the extent of volatility spillovers on the international equity markets are thus crucial. Similar to how rumors spread on social media, financial networks influence the risk of contagion, thereby playing a vital part in stabilizing the international financial system (Shen et al., 2022). Liu et al. (2021) assert that the COVID-19 pandemic has greatly affected the spread of

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shocks across equity markets than that of the 2008 global financial crisis (GFC). The 2008 GFC emerged in the subprime mortgage crisis and resulted in the collapse of large banks in the U.S. market before spreading to other markets and impacting the entire economic activities. The COVID-19 pandemic is a health disaster, with governments implementing lockdowns and travel restrictions out of fear for human life. As a result, supply chains and economic activities were disrupted, and financial markets were immediately influenced (Jebabli et al., 2022).

The volatility spillover from developed markets to emerging markets is a phenomenon supported by several empirical results (Ng, 2000; Worthington & Higgs, 2004; Chow, 2017; Vo & Tran, 2020). This volatility transmission implies that emerging markets are susceptible to minor fluctuations from developed markets. However, the contagion from developed to emerging markets varies across different markets (Boubaker & Jouini, 2014; Worthington & Higgs, 2004). If developing and developed markets have weak connections, jumps from developed markets would be less likely to affect their developing counterparts. Inversely, if emerging equity markets depend on advanced equity markets, their volatility will be highlighted in developed markets. Many recent studies including ones by Lien et al. (2018); Hung (2019); Vo and Tran (2020) have underlined the consequence of the 2008 GFC on the relationships between international equity markets). In short, those studies' empirical results show that the financial crisis considerably increases the risk of contagion from the U.S. to other stock markets.

Rare evidence shows that volatility is also likely to spread from emerging equity markets to advanced markets. For instance, Wang and Wang (2010) found that when the U.S. or Japanese equity markets experience volatility, it tends to spill over into extended Chinese markets and otherwise. Still, the dominance effect of volatility transmission of developed over emerging markets did not present. During the 1997 currency crisis, Li and Giles (2015) observed that volatility in Asian emerging markets spread to developed markets including the U.S. and Japan. Majdoub and Mansour (2014) point out that there is no definitive evidence that shocks in U.S. markets affect the ones in Islamic emerging stock markets. Existing proof has suggested that volatility transmissions between equity markets depend on market integration, market openness, and unprecedented global market shocks.

China's largest export market is the U.S., and China is also considered the second-biggest foreign creditor of the United States (Morrison, 2010; Vuong, Wu, et al., 2022). The relationship between the U.S. and China is complicated and tense due to events such as the Korean War, the Vietnam War, and more recently, the Taiwanese and Hong Kong issues. The trade war between the two countries climaxed in 2018 when commercial accusations between the two countries intensified. China has leveled accusations against the United States due to its import restrictions on Chinese high-tech products. Meanwhile, the U.S. side expresses its views on intellectual property rights and commercial surplus. The U.S. government is concerned that China intends to compromise the national security and international standing of the U.S. (Liu & Woo, 2018). China particularly enforced punitive taxes on 128 types of U.S. goods on April 1, 2018, in retaliation for the March 2018 national security taxes on imports and aluminum imposed by the Trump administration. To rectify the trade imbalance between the two countries, the Trump administration placed tariffs on Chinese goods which were worth $250 billion (a 25% increase) at the end of September 2018. Moreover, the United States and China fiercely compete to expand their influence in Asian markets. Shen et al. (2022) state that the trade war between China and the U.S. significantly impacted China's stock market. Besides, Uludag and Khurshid (2019) emphasized that government interventions are expected to affect the open market along with the integration of equity markets. Thus, government policies on both sides are expected to significantly influence the degree of integration between the stock markets in China and the U.S.

The Chinese government has long established many regulations regarding restrictions on foreign investment in the Chinese financial sector. These restrictions may inhibit the volatility transmission from the Chinese stock market to the volatility of its counterparts' equity markets (Zhou et al., 2012). Before 2019, the Chinese government prohibited foreign investors from gaining control of Chinese domestic banks (no more than 20% of total equity for individual investors and 25% for affiliate investors) and were also restricted from owning less than 50% of the total equity in foreign banks, foreign wealth management funds, and foreign insurance companies. Foreign banks can establish 100% foreign-owned branches in China, but they must find a Chinese partner holding most shares. After years of applying strict regulations on foreign ownership in the financial sector, the Chinese government discovered that restrictive foreign investment policies are detrimental to the Chinese economy's growth. In July 2019, China's government decided to lift some restrictions on foreign investment in China's financial sector starting in 2020, as the Chinese economy has struggled with slowing growth and the U.S.-China trade war. From 1990 to the present, it cannot be disputed that China's GDP has proliferated. The Chinese economy outpaced other emerging-market economies. Most notably, China has become the second-largest global economy since 2004 according to the Purchasing Power Parity (PPP) Index but since 2010, following the GDP Index. By 2030, the Chinese stock market is anticipated to surpass the U.S. equity market and turn into the world's biggest stock market due to its rapid growth rate (Liu et al., 2013). For these reasons, volatility transmission from China's market to other stock markets has drawn the attention of many academics (Hung, 2019; Majdoub & Sassi, 2017; Zhong & Liu, 2021; Zhou et al., 2012). Nowadays, the direct spillover transmission from China's market to the U.S. market remains an unanswered research question.

The COVID-19 tragedy originating in Wuhan, China, at the end of 2019 has severely and swiftly affected the entire international market (Akhtaruzzaman, Boubaker, Lucey, & Sensoy, 2021; Zhang et al., 2020). In early 2020, this disaster was at its most severe in the U.S. (Corbet et al., 2021). March 2020 witnessed one of the most formidable stock markets crashes in financial market history (Mazur et al., 2021). At the end of the first quarter of 2020, several stock indexes simultaneously reached their lowest points. The COVID-19 tragedy has negatively impacted the international financial market. This is the consequence of policies implemented to limit the economic downturn brought about by the tragedy, such as cutting interest rates or releasing COVID-19 relief packages (Choi, 2022).

Despite these considerable fluctuations, the "big players" in the international stock markets have not yet changed. According to STATISTA,[1] the U.S. stock market accounts for roughly 44.33% of the total market value of global stocks. The entire market value of the Chinese stock market is only one-fifth that of the U.S. From a behavioral finance perspective, most people are shown to be irrational when feeling anxious, so extreme disaster conditions affect investor behavior (Lee et al. 1991). While Kaplanski and Levy (2010) explained how aviation disasters affect stock price variations, Sun et al. (2021) showed that securities investors act irrationally during the COVID-19 disaster. Additionally, Liu et al. (2021) proved that fear and anxiety increase pessimistic attitudes toward investment decisions in the financial markets during the COVID-19 outbreak. These arguments urge us to explore whether the COVID-19 disaster impacted stock investors in stock markets in the U.S. and China in March 2020.

This study was conducted for several reasons: First, though emerging markets are fragile, they have been asserting their position in the international market. China is an excellent reflection of this. To our understanding, most prior research has focused on volatility transmission from the U.S. to Chinese stock markets and the role of the 2008 GFC, while volatility transmission from the Chinese to the U.S. stock markets has been neglected. Second, China and the U.S. stock markets are the world's two largest and represent the most significant emerging and the largest developed markets. Determining the volatility spread from China's stock market to the U.S. one is essential for many global investors. According to our conjectures, political and commercial barriers in the U.S.-China bilateral nexus and foreign investment restrictions in China's financial sector, which have persisted for decades, could hinder the degree of contagion between the equity markets of the U.S. China. Third, Liu et al. (2021) showed that the global stock market experienced a terrible crash due to the COVID-19 tragedy in early 2020. Shaikh and Huynh (2021) emphasize that the fear of securities investors during the tragedy appears to be higher than during the two previous crises (the stock market crash of 1987 and the 2008 GFC). Therefore, we forecast that the COVID-19 disaster will significantly increase the volatility transmission from the Chinese to the U.S. equity markets.

