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What influences stock market co-movements between China and its Asia-Pacific trading partners after the Global Financial Crisis?

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ABSTRACT

This paper investigates the stock market co-movements between China and its 12 trading partners in the Asia-Pacific region after the Global Financial Crisis. The Dynamic Conditional Correlation (DCC) - Mixed Data Sampling (MIDAS) model is adopted to extract short and long-run correlations. The author utilizes the weekly conditional correlations to detect contagion and explores transmission mechanisms by regressing the monthly economic and financial variables on the monthly conditional correlations. The empirical results show that recent events (specifically, the Shanghai stock market crash, the US-China tariff war, and the COVID-19 pandemic) have increased the contagion incidences across the stock markets in China and its trading partners. Moreover, bilateral trade and market similarities are major drivers of stock market co-movements between China and developed partners as well as between China and emerging partners. Apart from country-pair-specific factors, common factors (such as the Chinese illiquidity pressure) also affect the co-movements between Chinese and its partners' stock markets during the whole and turmoil periods. Besides, the regression results for contagion episodes are mixed. On the one hand, stock market co-movements are irrelevant to most economic fundamentals, indicating pure contagion. On the other hand, differences in industrial production growth and market size affect stock market co-movements between China and its emerging partners.

1. Introduction

Due to advances in financial liberalization and increases in intraregional investment through financial markets, stock markets in Asia-Pacific are experiencing regional integration (Kim and McKenzie, 2008). On the one hand, deeper financial integration can promote the unification of financial resources, and therefore stimulate the growth of the real economy. On the other hand, cross-border capital flows can be volatile and aggravate market risk. Meanwhile, coordination of financial development across countries can enhance co-movements (i.e., volatility linkages) between stock markets, raising concerns about global asset allocation, as asset prices in different markets are simultaneously affected by unexpected shocks. Ongoing financial integration in this region is complicated, with varying levels of development in stock markets, including both highly developed markets (such as those in the United States) and newly emerging markets (mainly in Asia). Compared to sophisticated stock markets in developed countries, emerging stock markets are rapidly growing in market capitalization and trading volumes. The surge and growth of those emerging markets benefit from the economic success of Asian economies, which attracted international capital flows, and China is at the centre of this.

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Although China established its stock market exchanges in the 1990s, later than many other countries in the Asia-Pacific region, by the end of January 2021,[1] the scale of the Chinese stock market ranked as the third-largest in the world, after markets in Japan and the United States. The Chinese stock market rapidly reached such a large scale over a limited period of 30 years and gradually improved the country's level of financial openness. Furthermore, some scholars believe that the rapid rise of the stock market in China since the 2000s augments China's financial influence on other regional stock markets compared to that of the United States (Kim et al., 2015a, 2015b). The rising power of China on the financial markets in the Asia-Pacific region is probably associated with its stronger connections with other countries, especially in the form of trade ties. After officially joining the World Trade Organization (WTO) in 2000, China is now embedded more and more deeply into global value chains (GVCs) and has increased its share in global trade to nearly 15% (China: The rise of a trade titan | UNCTAD, 2021(Website)). The leading position of China in the global economy reinforces the process of liberalizing domestic financial markets to attract capital flows and therefore consolidate Chinese financial influence. Moreover, along with the success of negotiations for the Regional Comprehensive Economic Partnership (RCEP) trade deal,[2] there is a prospect that the Asia-Pacific region will gradually recover from the protectionism accelerated by US-China trade frictions and China's expanding influence on other countries in this region will remain in future years (Shimizu, 2021).

Given the crucial role China plays in the Asia-Pacific region as outlined above, empirical research on the pattern of stock market co-movements between China and its key trading partners is pertinent to provide some insights into facilitating financial stability in this region. There are burgeoning empirical studies on the degree of financial integration within the Asia-Pacific region. Early literature in this field pays more attention to volatility spillovers from the Japanese and United States stock markets than Chinese markets (e.g., Ng, 2000). Later, the Global Financial Crisis 2007–2008 (GFC) further encouraged many scholars to notice the enhanced stock market integration in the Asia-Pacific region along with the existence of co-movement (Loh, 2013) or contagion (Dewandaru et al., 2016). Most of the studies related to the GFC focus on the influence of disturbances triggered in United States markets. Some of them also find that the mainland China stock market is increasingly integrated with other markets in this region during the GFC (e.g., Burdekin and Siklos, 2012; Kim et al., 2015a, 2015b; Nieh et al., 2012). Since then, more and more scholars notice China's rising power in the process of financial coordination in the Asia-Pacific region, and mainland China's financial market has gradually become a new focus of regional financial studies in terms of volatility linkages. The latest literature confirms that the strengthening of financial connections is persistent after the GFC and demonstrates that the influence of mainland China stock market on many regional markets has risen to meet Japan's, and even the United States', level of influence (e.g., Ahmed and Huo, 2019; Chow, 2017; Shu et al., 2018; Younis et al., 2020).

Apart from those studies on examining the existence and magnitude of volatility linkages across stock markets, many academic papers explore the mechanisms and underlying factors of stock market co-movements. As for theoretical justifications, the information spillover and market efficiency theories regard information on stock markets as crucial determinants of stock market co-movements. Behaviour finance argues that there is a herding action leading to correlation between markets when investors are affected by subjective factors. In terms of an increasing amount of empirical research, scholars are investigating potential factors driving the stock market from various perspectives. Early studies point out that real linkages, financial linkages, market similarity, and financial openness can facilitate stock market co-movements (e.g., Bracker et al., 1999; Forbes and Chinn, 2004; Pretorius, 2002; Quinn and Voth, 2008). The Global Financial Crisis witnessed market turbulence worldwide and sparked the discussion of factors affecting co-movements across stock markets during the crisis period. The real and financial linkages between the United States and other countries are widely examined to account for volatility spillovers from the US stock market (e.g., Balli et al., 2015; Kim et al., 2015a, 2015b; Prasad et al., 2018), and co-movements between US and other countries' stock markets (e.g., Didier et al., 2012; Huang, 2020). In addition, some scholars examine co-movements among international stock markets during the GFC rather than confining their studies to correlations with the US stock market (e.g., Mobarek et al., 2016; Niţoi and Pochea, 2019; Thomas et al., 2019). These previous studies cover a wide range of markets (developed, emerging, and frontier) and distinguish the influence of the GFC on stock markets in different regions (European Union as well as Asia-Pacific Area). By comparison, there are much fewer studies particularly explaining stock market co-movements between China and other countries since China is not among the key economies affected by the GFC.