This study seeks to provide comprehensive insight into the volatility spillovers from the Chinese to the U.S. stock markets from January 2001 through October 2020, with a concentration on the spillovers from the Shanghai Composite (SSEC) Index of the Chinese stock market to the Standard & Poor's 500 (S&P500) Index of the U.S. stock market. In addition to the SSEC and S&P500, our research also uses the Shenzhen Composite Index and U.S. stock market indexes (Nasdaq Composite Index and Dow Jones Industrial Average Index) to strengthen the results. Moreover, we use a different volatility measure for the returns of the S&P500 and SSEC to provide a more robust analysis. The scope of our research is depicted briefly in Fig. 1.

Our research first employed the Iterative Cumulative Sum of Squares (ICSS) algorithm to detect the volatility breakpoints of China's stock market returns (Inclan & Tiao, 1994). We then applied a variant form of the EGARCH (1,1) model with the detected structural breakpoints to model the volatility spillovers from the Chinese to the U.S. stock markets from January 2001 to October 2020. Our findings show that, since 2004, the volatility shocks of China's stock market have negatively and persistently affected the volatility of the U.S. stock market. The U.S. equity market appeared to be less susceptible to the volatility risk of China's equity market. However, we detected the volatility shock on the Chinese stock market in March 2020 forcefully promoted volatility transmission from the Chinese to the U.S. equity markets. At that time, China was the source of the tragedy that drowned the international stock market. This prominent finding implies that the COVID-19 pandemic accelerates the spread of investor fear from the Chinese to the U.S. stock markets; it also provides valuable proof of asymmetric volatility transmission from the Chinese to the U.S. equity markets. Our findings are consistent with various stock indexes in equity markets, and alternative volatility measures of S&P500 and SSEC returns.

Our study adds to the current literature in three key areas. Firstly, unlike previous studies, our research utilizes an extensive database containing numerous representative stock indexes from the Chinese or U.S. stock markets from January 2001 to October 2020. The selected research period covers the massive impact of the COVID-19 pandemic originating in China. In addition, our research methodology identifies the source of volatility, the instances of excessive volatility, and the degrees of volatility transmission from the Chinese to the U.S. stock markets. Secondly, practical results verify that China's equity market has been loosely integrated with the U.S. market for nearly two decades. Most prominently, found results emphasize the stimulative effect of COVID-19 on the volatility spillover from the Chinese to the U.S. equity markets in March 2020. Finally, our outstanding contribution is to give insight into the investors' sentiment in the two largest global stock markets, particularly during the onset of the COVID-19 tragedy. These findings enable investors, financial institutions, and policymakers to develop risk mitigation strategies proactively.

The introduction is first presented. The remaining sections of this research are designed as follows: A literature review of volatility spillovers is presented in Part 2. Part 3 consists of our sample, Methodology, and Empirical models. In the fourth part, fundamental analysis and major analyses of the volatility transmission from the Chinese to the U.S. equity markets are conducted. The final section provides conclusions and implications.

2. Theoretical background and research hypotheses

According to Baele (2005) and Akhtaruzzaman, Boubaker, and Sensoy (2021), trade liberalization strengthens integration and affects stock market interdependence. Volatility in one market or sector would be likely to influence others, so discovering spillover effects is important for understanding the pathway of risk transmission (Shen et al., 2022). Global shocks from within or outside the financial system substantially impact volatility, so investors, financial institutions, and policymakers in the equity markets must acquire a deeper insight into the causes of volatility and cross-market correlation. Trade liberalization promotes capital flows to create momentum for financial development (Kim et al., 2010). The volatility spread among equity markets determines their degree of

[1] STATISTA is a reputable market data research company, located in Germany.

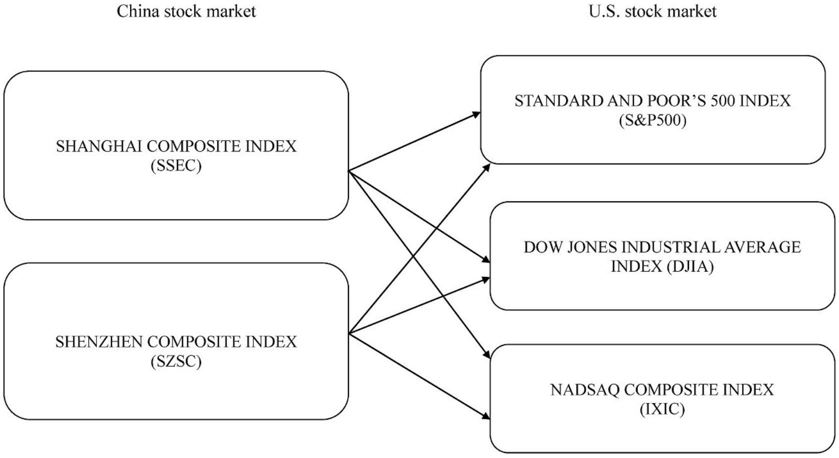


Fig. 1. Examining the volatility spillovers from the Chinese to the U.S. stock markets.

openness (Majdoub & Mansour, 2014), so the volatility spillover between stock markets is significant if the degree of integration between them is high. Bearish markets have greater volatility than bullish markets, which is an additional aspect of the volatility issue. According to Albu et al. (2015), asymmetric volatility occurs when downside market volatility is greater than upside market volatility. Strong evidence of asymmetry was provided by demonstrating that volatility spillovers are more evident when market-to-trading news is negative (Koutmos & Booth, 1995). Chen and Ghysels (2011) found that either extreme good news (abnormal high positive returns) or bad news (negative returns) booster stock market volatility, but bad news has a more serious influence. According to the fundamental view of asymmetric volatility spillover, an unusual decrease in stock market returns will considerably ascend the stock market volatility.

In the integration context, volatility spillovers and interdependence between global equity markets are unavoidable (Arfaoui et al., 2022; Maghyereh et al., 2022; Zehri, 2021; Zorgati & Garfatta, 2021). Volatility contagion is universally observed among affiliate stock markets, such as European stock markets (Kanas, 1998); East Asian stock markets (Yilmaz, 2010); Asian stock markets (Joshi, 2011); North American, European, and Asian stock markets (Singh et al., 2010); or even volatility transmission from stock markets in East Asia to stock markets in Southeast markets (Wu, 2020). That suggests that global integration facilitates volatility spillovers. Spillover effects acquired from the U.S. stock market have been widely indicated in European stock markets (Baele, 2002); Islamic stock markets (Majdoub & Mansour, 2014); BRICS stock markets (Mensi et al., 2014, 2016; Sui & Sun, 2016); ASEAN-6 stock markets (Vo & Tran, 2020); and the East Asian stock markets (Zehri, 2021). Numerous pieces of evidence demonstrate that the volatility of stock markets in the U.S. and Asia during the two crises are intrinsically linked. Li and Giles (2015) demonstrated that the volatility transmission between the U.S. and Asian emerging stock markets (including China) was powerful and bidirectional during the currency crisis in 1997. Lien et al. (2018) found severe volatility transmissions from the U.S. stock market to others in East Asia (excluding China) during two major crises in 1997 and 2008. Vo and Tran (2020) explored that during the financial crisis, the volatility shocks of the U.S. stock market caused notable volatility shocks in Southeast Asian equity markets. Zehri (2021) demonstrated volatility spillovers from the stock markets in the U.S. to East Asia became more enormous during COVID-19.

Meanwhile, few studies have provided proof to support the volatility spillover between the stock markets in China and the U.S. Adopting a multivariate GARCH model, the first study examines the relationship between the stock markets in China and the U.S. from January 2000 to August 2005 and found no evidence to support direct spillover effects from the U.S. stock market to China's stock market (Li, 2007). Then, Moon and Yu (2010) extended their research period from January 1999 to June 2007 to examine the volatility transmission from the U.S. to the Chinese stock markets. As opposed to Li's (2007) study, they use Andrews's (1993) method to identify a single structural breakpoint in the mean of Chinese stock market returns, and after then, employ the GARCH-m (1,1) model. However, Moon and Yu (2010) discovered proof of a spillover effect from the U.S. to the Chinese stock market after a specific breakpoint (December 2, 2005), but this effect does not absolutely appear before the breakpoint. In addition, Wang and Wang (2010) also did not find evidence of a spillover effect from the U.S. to China's stock market from 1994 to 2004. Later studies focused primarily on the role of the GFC in 2008. Specifically, Zhou et al. (2012), Uludag and Khurshid (2019), and Mensi et al. (2016) examined the dominance of volatility spillovers from the U.S. to the Chinese stock markets along with other equity markets in two years (2007 and 2008). These studies suggest that the role of the 2008 GFC may have been a driving factor in the observed volatility transmission from the U.S. to the Chinese stock market.

Since 2004, China's economy has turned into the second global largest (after the U.S.), defined by the PPP index. This critical event proves the efficiency of China's innovative and open economic policies during the last 20 years. Despite being an emerging market, its equity market also has substantial impacts on other equity markets. Employing the VAR model, Zhou et al. (2012) showed that volatility spillovers from the Chinese stock market to those in Hong Kong have been more remarkable than in European and other Asian equity markets. Hung (2019) adopted the GARCH-BEKK model to demonstrate the effects of the Chinese stock market volatility on the Southeast Asian one from July 2000 to July 2018. Allen et al. (2013) employed various time series models to provide proof of volatility spillovers from China's stock market to advanced stock markets in the pre-GFC. Meanwhile, they indicated that the volatility of the U.S. stock market during the 2008 GFC had significantly impacted the volatility of China's stock market. Li and Giles (2015) demonstrated that the volatility of China's stock market notably impacted the U.S. equity market during the 1997 currency crisis. In addition, Uludag and Khurshid (2019) employed the VAR (1)-GARCH (1) model to demonstrate volatility spillovers that occurred in both directions between the Chinese stock market and G7 equity markets as well as E7 stock markets from 1995 to 2015. In contrast to the traditional view, volatility transmitted from developed to emerging markets is found comparatively. Specifically, recent research has suggested that Chinese stock market volatility can affect the volatility of emerging partners and developed counterparts. Nonetheless, no research has conclusively demonstrated the direct volatility effects of the Chinese equity market on the U.S. stock market.

To protect national economic security, the Chinese and Russian governments issued regulations on investment laws identifying restrictions on foreign investors whereas other countries have granted foreign investors preferred treatment. The Chinese government imposes stricter restrictions on foreign investment than the Russian government (Alekseenko & Chengyuan, 2017), such as the Catalogue for the Guidance of Foreign Investment Industries, which lists restricted or prohibited areas of business activities for foreign investors. In some cases, the Chinese party must hold at least 50% of the shares. These restrictions suggest that China will prudently open its domestic market. In recent years, constant trade and non-trade conflicts between China and the U.S. created significant uncertainty regarding economic and stock market developments (Gu et al., 2021). It is not difficult to understand why the U.S.-China bilateral nexus has attracted the attention of and been exploited by numerous scholars. Wang et al. (2021) illustrated empirical proof of the different effects of trade disputes on the stock market. He et al. (2021) showed the heterogeneity of the impact caused by trade disputes, as trade disputes have positively affected the U.S. stock market but had negative effects on China's stock market. The sensitivity of the two parties' stock markets to trade disputes can vary and lead to some spillover effects on other sectors (Shen et al., 2022). Gu et al. (2021) describe the Chinese investors' responses to the anomalies caused by the U.S.-China trade disputes. To our understanding, there is a shortage of research examining the volatility spillovers from the Chinese stock market to the U.S. stock market over the past two decades. Thus, we aim to expand the scarce literature examining the volatility effects of China's equity market on the U.S. equity market and address several unanswered questions regarding this complicated relationship. To satisfy research purposes, we employed a variant of the EGARCH (1,1) model that accounts for structural breaks in the various time series (Vo & Tran, 2020). We anticipate that trade barriers between the U.S. and China and foreign investment restrictions in China will impede or mitigate the transmission of volatility risk from the Chinese to the U.S. stock markets. Accordingly, our paper seeks to shed light on two primary questions:

Q.1 Did volatility spillovers from the Chinese to the U.S. stock markets occur from January 2001 to October 2020?
Q.2 How did volatility transmission from the Chinese to the U.S. stock markets fluctuate over time?

The SARS-CoV-2 virus initiated the COVID-19 epidemic in mainland China at the end of December 2019. When cases outside of mainland China were detected with rapid infections and posed a threat to humanity, the epidemic has been considered a "global pandemic"[2] since March 2020 (Zorgati & Garfatta, 2021). In the first quarter of 2020, the stock market witnessed an unprecedented plunge (Jebabli et al., 2022). On the U.S. market, the S&P 500, Nasdaq Composite, and Dow Jones Industrial Average (DJIA) index changed by −20.0%, −14.2%, and −23.1%, respectively, from December 31, 2019, to March 31, 2020. In the Chinese market, the Shanghai Composite Index hit a 13-month low on March 23, 2020. At that time, the CSI 300 index suddenly fell 16%.[3] The COVID-19 tragedy created a heavy worldwide economic recession and severe stock market shocks (Frezza et al., 2021), and increases spillover transmission between equity markets (Liu et al., 2022). The COVID-19 pandemic raises unprecedented uncertainty, lowered securities valuations, and pushed financial markets to their lowest points since the 2008 GFC (Abuzayed et al., 2021). Fear of the negative impact of the tragic virus could increase the likelihood of a stock market crash. Huynh et al. (2021) showed that investors were more fearful during the COVID-19 pandemic than they did during the previous two financial crises. Through empirical investigation, Liu et al. (2021) found that fear sentiment drove the crash in China's stock market. Additionally, a higher level of stock market volatility was related to heightened fears of securities investors (Vuong, Nguyen, & Keung Wong, 2022). Maghyereh et al. (2022) discovered that the explosion in risk transmission and asymmetry emerged in the global equity market when the COVID-19 pandemic outstarted. Most especially, the contagion effect of bad volatility in the financial system is higher compared to the spillover effect of good volatility. Although China was the first COVID-19 epicenter in the world, the U.S. was the hardest-hit area by the COVID-19 pandemic in 2020. According to the U.S. Bureau of Economic Analysis (BEA), the GDP growth rate of the world's largest economy shrank to 3.5%, the lowest rate since 1946 and the first decline since the 2008 GFC. Zorgati and Garfatta (2021) demonstrated that the spatial spillover effect occurred between China and geographically remote countries, including the U.S.; conversely, it is absent in geographically close countries during the tragedy. Nevertheless, the catalytic role of the COVID-19 pandemic in volatility transmission from China's stock market to the U.S. equity market has not been addressed. Thus, the third hypothesis is proposed to fill an existing gap in the literature.

Q.3 Did the COVID-19 pandemic substantially motivate volatility spillovers from the Chinese to the U.S. stock markets in the early months of 2020?