Moreover, the increasing influence of the Chinese stock market did not attract substantial attention until recent years, and therefore empirical studies explaining the characteristics of stock market co-movements related to the Chinese market are scarce (Wang and Guo, 2020). This paper is aimed at enriching research in this field from two perspectives. Firstly, although previous studies confirm that the Chinese stock market is more integrated with other markets in the Asia-Pacific region after GFC, there is little literature examining the factors influencing stock market co-movements in the process of this integration. Therefore, this study contributes to the extant literature by identifying potential factors driving stock market co-movements between China and its trading partners in the Asia-Pacific region. Secondly, while many scholars examine co-movements within global stock markets during the period of GFC, fewer scholars pay attention to sudden shocks after the GFC. Three events (i.e., Shanghai stock market crash, US-China tariff war, and COVID-19 pandemic) occurred after the GFC and caused stock market disturbances in China. We distinguish the turmoil period covering these events as the sub-sample period to understand the impact of these shocks on the stock market co-movements between China and other economies. The Shanghai stock market crash (2015–2016) was largely influenced by a decline in China's economic growth, which led to a decrease in China's foreign trade. In contrast, tensions between the US and China rebalanced trade flows within the region. Furthermore, the outbreak of the COVID-19 pandemic in 2020 disrupted international trade. We can see that these three

[1] According to the *Statista*: https://www.statista.com/statistics/710680/global-stock-markets-by-country/

[2] The RCEP trade deal was agreed by China and 14 Asia-Pacific countries on 15 November 2020.

events share similar patterns in their influence on China's Asia-Pacific trading partners because all these partners are exposed to China's trade risk. In addition, Ahmed and Huo (2019) note that the Shanghai stock market crash (2015–2016) enhanced volatility linkages between mainland China and significant economies in the Asia-Pacific region during the period of turmoil. The US-China tariff war triggered in 2018 also positively affected stock market co-movement among mainland China, Hong Kong, and United States (Shi et al., 2021).

We attempt to answer the following three questions: First, what is the evolving pattern of stock market co-movement between China and its trading partners after the Global Financial Crisis? According to the World Economic Outlook (October 2020) of the International Monetary Fund (IMF), the major economies ranked by Gross Domestic Product based on Purchasing Power Parity in Asia-Pacific Region include China, United States, India, Japan, Indonesia, South Korea, Australia, Taiwan, Thailand, Malaysia, Singapore, Hong Kong, and New Zealand.[3] With a focus on the Chinese stock market, we classify stock markets in 12 economies (i.e., 12 of China's trading partners) into two categories, 'developed market' and 'emerging market,' according to the MSCI Market Classification Market Framework, 2020. And then, we employ the Dynamic Conditional Correlation (DCC) - Mixed Data Sampling (MIDAS) model to estimate time-varying stock market correlations between China and each economy and conduct analyses for two groups of markets separately. The Dynamic Conditional Correlation (DCC) model, proposed by Engle (2002), is widely adopted to investigate time-varying characteristics of stock market co-movements (e.g., Chiang et al., 2016; Ma et al., 2019; Mensi et al., 2016; etc.). This model enables scholars to compute daily conditional correlations from daily return series. However, short-run dynamic conditional correlations only depict temporal degeneration of volatility linkages but cannot be linked to lower-frequency macroscopic factors. The DCC-MIDAS model is an essential expansion of the original DCC model, which allows for distinguishing short- and long-run dynamic conditional correlations under the economic principle that there are different short- and long-run sources that affect volatility (Colacito et al., 2011).

The second question is: Did the Shanghai stock market crash, US-China tariffs war, and COVID-19 pandemic intensify volatility linkages between stock markets? We detect the intensification of stock market co-movement by identifying contagion episodes across country pairs[4] to see whether events drive contagion incidences. We regard an episode as contagious if a significant increase is detected in time-varying correlations, based on the definition of financial contagion in Forbes and Rigobon (2002). Following the practice of previous studies (Buchholz and Tonzer, 2016; Niţoi and Pochea, 2019), we use time dummies to capture significant increases in weekly conditional correlations. The latter are extracted by the DCC-MIDAS, and dummies are constructed in the autoregressions of conditional correlations. We conduct autoregressions for each pair of China and trading partners separately and collect contagion episodes across country pairs.

Finally, the third question we are curious about is: Which factors influence the stock market co-movements between China and these 12 economies? As a reliable method to derive low-frequency components from pairwise conditional correlations, DCC-MIDAS solves the problem of frequency mismatching when investigating the periodic influence of fundamentals on financial market co-movements (e.g., Mobarek et al., 2016; Niţoi and Pochea, 2019). We consider a set of explanatory variables classified into three categories, the time-and-country-pair varying indicators for economic integration, stock market similarity, and China-related characteristics such as the proxy for illiquidity pressure in China. The choices of these variables are based on a review of literature and an understanding of the Chinese financial system. To examine the influencing factors for stock market co-movement between China and its trading partners more elaborately, we distinguish the period of turmoil covering key events over the entire sample, and then examine whether the nexus between stock market co-movement and explanatory factors become significant or insignificant under disturbances. Moreover, we also consider the nature of contagion by adding interaction terms of contagion indicators and selected factors to test whether economic fundamentals are likely to be significant channels in propagating shocks (Giordano et al., 2013).

The remainder of this paper is structured as follows: Section 2 and Section 3 introduce the methodology and data respectively. Section 4 presents and discusses the empirical results and Section 5 conducts the robustness checks. Section 6 concludes with the main findings.

2. Methodology

2.1. Estimation of long-run dynamic conditional correlations

We explore stock market co-movements on a long-run basis using the DCC-MIDAS model proposed by Colacito et al. (2011). This method extends Engle's (2002) Dynamic Conditional Correlation (DCC) model with short- and long-run component specifications. The other two critical gradients of the DCC-MIDAS method are the component GARCH model of Engle and Lee (1999) which provide ideas to replace the original DCC with a component specification; and the GARCH-MIDAS model of Engle et al. (2006)[5] which gives insights on extracting a long-run correlation component via mixed data sampling. We realize the DCC-MIDAS method in Matlab.[6] Market returns are calculated as the first difference of the natural logarithm of closing prices, in local currency over two consecutive trading days, for each market index. The vector of returns for k market indices is denoted as $r_t = [r_{1,t}, \ldots, r_{k,t}]'$. It is assumed that the vector r_t

[3] As a common practice, mainland China (denoted as China) and Hong Kong are regarded as two individual economies in Asia-Pacific region.