[2] The announcement of the World Health Organization (WHO) on March 11, 2020.
[3] Source from Bloomberg.

3. Sample, methodology, and empirical models

3.1. Sample

Our primary aim is to investigate the volatility transmission from the Chinese to the U.S. equity markets from January 2001 to October 2020. The Standard & Poor's 500 Index (hereafter S&P500), the Nasdaq Composite Index, and the Dow Jones Industrial Average Index (hereafter DJIA) are the three U.S. stock market indexes we employed. The S&P500 Index is the one that best represents the U.S. stock market. The Shanghai Composite Index (hereafter SSEC) and the Shenzhen Composite Index (hereafter SZSC) are used to represent China's stock market. The Shanghai Composite Index is the primary indicator of the Chinese equity market. Our daily data about stock prices was acquired from Datastream/Thomson Reuters Eikon between January 2001 and October 2020.

3.2. Methodology

3.2.1. ICSS algorithm to detect structural breakpoints in the variance of volatility source returns

We employed the ICSS algorithm to certify the structural breakpoints in the Chinese stock market return variance (Inclan & Tiao, 1994). Then, using a variant form of the exponential generalized ARCH (EGARCH) model, we examined the effects of detected breakpoints on the volatility of U.S. stock market returns.

The ICSS algorithm provides an alternative hypothesis that unconditional variance is stationary over the period, separated by the volatility breakpoints. The following briefly summarizes the ICSS algorithm's steps for identifying structural breakpoints. Assuming N is the total observations in a time series; K represents the number of volatility breakpoints in the volatility of China's stock market returns; $C_1 < C_2 < \ldots < C_k$ are k breakpoints. During the observed period, the unconditional variance of stock returns on the Chinese market is illustrated in Eq. (1):

$$var\left(r_t^{CN}\right) = \{\sigma_0^2 \;\; 1 < t \leq C_1 \; \sigma_1^2 \;\; C_1 < t \leq C_2 \ldots \;\; \ldots \sigma_k^2 \;\; C_{k-1} < t \leq C_k \tag{Eq.(1)}$$

$$CRSS_j = \sum_{t=1}^{j} e_t^2 \tag{Eq.(2)}$$

where j = 1,2, …, N; $CRSS_j$ is the cumulative residual sum of squares from the beginning of the time series to the j^{th} date, presented in Eq. (2). Assuming j equals N, C_N is the residual sum of squares of all observations, and D_j is used for statistical testing at j^{th} break date, defined by Eq. (3),

$$D_j = \left[\frac{C_j}{C_N}\right] - \frac{j}{N} \tag{Eq. (3)}$$

$D_0 = D_N = 0$ indicating that the first and last test statistics corresponding to the first and last observations, respectively, are equal to zero. If there is no change in the variance (null hypothesis H_0: no breakpoint), the test statistic (D_j) will fluctuate around the "zero" value. Following the null hypothesis, D_j fluctuates between the critical lower and upper bounds. If D_j's absolute value exceeds the critical values, the null hypothesis (H_0) will be rejected, and we conclude that a volatility breakpoint exists. This procedure is repeated on subsamples to possibly identify multiple breakpoints in a long time series. This is an advantage of the ICSS algorithm compared with Andrews's (1993) method. However, the ICSS algorithm only uses unconditional variance (Smith, 2008). In this research, MATLAB software is used to implement the ICSS algorithm to recognize the volatility breakpoints of China's stock market return volatility. After completing this process, we examined the volatility transmission from the Chinese to the U.S. equity markets using a variant form of the EGARCH (1,1) model with control over the excessive volatility breakpoints of the Chinese stock market returns in the volatility equation of U.S. stock market returns.

3.3. Modeling the volatility spillovers from the Chinese to the U.S. stock markets

The GARCH-style approach has received special consideration in the majority of previous works on volatility pattern analysis (Arouri et al., 2011). Nelson (1991) succeeded in developing the EGARCH model to measure and forecast stock return volatility. The original form of the EGARCH (1,1) model has the following form:

$$log\;(h_t) = \omega + \alpha\left|\frac{u_{t-1}}{\sqrt{h_{t-1}}}\right| + \beta\frac{u_{t-i}}{\sqrt{h_{t-i}}} + (h_{t-1}) \tag{Eq. (4)}$$

where h_t is the variance of stock returns, ω is constant, α expresses the ARCH effect, θ shows the GARCH effect, and β presents the asymmetric effect. In the case of ß<0, it indicates that bad news (negative shocks) generates more enormous volatility than good news (positive shocks).

Reyes (2001) used a bivariate AR (1)-EGARCH (1,1) model to detect the volatility transmission between different-sized stock indexes on the Tokyo stock market. Krause and Tse (2013) also employed a bivariate EGARCH (1,1) model to determine the spillover effect from the U.S. to the Canadian equity markets. The AR (1) model is used for adjusting the return series. Thus, we use the combination AR (1) model and a variant form of the EGARCH (1,1) model to investigate whether the excessive volatility breakpoints of

China's stock market possess an effect on the volatility of the U.S. stock market. The experimental model is represented by Eq. (5), as follows:

$$r\_US_t = a_0 + a_1 r\_US_{t-1} + \varepsilon_t \ \sim N(0, v\_US_t) \quad \text{Eq. (5)}$$

$$log\ (v\_US_t\Big) = \beta_0 + \beta_1 \left|\frac{\varepsilon_{t-1}}{\sqrt{v\_US_{t-1}}}\right| + \pi_j CNbreakpoint_j + log\ (\beta_2 v\_US_{t-1}\Big)$$

where r_US_t denotes the stock returns of the U.S. stock market on day (t); v_US_t denotes the variance of U.S. stock market returns on day (t); and $CNbreakpoint_j$ is an excessive volatility breakpoint dummy variable (j) at a structural breakpoint (j^{th}) in the variance of the Chinese stock market returns. A dummy variable (j) equals 1 from a breakpoint $(j-1)^{th}$ to a breakpoint (j^{th}) and 0 elsewhere. The coefficient (π_j) denotes the effect of the structural breakpoint ($CNbreakpoint_j$) of China's equity market volatility on the volatility of the U.S. equity market.

For another volatility measure of China's stock market returns, we mainly focus on the S&P500 Index of the U.S. stock market and the SSEC Index of China's stock market. In Eq. (6), the variance of the Chinese stock market returns (VOL_SSEC) is added to the variance equation of the EGARCH (1,1) model to replace the breakpoint dummy variables in Eq. (5), as follows:

$$r\_S\&P500_t = a_0 + a_1 r\_S\&P500_{t-1} + \varepsilon_t \ \sim N(0, v\_S\&P500_t) \quad \text{Eq. (6)}$$

$$log\ (v\_S\&P500_t\Big) = \beta_0 + \beta_1 \left|\frac{\varepsilon_{t-1}}{\sqrt{v\_\&P500_{t-1}}}\right| + \Omega VOL\_SSEC + log\ (\beta_2 v\_S\&P500_{t-1}\Big)$$

where $r\_S\&P500_t$ denotes the stock return of the S&P500 Index;$v\_\&P500_t$ denotes the variance of S&P500 returns; VOL_SSEC is the variance of SSEC returns; and Ω coefficient represents the effect extent of the variance of China's stock market returns on the volatility of U.S. equity market returns. We use sub-samples corresponding to the pre-2004 period[4] and post-2004 period to clarify the extent of volatility transmission from China's stock market to the U.S. stock market before and after China's economy became the second global largest, based on the PPP Index in 2004.

4. Analyzing empirical results for the volatility spillovers from the Chinese to the U.S. stock markets

4.1. Fundamental analyses

Descriptive statistics for the entire stock market returns in both the Chinese and U.S. equity markets are displayed in Table 1, including the Shanghai Composite returns (R_SSEC), Shenzhen Composite returns (R_SZSC), S&P500 returns (R_S&P500), Nasdaq Composite returns (R_IXIC) and DJIA returns (R_DJIA). Overall, the mean values of stock returns range from 0.0001 to 0.0003. The standard deviation indicators demonstrate the Chinese stock market returns are less stable than those of the U.S. market. Generally, emerging equity markets have seemed more volatile than developed stock markets.

The stationary tests for the stock return series on the Chinese and U.S. stock markets are displayed in Table 2. We employ the Augmented Dickey and Fuller (1979) – ADF test, the Phillip and Perron (1988) PP test, and the Kwiatkowski et al. (1992) KPSS test. The results of the ADF and PP tests reject the non-stationarity of the null hypothesis (H_0) at a significance level of 1% for both stock market returns in China and the U.S. The KPSS test's findings cannot dismiss the stationarity of the null hypothesis (H_0) for both the U. S. stock market returns and China's stock market returns at any significant level. All stationary tests conclude that all stock returns on both the stock markets of China and the U.S. are stationary.

The ICSS algorithm is utilized by MATLAB software to detect structural breakpoints in the variance of China's stock market returns. From January 2001 to October 2020, we observed 26 structural breakpoints in the variance of Shanghai Composite returns, and 22 structural breakpoints in the variance of the Shenzhen Composite returns. All break dates corresponding to the detected breakpoints are presented in Table 3. Two of China's stock market indexes experienced excessive volatility on March 26, 2020. Fig. 2 describes the structural breakpoints in the variance of the Chinese stock market returns as the red vertical lines sequentially for the SSEC Index and the SZSC Index.

Table 4 lists the estimated results of the AR (1)-EGARCH (1,1) model of the volatility of U.S. stock market returns, excluding the detected volatility breakpoints in Table 3. Results corresponding to the S&P500 Index, the DJIA Index, and the Nasdaq Composite Index are respectively presented in Column (1), Column (2), and Column (3).

4.2. Empirical results for the volatility spillovers from the Chinese to the U.S. stock markets

4.2.1. Modeling the volatility of S&P500 returns by using structural breakpoints in the variance of the Chinese stock market returns

First, we investigated the volatility spillovers from the Chinese stock market to the S&P500 Index of the U.S. stock market using the volatility breakpoints of the Shanghai Composite (SSEC) returns and the Shenzhen Composite (SZSC) returns. Table 5 reports the

[4] The pre-2004 period is determined from January 2001 to December 2003, and the post-2004 period starts from January 2004 to October 2020.

Table 1
Summarize statistics.

Indicator	Chinese stock market		U.S. stock market		
	R_SSEC	R_SZSC	R_S&P500	R_DJIA	R_IXIC
Mean	0.0001	0.0003	0.0002	0.0002	0.0003
Median	0.0006	0.0013	0.0006	0.0005	0.0010
Maximum	0.0940	0.0924	0.1096	0.1076	0.1325
Minimum	−0.0926	−0.0893	−0.1277	−0.1384	−0.1315
Std. Dev.	0.0156	0.0176	0.0125	0.0120	0.0149
Obs.	4807	4805	4989	4989	4989

Note: R_SSEC is the Shanghai Composite's returns; R_SZSC is the Shenzhen Composite's returns; R_S&P500 is the S&P500's returns; R_IXIC is the Nasdaq Composite's returns; R_DJIA is the Dow Jones Industrial Average's returns. The daily stock prices are downloaded from Datastream/Thomson Reuter Eikon from January 2001 to October 2020.

Table 2
Unit root tests.

Stationarity tests	Chinese stock market		U.S. stock market		
	R_SSEC	R_SZSC	R_S&P500	R_DJIA	R_IXIC
ADF test	−67.9529 [c]	−64.8896 [c]	−79.8016 [c]	−79.7435 [c]	−76.5705 [c]
PP test	−68.0028 [c]	−65.1794 [c]	−80.0609 [c]	−79.7853 [c]	−76.6733 [c]
KPSS test	0.0788	0.1100	0.1916	0.1176	0.2784
Test critical values		1% level			−3.4315
		5% level			−2.8619
		10% level			−2.5670
Asymptotic critical values:		1% level			0.7390
		5% level			0.4630
		10% level			0.3470

Note: [a] significant at 10% level; [b] significant at 5% level; [c] significant at 1% level; ADF is Augmented Dickey–Fuller test; PP is Phillip – Perron test; KPSS test is Kwiatkowski-Phillips-Schmidt-Shin test; where.
+ ADF and PP tests give the Null hypothesis (H_0): "the stock return series is non-stationary", where.
+ KPSS test give the Null hypothesis (H_0): "the stock return series is stationary", where.

estimated results of the AR (1)-EGARCH (1,1) model for the 26 volatility breakpoints of the SSEC returns in Column (1) and the 22 volatility breakpoints of the SZSC returns in Column (2), respectively.

In the post-2004 period, the volatility of the S&P500 returns was persistently and negatively impacted by the volatility shocks of the SSEC returns, as indicated by the empirical results in column (1). After 2003, most dummy variables corresponding with volatility breakpoints in the variance of the SSEC returns were significant and negative in the variance equation. A notable volatility breakpoint was on March 26, 2020. The coefficient is at the 1% level of significance and above 0.1. This indicates that this volatility breakpoint of the SSEC returns has the greatest and most positive effect on the volatility of the S&P500 returns. The international equity market was not immune to the consequence of the COVID-19 tragedy, which began in China at the end of 2019. The crash in the global stock market occurred from February 20, 2020, to April 7, 2020. This event is comparable to the 1929 Wall Street Crash. The most extensive global stock indexes, including the S&P500 Index, the SSEC Index, the Nikken 225 Index, the Nasdaq Composite Index, and the KOSPI Index, all declined on March 23, 2020. Thus, it is not surprising that the volatility breakpoint of the SSEC returns at the end of March 2020 has the most negative impact on the U.S. stock market volatility.

Aside from the SSEC Index, the Shenzhen Composite (SZSC) Index is equally representative of the Chinese stock market. In succession, we use the AR (1)-EGARCH (1,1) model to estimate the volatility transmission from the SZSC Index to the S&P500 Index. Overall, the empirical results in column (2) are comparatively identical to those in column (1). The majority of dummy variables in the variance equation are significantly and negatively linked with the volatility of the S&P500 returns, indicating that the volatility jumps in the Chinese stock market have affected continuously and negatively the volatility of the U.S. stock market since 2004. Similar to the SSEC Index, there is a volatility breakpoint of the SZSC returns on March 26, 2020, with a coefficient value greater than 0.1. The findings in Table 5 illustrate strong evidence that the devastating impact of the COVID-19 pandemic onset from China accelerates the positive volatility spread from the Chinese to the U.S. stock market in March 2020.