[4] The country-pair term in this article is actually country(/region)-pair because Hong Kong is a special administrative region of China.

[5] On the economic sources of stock market volatility. NYU and UNC Unpublished Manuscript.

[6] Toolbox: https://www.mathworks.com/matlabcentral/fileexchange/45150-midas-matlab-toolbox. It is the repack of Mixed Data Sampling regressions (MIDAS) written by Eric Ghysels and collaborators. Eric Ghysels is one of the authors propose DCC-MIDAS model.

follows the process:

$$r_t \sim i.i.d.N(\mu, H_t) \tag{1}$$

$$H_t = D_t R_t D_t \tag{2}$$

where μ is the vector of unconditional means, H_t is the conditional covariance matrix and D_t is a diagonal matrix with standard deviations and: $R_t = \mathrm{E}_{t-1}[\varepsilon_t \varepsilon_t{}']$; $\varepsilon_t = D_t{}^{-1}(r_t - \mu)$. Therefore, $r_t = \mu + H_t{}^{1/2}\varepsilon_t$. And ε_t is known as the vector of standardized residuals and assumed to follow the multivariate normal distribution: $\varepsilon_t \sim i.\ i.\ d.\ N(0, I_k)$.

We take a two-step procedure of DCC-MIDAS to calculate pairwise DCCs by daily returns and convert daily DCCs into monthly estimators, preparing for regressing conditional correlations on monthly macroeconomic indicators. In the first step, conditional variances are estimated by univariate GARCH-MIDAS models. Returns of each market index ($i = 1, \ldots, k$) follow the GARCH-MIDAS process (Note: t and τ are introduced as time scales. Particularly, $g_{i,\ t}$ changes daily and $z_{i,\ \tau,}$ moves only once every N days):

$$r_{i,t} = \mu_i + \sqrt{z_{i,\tau,} g_{i,t}}\varepsilon_{i,t}, \forall t = \tau N, \ldots., (\tau + 1)N \tag{3}$$

where $g_{i,\ t}$ follows a GARCH (1,1) process:

$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{\left(r_{i,t-1} - \mu_i\right)^2}{z_{i,\tau}} + \beta_i g_{i,t-1} \tag{4}$$

while the MIDAS component $z_{i,\ \tau,}$ is a weighted sum of $K_v{}^i$ lags of realized variances (RV) over a long horizon:

$$z_{i,\tau,} = \overline{z}_i + \theta_i \sum_{k=1}^{K_v^i} \varphi_k\left(\omega_{v1}^i, \omega_{v2}^i\right) RV_{i,\tau-k} \tag{5}$$

where the realized variances involve N daily squared returns, $RV_{i,\tau} = \sum_{j=(\tau-1)N+1}^{\tau N}\left(r_{i,j}\right)^2$. $\varphi_k(\omega_{v1}{}^i, \omega_{v2}{}^i)$ is called Beta weight[7]: $\varphi_k\left(\omega_{v1}^i, \omega_{v2}^i\right) = \frac{\left(k/K_v^i\right)^{\omega_{v1}^i - 1}\left(1 - k/K_v^i\right)^{\omega_{v2}^i - 1}}{\sum_{j=1}^{K_v^i}\left(j/K_v^i\right)^{\omega_{v1}^i - 1}\left(1 - j/K_v^i\right)^{\omega_{v2}^i - 1}}$.

In this paper, we extract the monthly DCC by setting period $N = 23$. When calculating dynamic conditional correlations between Chinese and a partner's stock markets, we first exclude the trading days on which either of the two markets is closed. And then, we find that 23 is the maximum number of common trading days for a month in all pairs. Considering the practice from previous studies (e.g. Aloui and Hkiri, 2014) which avoid spurious conditional correlations by placing zeros for the time slots not all series are available, we fill a month of common trading days fewer than 23 with zeros at the end of that month.

As for the second step, the standardized residuals have a correlation matrix with GARCH-MIDAS-like dynamics. Let Q_t be a quasi-correlation matrix with the typical element $q_{i,\ j,\ t}$ (i.e., the conditional covariance between returns of asset i and asset j) expressed as:

$$q_{i,j,t} = \overline{m}_{i,j,t}(1 - a - b) + a\varepsilon_{i,t-1}\varepsilon_{j,t-1} + bq_{i,j,t-1} \tag{6}$$

where $\varepsilon_{i,\ t-1}$, $\varepsilon_{j,\ t-1}$ are the standardized residuals of the previous period obtained from univariate GARCH-MIDAS process. The long-run component $\overline{m}_{i,j,t}$ is determined by the $K_c{}^{ij}$ lags of $c_{i,\ j,\ t-1}$, $c_{i,\ j,\ t-2}$, …, $c_{i,\ j,\ t-Kc^{ij}}$ under Beta weights.[8] That is,

$$\overline{m}_{i,j,t} = \sum_{k=1}^{K_c^{ij}} \varphi_k\left(\omega_{c1}^{ij}, \omega_{c2}^{ij}\right) c_{i,j,t-k} \tag{7}$$

where $c_{i,j,t} = \frac{\sum_{l=t-N}^{t}\varepsilon_{i,l}\varepsilon_{j,l}}{\sqrt{\sum_{l=t-N}^{t}\varepsilon_{i,l}^2}\sqrt{\sum_{l=t-N}^{t}\varepsilon_{j,l}^2}}$. Correlations can then be calculated as: $\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}$.

We follow Colacito et al. (2011) and Engle et al. (2013) to compare different DCC-MIDAS models with different K lags via maximum profiling of the likelihood function. And then we choose the number of lags at which the highest maximum likelihood value is achieved, along with considering the accurate estimation of matrix, statistical significance of coefficients, and sample size. In this study, the total number of MIDAS lags ($K_v{}^i$ and $K_c{}^{ij}$) in two-step procedure for most of country pairs is 24 when extracting monthly DCC, which corresponds to the so-called two MIDAS years.

[7] We changed the setting of two-parameter beta weight to one-parameter beta weight by fixing the weight ω_1 to one if estimates for ω_1 and ω_2 were jointly insignificant at 10% significance level at the first or second step of DCC-MIDAS approach under a series of lag settings. The expression of one-parameter beta weight is: $\varphi_k(\omega_2) = \frac{(1-k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K}(1-j/K)^{\omega_2 - 1}}$, a restricted version of two-parameter beta (Engle et al., 2013).

[8] As in the Colacito et al. (2011), the structure of beta-weights (i.e. the choice of two-parameter or one-parameter weights) is uniform for the first and second steps of DCC-MIDAS approach.

2.2. Identification of the contagion episode

Following the definition of financial contagion in Forbes and Rigobon (2002), we identify an episode as contagious only if a significant increase in time-varying correlations is detected. There is no consensus on how to measure the contagion, and we adopt the basic version of the approach in Buchholz and Tonzer (2016). Since daily data is affected by non-synchronous trading hours and noises, we estimate contagion episodes using weekly conditional correlations (Niţoi and Pochea, 2019). Weekly DCCs are extracted from the DCC-MIDAS model.[9]

$$\overline{\rho}_{ij,t} = \lambda_0 + \lambda_1 \overline{\rho}_{ij,t-1} + \delta_m Dum_m + \varepsilon_{ij,t} \tag{8}$$

where $\overline{\rho}_{ij,t}$ is Fisher-Z[10] adjusted weekly conditional correlations of stock returns and Dum_m is a dummy variable taking the value of 1 for a given month and 0 otherwise. Considering the limitations of the arbitrary selection for the crisis dummy (Billio and Pelizzon, 2003), we do not divide the sample into specific periods for generating dummy variables. Given that serial correlation and ARCH tests reveal that significant serial correlation and heteroscedasticity exist, the conditional variance equation follows the GARCH (1,1) specification. A significant and positive estimate of δ_m indicates a corresponding episode contagious at 5% significance level. We identify contagion episodes sequentially for each pair of China and a trading partner from the first month to the last month of sample period excluding the MIDAS years (i.e. January 2012 to December 2020 in this study): in the first set of regression, Dum_1 equals to 1 in Jan. of the first year and 0 otherwise; in the second set of regression, Dum_2 equals to 1 in Feb. of the first year and 0 otherwise; and so on.

2.3. Regression analysis of factors influencing stock-market co-movements

To investigate factors driving the stock market co-movements between China and its trading partners, we can utilize the gravity-type regressions adopted by the Niţoi and Pochea (2019) when investigating the financial integration of the European Union. We explore the following three forms of panel data regression in this study: The first (baseline) form shown as Eq. (9) is to investigate the effects of mixed factors (including both country-pair sharing and country-pair specific factors) on stock market co-movements.

$$\overline{\rho}_{ij,t} = \alpha + \boldsymbol{X}'_{\boldsymbol{ij,t}}\beta + \gamma_{t_s} + \varepsilon_{ij,t} \tag{9}$$

where $\overline{\rho}_{ij,t}$ is Fisher-Z adjusted monthly conditional correlations of stock returns, α_0 is the overall constant, $\boldsymbol{X_{ij,t}}'$ comprises variables that can be time-varying and common to all country pairs, specific to country pair and constant over time, or time-and-country-pair varying, γ_{t_s} represents a series of time dummies to adjust the potential seasonal difference between months and $\varepsilon_{ij,\,t}$ is an error term.

Further, when also controlling the country pair fixed effects, according to Niţoi and Pochea (2019), only time-and-country-pair varying variables are included in the regression model (see Eq. (10)). The second form regression provides a robustness check on the results from the baseline form.

$$\overline{\rho}_{ij,t} = \alpha + X'_{ij,t}\beta + \delta_{ij} + \gamma_{t_s} + \varepsilon_{ij,t} \tag{10}$$

where $X_{ij,\,t}'$ is a vector of variables that can only be time-and-country-pair varying, δ_{ij} and γ_{t_s} represent country pair fixed effects and seasonal time fixed effects (time dummies same as in Eq. (9)) respectively.

Besides, we consider which factors might influence stock market co-movement between China and its Asia-Pacific trading partners during periods of contagion. According to the estimation explained in the Section 2.2, we can construct the contagion indicator that takes a value of 1 if contagion is detected during a particular month, 0 otherwise. The contagion indicator is also time-and-country-pair varying. Previous studies point out that macroeconomic variables and market characteristics can affect transmission of shocks when contagion occurs (e.g., Bekaert et al., 2014; Gkillas et al., 2019; Leung et al., 2017). Therefore, we introduce interaction terms of the contagion indicator and time-and-country-pair varying variables (including proxies for economic integration and stock market similarities) into the second regression (see Eq. (11)).

$$\overline{\rho}_{ij,t} = \alpha + X'_{ij,t}\beta_1 + (X^*C)_{ij,t}\beta_2 + \delta_{ij} + \gamma_{t_s} + \varepsilon_{ij,t} \tag{11}$$

3. Data

3.1. Stock market indices

According to many previous studies (e.g., Ahmad et al., 2012), the crisis period of GFC ends in the fourth quarter, 2009. The data set

[9] When estimating weekly DCC, we exclude all common holidays for China and its paired trading country, and replace returns on non-common holidays with zeros to make use of all the available calendar dates (Ma et al., 2019). The fixed span of a period for weekly DCC is set as $N = 5$. And the total number of MIDAS lags also cover two years, consistent with the setting of monthly DCC.

[10] In order to ensure the normal distribution of the conditional correlation coefficients, we apply Fisher-Z transformation: $\overline{\rho} = (1/2)LN[(1+\rho)/(1-\rho)]$.

explored in this study comprises the daily closing prices of stock market indices from China and 12 trading partners for the sample period, 4 January 2010 to 31 December 2020. The first two years correspond to the so-called two MIDAS years. The countries/regions considered in our study are China, United States, India, Japan, Indonesia, South Korea, Australia, Taiwan, Thailand, Malaysia, Singapore, Hong Kong, and New Zealand. The historical data of market indexes are collected from Investing.com and CSMAR databases. We calculate the logarithmic rates of return for each market index to prepare for estimations of market co-movements. Table 1 presents the statistics description of stock market indices used in this study. The Morgan Stanley Capital International (MSCI) Market Classification Framework 2020 classify stock markets by three criteria: economic development, size and liquidity, and market accessibility. And the chosen stock markets can be classified into two categories, 'developed markets' and 'emerging markets'.