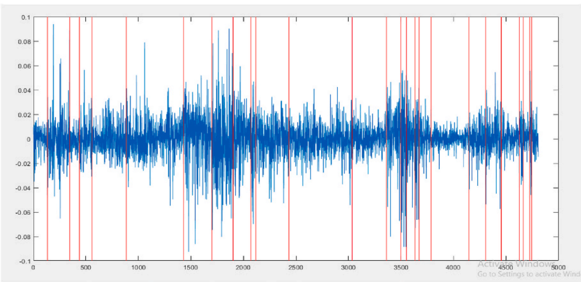
4.2.2. Modeling the return volatility of other U.S. Stock indexes using structural breakpoints in the variance of the Chinese stock market returns

Two robust tests were conducted with other U.S. stock market indexes, namely, the DJIA Index and the Nasdaq Composite Index, to strengthen our results in Table 5. First, we applied the ICSS algorithm to both the SSEC and the SZSC returns to detect breakpoints in

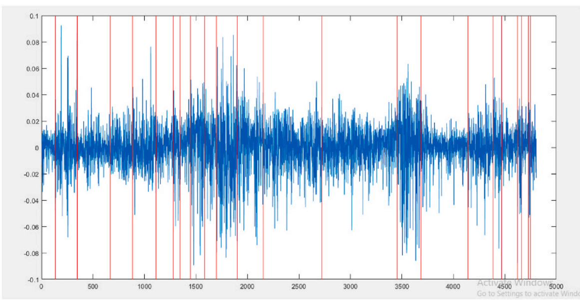
Table 3
Break dates corresponding to structural breakpoints are detected in the variance of Chinese stock market returns.

Structural breakpoints	SSEC	SZSC
1	30-Jul-2001	30-Jul-2001
2	25-Jun-2002	25-Jun-2002
3	8-Nov-2002	22-Oct-2003
4	16-May-2003	9-Sep-2004
5	9-Sep-2004	19-Aug-2005
6	8-Dec-2006	8-May-2006
7	21-Jan-2008	9-Aug-2006
8	20-Nov-2008	8-Jan-2007
9	29-Jul-2009	3-Aug-2007
10	12-Oct-2009	21-Jan-2008
11	24-Jan-2011	20-Nov-2008
12	24-Jul-2013	2-Dec-2009
13	21-Nov-2014	6-Apr-2012
14	16-Jun-2015	15-Apr-2015
15	31-Aug-2015	22-Mar-2016
16	4-Jan-2016	31-Jan-2018
17	3-Mar-2016	1-Feb-2019
18	16-Aug-2016	12-Jun-2019
19	6-Feb-2018	23-Jan-2020
20	8-Oct-2018	*26-Mar-2020*
21	20-May-2019	6-Jul-2020
22	23-Jan-2020	4-Aug-2020
23	4-Feb-2020	
24	*26-Mar-2020*	
25	1-Jul-2020	
26	27-Jul-2020	

Note: Break dates corresponding to volatility breakpoints are detected in the variance of the Chinese stock market returns from January 2001 to October 2020 by using the ISCC algorithm. Which, Chinese stock market includes two indexes.
- SSEC's return is the stock return of Shanghai Composite Index.
- SZSC's return is the stock return of the Shenzhen Composite Index.



26 breakpoints are detected in the variance of SSEC's returns



22 breakpoints are detected in the variance of SZSC's returns

Fig. 2. The structural breakpoints in the variance of Chinese stock market returns are detected by the ICSS algorithm (January 2001–October 2020).

Table 4
Modeling the volatility of stock market returns without using the detected structural breakpoints.

U.S. stock market								
S&P500 Index (1)			DJIA Index (2)			Nasdaq Composite Index (3)		
Variables	Coefficient	Std. Err	Variables	Coefficient	Std. Err	Variables	Coefficient	Std. Err
Mean Equation:								
Constant	0.0007 [c]	0.0001	Constant	0.0007 [c]	0.0001	Constant	0.0008 [c]	0.0001
R_S&P500(-1)	−0.0694 [c]	0.0150	R_DJIA(-1)	−0.0515 [c]	0.0145	R_IXIC(-1)	−0.0407 [c]	0.0149
Variance Equation:								
Constant	−0.4374 [c]	0.0275	Constant	−0.4397 [c]	0.0283	Constant	−0.3438 [c]	0.0257
L.EGARCH	0.2546 [c]	0.0112	L.EGARCH	0.2601 [c]	0.0108	L.EGARCH	0.2072 [c]	0.0109
L.ARCH	0.9734 [c]	0.0023	L.ARCH	0.9739 [c]	0.0024	L.ARCH	0.9790 [c]	0.0022

Note: a significant at 10% level; b significant at 5% level; c significant at 1% level.

Table 5
Modeling the volatility of S&P500's returns using structural breakpoints in the variance of Chinese stock market returns.

Variable	Shanghai Composite Index (1)			Shenzhen Composite Index (2)		
	Break date	Coefficient	Std. Err	Break date	Coefficient	Std. Err
Mean Equation						
Constant		−0.0007 [c]	0.0001		−0.0007 [c]	0.0001
R_S&P500(-1)		−0.0676 [c]	0.0163		−0.0678 [c]	0.0159
Variance Equation						
Constant		−0.7176 [c]	0.0713		−0.6888 [c]	0.0694
L.EGARCH		0.2347 [c]	0.0132		0.2392 [c]	0.0131
L.ARCH		0.9369 [c]	0.0069		0.9390 [c]	0.0067
Break point 1	30-Jul-2001	−0.0145	0.0249	30-Jul-2001	−0.0283	0.0261
Break point 2	25-Jun-2002	−0.0125	0.0230	25-Jun-2002	−0.0253	0.0243
Break point 3	8-Nov-2002	0.0411	0.0347	22-Oct-2003	−0.0282	0.0246
Break point 4	16-May-2003	−0.0082	0.0277	9-Sep-2004	−0.0960 [c]	0.0258
Break point 5	9-Sep-2004	−0.0789 [c]	0.0232	19-Aug-2005	−0.1078 [c]	0.0263
Break point 6	8-Dec-2006	−0.0960 [c]	0.0221	8-May-2006	−0.1071 [c]	0.0265
Break point 7	21-Jan-2008	−0.0264	0.0206	9-Aug-2006	−0.0655 [a]	0.0348
Break point 8	20-Nov-2008	0.0478 [a]	0.0248	8-Jan-2007	−0.1376 [c]	0.0277
Break point 9	29-Jul-2009	0.0436	0.0275	3-Aug-2007	−0.0383 [a]	0.0225
Break point 10	12-Oct-2009	−0.0372	0.0335	21-Jan-2008	−0.0209	0.0269
Break point 11	24-Jan-2011	−0.0368 [a]	0.0214	20-Nov-2008	0.0323	0.0259
Break point 12	24-Jul-2013	−0.0493 [b]	0.0205	2-Dec-2009	0.0018	0.0251
Break point 13	21-Nov-2014	−0.0967 [c]	0.0225	6-Apr-2012	−0.0441 [b]	0.0219
Break point 14	16-Jun-2015	−0.0729 [c]	0.0264	15-Apr-2015	−0.0928 [c]	0.0225
Break point 15	31-Aug-2015	0.0058	0.0309	22-Mar-2016	−0.0556 [b]	0.0247
Break point 16	4-Jan-2016	−0.0440	0.0315	31-Jan-2018	−0.1110 [c]	0.0235
Break point 17	3-Mar-2016	−0.0246	0.0505	1-Feb-2019	−0.0546 [b]	0.0226
Break point 18	16-Aug-2016	−0.0940 [c]	0.0235	12-Jun-2019	−0.0922 [c]	0.0278
Break point 19	6-Feb-2018	−0.0996 [c]	0.0224	23-Jan-2020	−0.1138 [c]	0.0267
Break point 20	8-Oct-2018	−0.0742 [c]	0.0231	26-Mar-2020	0.1491 [c]	0.0440
Break point 21	20-May-2019	−0.0341 [a]	0.0205	6-Jul-2020	0.0033	0.0263
Break point 22	23-Jan-2020	−0.1010 [c]	0.0251	4-Aug-2020	−0.1979 [c]	0.0801
Break point 23	4-Feb-2020	0.0720	0.1194			
Break point 24	26-Mar-2020	0.1817 [c]	0.0516			
Break point 25	1-Jul-2020	0.0208	0.0254			
Break point 26	27-Jul-2020	−0.1828 [b]	0.0835			

Note: [a] significant at 10% level; [b] significant at 5% level; [c] significant at 1% level.

their volatility. Then, we respectively estimated the volatility modeling of the DJIA Index using the detected volatility breakpoints corresponding to the SSEC Index in column (1) and the SZSC Index in column (2) of Table 6. This process was repeated for the Nasdaq Composite Index, and the estimated results from the AR (1)-EGARCH (1,1) model are presented in Table 7.