From Table 1, we can see that the NZX 50 index for the New Zealand stock market has the highest mean and lowest standard deviation of logarithmic returns. The CSI 300 index returns have the highest standard deviation for the sample period, compared to all other indices. It is noticeable that there are a lot of retail participants in the Chinese stock market, although the proportion of holdings by institutional investors has expanded in recent years (Wen et al., 2021). Also, China has a unique stock market compared to other countries/regions, including a variety of market situations under ongoing financial reforms. All series of returns have a negative skewness in terms of distribution, meaning that stocks have more weight in the left tail of the return distribution. The augmented Dickey-Fuller (ADF) statistic rejects the null hypothesis of unit root at the 1% significance level, indicating that each return series is stationary. Besides, all series of returns reject the null hypothesis of the ARCH test, suggesting the existence of heteroskedasticity and the preference for GARCH models.

3.2. A set of variables potentially influencing stock market co-movements

To investigate the potential drivers of stock market-co-movements, as mentioned in the section of Introduction, we consider three categories of variables in this study. We will briefly discuss these variables, while Table A in Appendix details them.

Common factors (i.e. China-related characteristics) include China ETF volatility index (VXFXI index), China term spread, and a dummy variable to distinguish economies that have relatively similar cultures with China. The VXFXI index measures the market expectation of 30-day volatility implicit in the prices of near-term China ETF options. Changes in VIXFXI index prices reflect the ascending/descending expectation of Chinese market risk. China's term spread (unit: %) between the 10-year government bond yield and the 3-month short-term interbank rate is a proxy for Chinese market stress from illiquidity. Previous studies highlight the important role that risk aversion and illiquidity risk play in asset co-movements (e.g., Bekaert et al., 2014; Buchholz and Tonzer, 2016). The dummy variable is designed to capture cultural proximity between China and other economies, as cultural differences may exacerbate information asymmetries and agency problems for international investors (Aggarwal et al., 2012).

Economic integration factors refer to the similarity in economic developments (in this paper, bilateral trade, industrial production growth, board money (M2) growth, inflation and changes in cross-border banking position). Pretorius (2002) classifies economic variables related to market interdependence into two categories: the extent to which two economies depend on each other; and the extent to which macroeconomic variables in two economies are the same. Specifically, bilateral trade is a typical variable that reflects the nature of dependency between countries via international trade (Bracker et al., 1999), while industrial production growth rate reflects the economic cycle pattern of manufacturing (Kong et al., 2020). Besides, M2 supply growth and inflation are monetary policy outcomes from different perspectives and useful in measuring monetary convergence between economies (Brada et al., 2005). Changes in cross-border position in banking sector can reflect the growth or shrink of linkages in banking sector, and cross-border banking linkages can transmit local shocks across national borders within the financial network (Tonzer, 2015).[11]

Stock market similarity factors include differences in market sizes and turnover ratios. On the one hand, relative stock market size may influence co-movement between two stock markets through information and transaction costs (Johnson and Soenen, 2002). On the other hand, the turnover ratio measures the liquidity of stock markets, and co-movements between liquid stock markets are expected to be higher due to reduced transaction costs (Thomas et al., 2019).

Our data behind discussion in this section are all collected on a monthly basis, except for the cross-border position in banking sector, for which differentials are calculated on a quarterly basis and converted to monthly data. Among these variables, China's volatility index and term spread are time-varying and common to all country pairs, while the culture dummy is specific to country pair and constant over time. All indicators for economic integration and stock market similarity are time-and-country-pair varying. Table 2 shows the mean of time-and-country-pair-varying variables from January 2012 to December 2020, excluding the two MIDAS years.

From Table 2, we notice that trade connections in the Greater China Area are relatively strong, with Hong Kong having the highest ratio of bilateral trade in the group of developed markets and Taiwan ranking second in the group of emerging markets. Previous studies already point out economic integration within the Greater China Area through trade and investment (e.g., Ash and Kueh, 1993). Regarding the absolute differences in industrial production growth with China, the average value for India is the highest among all considered partners. The differences in M2 supply growth and banking position percent change between China and 12 economies have similar means, while the divergences from China in inflation rate are also largest for India. Like China, India is a large emerging country that adopted a series of reforms in the 1980s to change its economic orientation towards the market regime and is on the track of economic development at its own pace (Das et al., 2019). As expected from the ranking of market capitalizations, the most minor difference is between China and Japan, while the scale of stock markets in the United States is much larger than that of stock markets in

[11] Due to the data availability, we collect the cross-border banking position exposed to the rest of world for each economy.

Table 1
Classification of stock markets and descriptive statistics of stock market indices.

Country/Region	Index	Mean (*100)	Min.	Max.	SD	Skew.	Kurt.	ADF stat.	ARCH LM stat.
Emerging Markets									
China	CSI 300	0.0145	−0.0915	0.0650	0.0146	−0.6925	4.906	−50.3***	2214***
India	NIFTY 500	0.0356	−0.1371	0.0741	0.0107	−1.2466	14.962	−50.2***	3442***
Indonesia	JKSE	0.0314	−0.0930	0.0970	0.0112	−0.4241	7.556	−49.5***	2515***
Malaysia	FBM KLCI	0.0092	−0.0541	0.0663	0.0066	−0.3140	9.155	−48.6***	2418***
South Korea	KOSPI	0.0194	−0.0877	0.0825	0.0104	−0.3822	7.623	−51.7***	1019***
Taiwan	TWII	0.0217	−0.0652	0.0617	0.0096	−0.6532	4.997	−50.0***	1878***
Thailand	SET	0.0255	−0.1143	0.0765	0.0107	−1.0412	13.453	−51.8***	3108***
Developed Markets									
Australia	ASX 200	0.0106	−0.1020	0.0677	0.0099	−0.8806	10.164	−57.7***	974***
Hong Kong	HSI	0.0082	−0.0602	0.0552	0.0117	−0.3288	2.403	−51.8***	1622***
Japan	Nikkei 225	0.0348	−0.1058	0.0773	0.0133	−0.4347	5.256	−53.2***	2315***
New Zealand	NZX 50	0.0489	−0.0635	0.0694	0.0066	−0.4890	12.264	−48.2***	1503***
Singapore	STI	−0.0006	−0.0764	0.0590	0.0087	−0.4928	7.012	−51.7***	1316***
United States	S&P 500	0.0433	−0.1277	0.0897	0.0111	−0.8636	16.328	−61.2***	1198***

Note: $R_{it} = Ln(P_{it}/P_{it-1})$ for market i on day t. Sample period: 4 January 2010 to 31 December 2020. JKSE denotes Jakarta Stock Exchange Composite Index. The FBM KLCI is also known as the FTSE Bursa Malaysia KLCI. TWII denotes Taiwan Stock Exchange Weighted Index. The ADF statistic tests for the null hypothesis of a unit root in time series. The ARCH statistic tests for the null hypothesis of homoskedasticity. Asterisks denote rejection of the null hypothesis at *10%, **5%, and ***1% significance levels.

Table 2
Average values of country-pair variables (01/2012–12/2020).

	Bilateral Trade	Industrial Production Growth	M2 Growth	Inflation	Cross-Border Banking Position	Relative Size	Turnover Ratio (%)
Panel A: developed trading partners							
Australia	0.1282	0.0104	0.0122	0.0040	7.0328%	0.7695	206.25
Hong Kong	0.2901	0.0255	0.0146	0.0068	6.8470%	0.4264	220.57
Japan	0.1434	0.0200	0.0224	0.0045	7.2518%	0.2392	157.55
New Zealand	0.1032	0.0131	0.0250	0.0039	10.9521%	0.9875	255.67
Singapore	0.0741	0.0418	0.0122	0.0047	7.0088%	0.8769	235.86
United States	0.1325	0.0139	0.0119	0.0040	7.6153%	3.4524	171.81
Panel B: emerging trading partners							
India	0.0563	0.0609	0.0259	0.0082	8.6386%	0.7400	216.20
Indonesia	0.0946	0.0367	0.0193	0.0054	7.7014%	0.9263	246.07
Malaysia	0.0934	0.0237	0.0173	0.0050	6.6828%	0.9245	236.37
South Korea	0.1472	0.0200	0.0171	0.0037	6.4060%	0.7780	128.48
Taiwan	0.1408	0.0214	0.0120	0.0055	8.2222%	0.8504	189.75
Thailand	0.0877	0.0249	0.0136	0.0049	7.5715%	0.9268	192.96

Note: Bilateral trade represents the average dependency ratio of trade between country i and j (fixed to China). The calculated equation: $[(X_{ij}/X_i) + (M_{ij}/M_i) + (X_{ji}/X_j) + (M_{ji}/M_j)]/4$ where X is exports, M is imports, ij refers to monthly trade flows from country i to country j, ji refers to trade flows from country j to country i; Industrial Production Growth represents the absolute difference in M-o-M growth rates of industrial production between country i and China; M2 Growth represents the absolute difference in M-o-M growth rates of M2 supply between country i and China; Inflation represents the absolute difference in inflation rates (calculated by Consumer Price Index, CPI) between country i and China; Cross-Border Banking Position represents the absolute difference in percent changes in cross-border gross banking position between country i and China; Relative Size represents the absolute difference in stock market capitalizations relative to Chinese market capitalization between country i and China; Turnover Ratio represents the absolute difference in stock market turnover ratios between country i and China.

China. Besides, absolute differences in turnover velocity is the least between China and South Korea, and most developed markets have a differential larger than 200%. The large gap in turnover ratios between China and other countries is commonly seen as the Chinese stock market has shown a superior turnover ratio in global terms, ranking highest annually in recent years (Knoema database[12]).

The regression analysis will be conducted to investigate the drivers of stock market co-movements with China for developed and emerging partners respectively. In order to avoid the problem of multicollinearity, we examine the correlation coefficient between the explanatory variables for both groups. Table 3 reports the coefficient matrix and shows that the correlation between each two explanatory variables is low.

[12] The rank of stock market turnover ratio in recent years: https://knoema.com/atlas/topics/Economy/Financial-Sector-Capital-markets/Stocks-traded-turnover-ratio

Table 3
The correlation coefficients among variables.

	Trade	Production	M2	Inflation	Position	Size	Turnover
Panel A: developed trading partners							
Trade	1.0000						
Production	−0.0219	1.0000					
M2	−0.0418	−0.0311	1.0000				
Inflation	0.1689	0.1672	0.0167	1.0000			
Position	−0.1122	0.0366	0.0714	0.0378	1.0000		
Size	−0.2138	−0.0714	−0.1341	−0.0877	0.0440	1.0000	
Turnover	−0.0163	0.1132	0.0327	0.0140	−0.0736	−0.1108	1.0000
Panel B: emerging trading partners							
Trade	1.0000						
Production	−0.1291	1.0000					
M2	−0.1702	0.0853	1.0000				
Inflation	−0.2203	0.2145	0.0722	1.0000			
Position	−0.1458	0.0921	0.0648	0.0585	1.0000		
Size	0.0591	−0.0217	−0.1092	−0.0919	−0.1523	1.0000	
Turnover	−0.1668	0.0828	0.1233	0.0559	−0.1052	0.3328	1.0000

Note: Trade denotes the variable for bilateral trade; Production, M2, Inflation and Position denote variables in terms of industrial production growth, M2 supply growth, inflation rate and cross-border banking position change respectively; Size and Turnover denote variables for market capitalization and market turnover ratio respectively. For the sake of space, we only report the correlation matrix during the whole period from Jan 2012 to Dec 2020. The correlations between different variables during the turmoil period also range between [−0.25, 0.35].

4. Empirical results

4.1. Co-movements between China and its trading partners' stock markets in the Asia-Pacific region

We investigate the long-run dynamics of stock market co-movements on a monthly basis by adopting the DCC-MIDAS method. The parameter estimates of the DCC-MIDAS method are reported in Table B1 and Table B2 in the Appendix.[13] Almost all estimates are statistically significant at 10% significance level and there are not jointly insignificant estimates for key parameters in the first step (i.e. a &) and the second step (i.e. a & b). Excluding the two years for MIDAS estimation, we obtain 9 * 12 = 108 monthly conditional correlations with the Chinese stock market for each trading partner from January 2012 to December 2020. Fig. 1 presents the graphic representations for stock market co-movements between China and developed trading partners, while Fig. 2 reveals the interactions between China and emerging trading partners. From Fig. 1, we can see that among the developed markets considered, conditional correlations with China for Japan and Singapore fluctuate around 0.3. In contrast, Australia, the US and New Zealand have lower levels of fluctuation. As expected, the average level of stock market co-movements between China and Hong Kong is highest since Hong Kong serves as an intermediate platform to attract international capital flows for the progress of Chinese financial liberalization (Yang et al., 2020). Despite that different pairwise conditional correlations evolve differently, it is commonly observed that a noticeable increase in magnitudes of volatility linkages appear around mid-2015 and early-2018. Moreover, except for China vs. the US, there is a notable increase in stock market co-movement at the beginning of 2020. The years 2015, 2018 and 2020 are start points for the Shanghai stock market crash, US-China trade wars, and the spread of the COVID-19 pandemic, respectively.