Results in Tables 6 and 7 are mainly identical to those presented in Table 5. Simply put, the empirical results using the DJIA Index and the Nasdaq Composite Index are consistent with the conclusions of the S&P500 Index. After 2003, the SSEC Index and the SZSC Index's volatility shocks had a negative and enduring effect on the volatility of both the DJIA Index and the Nasdaq Composite Index. Most essentially, the coefficient of the breakpoint dummy variable on March 26, 2020, was significant and greater than 0.1. In contrast, the rest of the breakpoint dummy variables influenced the volatility of U.S. stock market returns significantly and negatively. Obviously, when the COVID-19 pandemic broke out in March 2020, there was a positive volatility transmission from the Chinese to the U.S. stock markets. In other words, empirical findings regarding the volatility transmission from the Chinese to the U.S. stock markets are robust across all stock indexes.

Table 6
Modeling the volatility of DJIA's returns using structural breakpoints in the variance of Chinese stock market returns.

Variable	Shanghai Composite Index (1)			Shenzhen Composite Index (2)		
	Break date	Coefficient	Std. Err	Break date	Coefficient	Std. Err
Mean Equation						
Constant		0.0007 [c]	0.0001		0.0007 [c]	0.0001
R_DJIA(-1)		−0.0489 [c]	0.0160		−0.0509 [c]	0.0157
Variance Equation						
Constant		−0.7188 [c]	0.0711		−0.7059 [c]	0.0709
L.EGARCH		0.2391 [c]	0.0125		0.2445 [c]	0.0125
L.ARCH		0.9385 [c]	0.0069		0.9390 [c]	0.0069
Break point 1	30-Jul-2001	−0.0081	0.0273	30-Jul-2001	−0.0203	0.0292
Break point 2	25-Jun-2002	0.0002	0.0250	25-Jun-2002	−0.0115	0.0271
Break point 3	8-Nov-2002	0.0538	0.0337	22-Oct-2003	−0.0167	0.0279
Break point 4	16-May-2003	0.0030	0.0306	9-Sep-2004	−0.0865 [c]	0.0298
Break point 5	9-Sep-2004	−0.0706 [c]	0.0265	19-Aug-2005	−0.0883 [c]	0.0285
Break point 6	8-Dec-2006	−0.0847 [c]	0.0252	8-May-2006	−0.1030 [c]	0.0303
Break point 7	21-Jan-2008	−0.0253	0.0243	9-Aug-2006	−0.0528	0.0384
Break point 8	20-Nov-2008	0.0519 [a]	0.0277	8-Jan-2007	−0.1375 [c]	0.0329
Break point 9	29-Jul-2009	0.0369	0.0287	3-Aug-2007	−0.0413	0.0272
Break point 10	12-Oct-2009	−0.0536	0.0358	21-Jan-2008	−0.0151	0.0301
Break point 11	24-Jan-2011	−0.0362	0.0245	20-Nov-2008	0.0393	0.0295
Break point 12	24-Jul-2013	−0.0485 [b]	0.0241	2-Dec-2009	−0.0030	0.0284
Break point 13	21-Nov-2014	−0.0896 [c]	0.0264	6-Apr-2012	−0.0414 [a]	0.0250
Break point 14	16-Jun-2015	−0.0492 [a]	0.0286	15-Apr-2015	−0.0879 [c]	0.0270
Break point 15	31-Aug-2015	0.0100	0.0350	22-Mar-2016	−0.0526 [a]	0.0291
Break point 16	4-Jan-2016	−0.0412	0.0351	31-Jan-2018	−0.1009 [c]	0.0276
Break point 17	3-Mar-2016	−0.0371	0.0560	1-Feb-2019	−0.0415	0.0269
Break point 18	16-Aug-2016	−0.0872 [c]	0.0272	12-Jun-2019	−0.0787 [b]	0.0313
Break point 19	6-Feb-2018	−0.0866 [c]	0.0254	23-Jan-2020	−0.0871 [c]	0.0295
Break point 20	8-Oct-2018	−0.0586 [b]	0.0261	26-Mar-2020	0.1723 [c]	0.0473
Break point 21	20-May-2019	−0.0262	0.0276	6-Jul-2020	0.0278	0.0312
Break point 22	23-Jan-2020	−0.0744 [c]	0.0271	4-Aug-2020	−0.1408 [a]	0.0726
Break point 23	4-Feb-2020	0.1202	0.1058			
Break point 24	26-Mar-2020	0.1976 [c]	0.0536			
Break point 25	1-Jul-2020	0.0433	0.0296			
Break point 26	27-Jul-2020	−0.1432 [a]	0.0774			

Note: [a] significant at 10% level; [b] significant at 5% level; [c] significant at 1% level.

4.2.3. Modeling the volatility of U.S. Stock market returns by using the variance of China's stock market returns

In 2004, after nearly three decades of economic reform and opening, the Chinese economy continued to assert its position in the international market as a powerful economy alongside the U.S. economy. It is more likely that the volatility of the Chinese stock market will significantly impact the volatility of other equity markets (Allen et al., 2013). Using another volatility measure of China's stock market, we investigated its impact on the volatility of the U.S. stock market returns. The variance of SSEC returns is used to calculate the volatility of Chinese stock market returns. The volatility of S&P500 returns represents the volatility of the U.S. stock market returns. To shed light on our findings in Tables 5–7, we examine the volatility transmission from the Chinese to the U.S. stock markets during different periods (pre-2004, post-2004, and whole sample), respectively, in columns (1), (2) and (3) of Table 8.

First, the coefficient of the VOL_SSEC variable is negatively and significantly associated with the volatility of S&P500 returns in column (3), suggesting that the volatility jumps in China's stock market negatively impact the volatility of the U.S. stock market. Second, the VOL_SSEC variable's negative coefficient is significant in the period after 2004 but not before 2004. Empirical results from various subperiods demonstrated that since 2004, the volatility of the Chinese stock market has negatively influenced and persistently the volatility of the U.S. stock market. To put it in another way, the estimated results in Tables 5–7 are robust even though we employed an alternative measure of the volatility of the Chinese stock market returns.

5. Conclusions and policy implications

Several months after the COVID-19 outbroke in China, this pandemic has spread steadily worldwide and threatened global health. Nevertheless, its adverse impact on other sectors, including global financial markets, might take more time to recover. This explains our motivation for conducting this research which covers an extensive range of selected data from stock markets in China and the U.S. Our findings have shown that this global tragedy still has a significant and long-lasting impact on various financial markets. Nowadays, China represents the largest global emerging market while the U.S. represents the most developed market. This study examines the volatility transmission path from the Chinese to the U.S. stock market as predicted by the U.S.-China bilateral relationship and the limits of foreign investment policy in the Chinese financial sector a long time ago. Our paper analyzes the devastating effect of the COVID-19 tragedy, which originated in China in early 2020, using the daily stock market prices of China and the U.S. from January 2001 to October 2020. We apply a variant form of the EGARCH (1,1) model with control over the excessive volatility breakpoints of the

Table 7
Modeling the volatility of Nasdaq Composite's returns using structural breakpoints in the variance of Chinese stock market returns.