Regarding the group of emerging markets, Fig. 2 demonstrates that there are distinct increases in conditional correlations between China and emerging stock markets around mid-2015, early-2018, and early-2020, indicating common shocks shared with the group of developed markets. Furthermore, dynamic conditional correlations across different country pairs within this group own more similar patterns than those reflected in Fig. 1. All pairs of stock market co-movement fluctuate below 0.6, with distinct fluctuations most frequently observed in 'China vs. South Korea' correlations. As major developing countries in East Asia, China and South Korea started negotiations on the Bilateral Free Trade Agreement in 2012 and finally reinforced their partnership in 2015. The enhancement of trade ties between China and South Korea may aggravate changes in their stock markets' volatility linkages.

Besides, Table 4 summarizes descriptive statistics of monthly conditional correlations between stock markets in China and these 12 Asia-Pacific economies, elaborating the images of Fig. 1 and Fig. 2. It is noteworthy in Panel A that the means and standard deviations of correlations for Asian economies (i.e. Hong Kong, Japan, and Singapore) are larger than those for Pacific countries (i.e. Australia, New Zealand, and the United States). This finding is consistent with previous studies presenting the regional power of China on Asian stock markets (e.g. Shu et al., 2018; Younis et al., 2020). As for Panel B, Taiwan and South Korea stock markets have higher average levels of volatility linkages with the Chinese stock market, indicating the deeper integration among East Asian stock markets. Furthermore, standard deviations of all pairwise conditional correlations (except for India and Malaysia) in this panel are larger than those for western countries in Panel A. Since all economies in Panel B are from Asia, we find that among the 12 Chinese trading partners

[13] In table B(1&2), we also report the constraints of GARCH model indicated in previous studies (e.g. Ling and McAleer, 2002; Ng and McAleer, 2004) since the first step of DCC-MIDAS are based on the GARCH process. And the return series for China and its trading partners fit the GARCH (1,1), related tests are available from the author upon request.

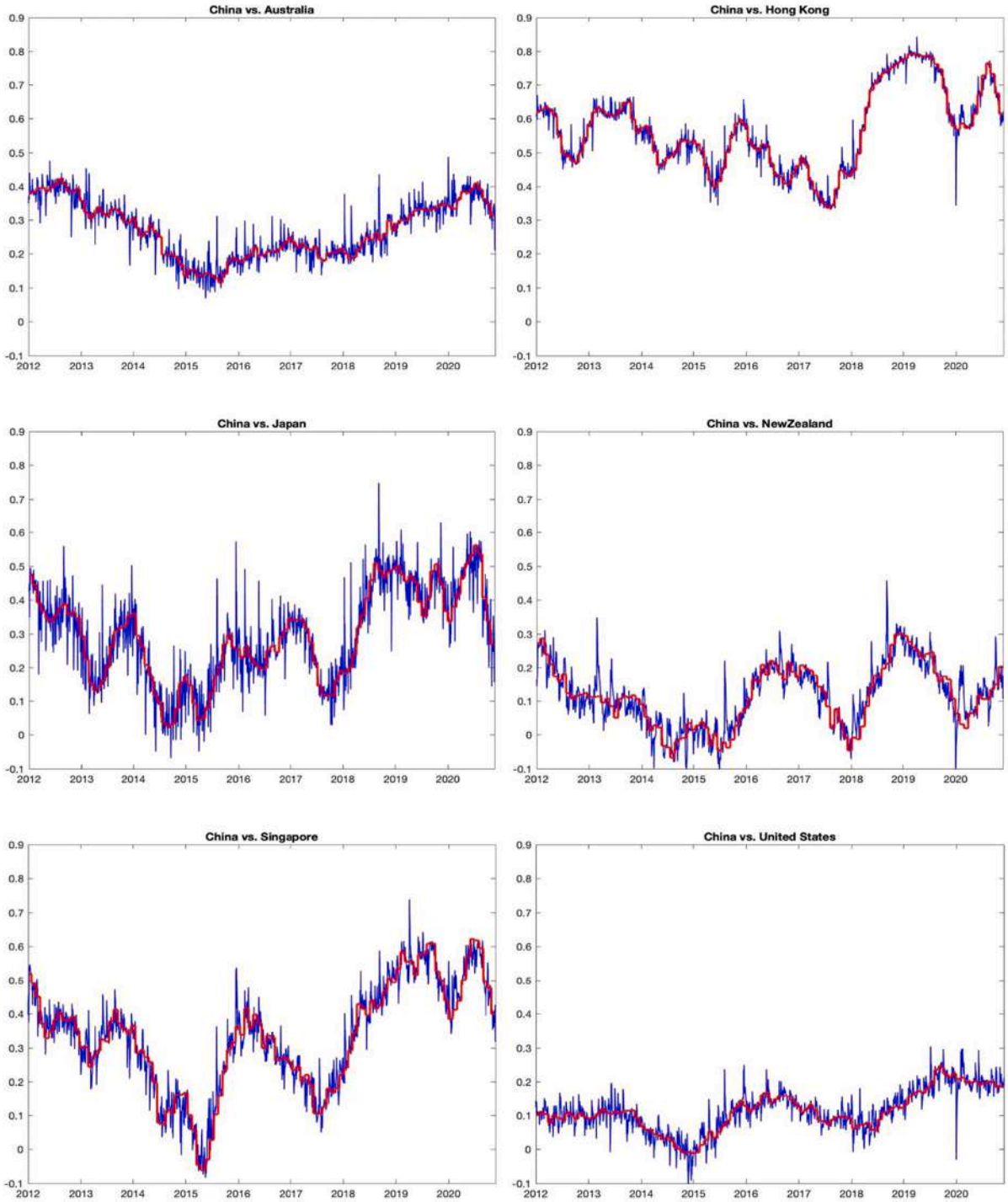

Fig. 1. Co-movements between Chinese and developed stock markets. The monthly conditional correlations (denoted by the red line) are extracted from the total conditional correlations (denoted by the blue line) by the DCC-MIDAS approach. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

chosen in this paper, stock market co-movements between China and Asian economies (no matter developed or emerging markets) tend to be more volatile. This finding may be due to the possibility that Asian stock markets are more easily influenced by Chinese shocks.