Variable	Shanghai Composite Index (1)			Shenzhen Composite Index (2)		
	Break date	Coefficient	Std. Err	Break date	Coefficient	Std. Err
Mean Equation						
Constant		0.0008 [c]	0.0001		0.0008 [c]	0.0001
R_IXIC(-1)		−0.0362 [b]	0.0157		−0.0367 [b]	0.0155
Variance Equation						
Constant		−0.5961 [c]	0.0708		−0.5704 [c]	0.0669
L.EGARCH		0.1868 [c]	0.0136		0.1881 [c]	0.0137
L.ARCH		0.9434 [c]	0.0076		0.9456 [c]	0.0071
Break point 1	30-Jul-2001	0.0299	0.0246	30-Jul-2001	0.0188	0.0250
Break point 2	25-Jun-2002	0.0151	0.0193	25-Jun-2002	0.0059	0.0201
Break point 3	8-Nov-2002	0.0207	0.0339	22-Oct-2003	−0.0222	0.0196
Break point 4	16-May-2003	−0.0128	0.0214	9-Sep-2004	−0.0625 [c]	0.0219
Break point 5	9-Sep-2004	−0.0501 [c]	0.0192	19-Aug-2005	−0.0988 [c]	0.0221
Break point 6	8-Dec-2006	−0.0881 [c]	0.0191	8-May-2006	−0.1035 [c]	0.0236
Break point 7	21-Jan-2008	−0.0512 [c]	0.0179	9-Aug-2006	−0.0484	0.0309
Break point 8	20-Nov-2008	0.0203	0.0191	8-Jan-2007	−0.0995 [c]	0.0225
Break point 9	29-Jul-2009	0.0091	0.0211	3-Aug-2007	−0.0635 [c]	0.0195
Break point 10	12-Oct-2009	−0.0565 [c]	0.0265	21-Jan-2008	−0.0407 [a]	0.0239
Break point 11	24-Jan-2011	−0.0550 [c]	0.0180	20-Nov-2008	0.0105	0.0199
Break point 12	24-Jul-2013	−0.0606 [c]	0.0175	2-Dec-2009	−0.0221	0.0195
Break point 13	21-Nov-2014	−0.0913 [c]	0.0199	6-Apr-2012	−0.0545 [c]	0.0179
Break point 14	16-Jun-2015	−0.0854 [b]	0.0228	15-Apr-2015	−0.0910 [c]	0.0193
Break point 15	31-Aug-2015	−0.0058	0.0269	22-Mar-2016	−0.0604 [c]	0.0200
Break point 16	4-Jan-2016	−0.0575 [c]	0.0258	31-Jan-2018	−0.0968 [c]	0.0205
Break point 17	3-Mar-2016	−0.0235	0.0358	1-Feb-2019	−0.0512 [c]	0.0191
Break point 18	16-Aug-2016	−0.0887 [c]	0.0208	12-Jun-2019	−0.0715 [c]	0.0219
Break point 19	6-Feb-2018	−0.0909 [c]	0.0203	23-Jan-2020	−0.1067 [c]	0.0235
Break point 20	8-Oct-2018	−0.0704 [c]	0.0208	26-Mar-2020	0.1189 [c]	0.0376
Break point 21	20-May-2019	−0.0305	0.0193	6-Jul-2020	−0.0288	0.0206
Break point 22	23-Jan-2020	−0.0989 [c]	0.0227	4-Aug-2020	−0.0869	0.0589
Break point 23	4-Feb-2020	0.0465	0.1225			
Break point 24	26-Mar-2020	0.1433 [c]	0.0446			
Break point 25	1-Jul-2020	−0.0200	0.0199			
Break point 26	27-Jul-2020	−0.0640	0.0605			

Note: [a] significant at 10% level; [b] significant at 5% level; [c] significant at 1% level.

Table 8
Modeling the volatility of U.S. stock market returns using the variance of Chinese stock market returns for the different sub-periods.

Period	Pre-2004	Post-2004	Whole sample
Variable	(1)	(2)	(3)
Mean equation			
Constant	−0.0003 (0.0003)	−0.0007 [c] (0.0001)	−0.0007 [c] (0.0001)
R_S&P500(-1)	−0.0230 (0.0366)	−0.0781 [c] (0.0170)	−0.0700 [c] (0.0155)
Variance equation			
Constant	−0.1798 [a] (0.0939)	−0.0786 [c] (0.1074)	−0.3518 [c] (0.0722)
L.EGARCH	0.1513 [c] (0.0268)	0.2780 [c] (0.0132)	0.2603 [c] (0.0113)
L.ARCH	0.9910 [c] (0.0055)	0.9635 [c] (0.0034)	0.9705 [c] (0.0026)
VOL_SSEC	−0.0056 (0.0197)	−0.1303 [c] (0.0317)	−0.0320 [a] (0.0180)

Note: [a] significant at 10% level; [b] significant at 5% level; [c] significant at 1% level; R_S&P500 is the S&P500's returns and VOL_SSEC is the variance of SSEC's returns from January 2001 to October 2020. In which.
(1) The pre-2004 period starts from January 2001 to December 2003.
(2) The post-2004 period starts from January 2004 to October 2020.

Chinese stock market returns.

Our study asserts that globalization certainly facilitates the spread of volatility in the international equity market. This connection between the Chinese stock markets and the U.S. is not exceptional. This paper demonstrates that the nature of the bilateral U.S.-China relationship and the mechanism for foreign financial investment in China over many decades significantly influence the degree of volatility transmission between the two largest global equity markets. Most importantly, the global market's tremendous crash (March 2020) acts as a vigorous stimulant for the volatility contagion between the equity markets of China and the U.S. Estimated results showed that the volatility of the U.S. stock market has been influenced frequently and negatively by the volatility of the Chinese stock market since 2004. When the first COVID-19 wave emerged and unexpectedly engulfed the entire international stock market, particularly the U.S. market, we detected that the most significant positive volatility spillover from the Chinese stock market to the U.S.

stock market occurred at the end of March 2020.

Our paper suggests several policy implications, as follows: First, during the past two decades, the degree of integration between the U.S. and China's stock markets has been minimal. Possible causes comprise the U.S.-China bilateral nexus and the limitations of foreign investment policy in the Chinese financial sector, which have persisted for many years. Therefore, we can assert that China has been slowly and carefully opening its market to combat the manipulation of foreign investors, especially those in the U.S. market. Second, despite the fear of Chinese investors and extreme shocks in China's equity market having a strong impact, they could not amplify the tremendous confusion among U.S. investors. Yet the COVID-19 pandemic, acting as an irritant, has significantly raised the fear of investment risks from the Chinese and U.S. stock markets. Third, our empirical evidence is useful for securities investors in both China and the U.S. equity markets in mitigating the risks associated with their investment decisions. Further, this study implies that financial derivatives for hedging stock volatility are essential for securities investors, especially when facing colossal stock market crashes. Four, the removal of barriers in the U.S.-China bilateral relationship and foreign investment restrictions in the Chinese financial sector is necessary to attract investments from their partners, thereby increasing capital mobility in the international equity market.

CRediT authorship contribution statement

Giang Thi Huong Vuong: Conceptualization, design of study, Data curation, Formal analysis, Writing – original draft, Revising the manuscript critically for important intellectual content. **Manh Huu Nguyen:** Data curation, Formal analysis, Writing – original draft, Revising the manuscript critically for important intellectual content. **Anh Ngoc Quang Huynh:** Formal analysis, Revising the manuscript critically for important intellectual content, Approval of the version of the manuscript to be published (the names of all authors must be listed).

Declaration of competing interest

All authors declare that (s)he has no relevant or material financial interests that relate to the research described in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeca.2022.e00276.

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