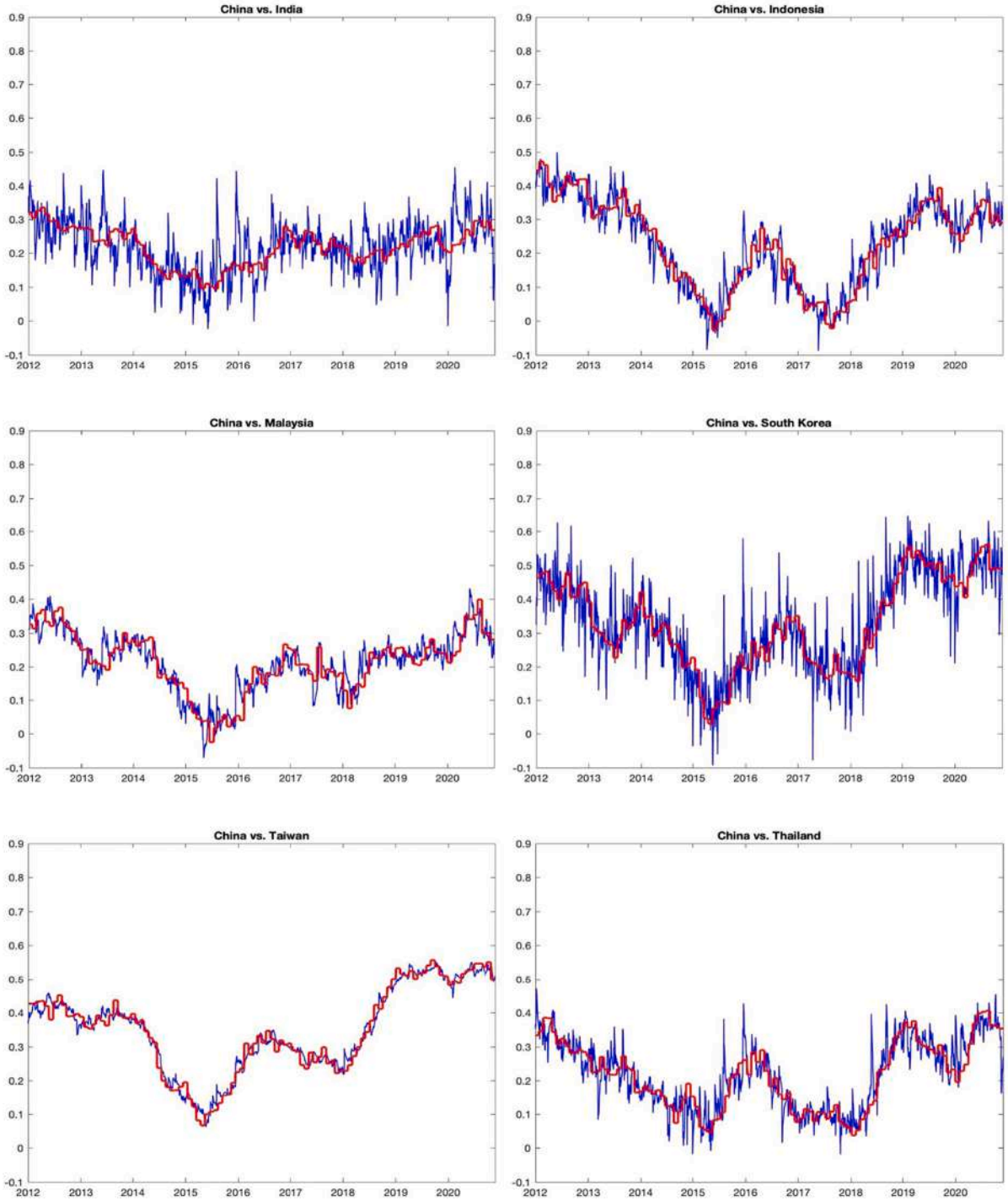

Fig. 2. Co-movements between Chinese and emerging stock markets. The monthly conditional correlations (denoted by the red line) are extracted from the total conditional correlations (denoted by the blue line) by the DCC-MIDAS approach. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Descriptive statistics of monthly DCC-MIDAS estimates.

	Mean	Max.	Min.	STD
Panel A: developed trading partners				
Australia	0.27029	0.42224	0.11527	0.08270
Hong Kong	0.56782	0.79342	0.33818	0.11880
Japan	0.29493	0.56179	0.02490	0.13470
New Zealand	0.11487	0.29966	−0.06739	0.09249
Singapore	0.33184	0.62186	−0.06162	0.15750
United States	0.11190	0.24692	−0.01110	0.05888
Panel B: emerging trading partners				
India	0.21871	0.33694	0.09531	0.05639
Indonesia	0.22647	0.47239	−0.02635	0.12982
Malaysia	0.21217	0.39917	−0.02448	0.08983
South Korea	0.32855	0.56094	0.03028	0.13188
Taiwan	0.35010	0.55708	0.06685	0.12832
Thailand	0.21463	0.40594	0.03764	0.10027

4.2. Contagion incidence among trading partners' stock market co-movements with China

To better understand the regularities of co-movement between Chinese and these 12 economies' stock markets, we calculate the contagion incidence within the 'China vs. Developed Partners' group and 'China vs. Emerging Partners' group for January 2012 to December 2020 separately. The contagion incidence is based on the count of contagion episodes for each month across country pairs. To be more specific, there are six pairs of stock market co-movement in each group, and 108 (=9 * 12) episodes are tested in the autoregressions of each pairwise weekly conditional correlation, separately and sequentially, to identify contagion episodes. For each month, we count the total number of country pairs whose corresponding episode is contagious. The maximum of contagion incidence in a month within each group is 6, which means that all pairs of weekly conditional correlations significantly increase in this month.

In this paper, we recognize periods of turmoil as follows: the crisis period of Shanghai stock market crash is from June 2015 to February 2016, as the Shanghai Stock Composite Index suffered a sharp fall on 12 June 2015 and finally recovered from the bottom in early February 2016 (Khoojine and Han, 2019); the intense period of US-China tariff war is from March 2018 when Trump signed a memorandum of China-specific tariffs to December 2019 when US and China agreed on the Phase One Deal; and the COVID-19 pandemic spread from January 2020 till the end of sample (i.e. December 2020).

The results of monthly contagion incidence are summarized in Figs. 3 and 4, for developed and emerging trading partners respectively. Both figures support the claim that the frequency of contagion episodes is mainly driven by events, with more contagion episodes detected in the years 2015, 2016, 2018, and 2020. Looking at the plot for developed markets (see Fig. 3), we notice that the peak of contagion incidence appears in March 2018. The second-highest level of incidence is reached in January 2019 and March 2020. We consider that stock market co-movements between China and its developed partners are most influenced by the US-China trade

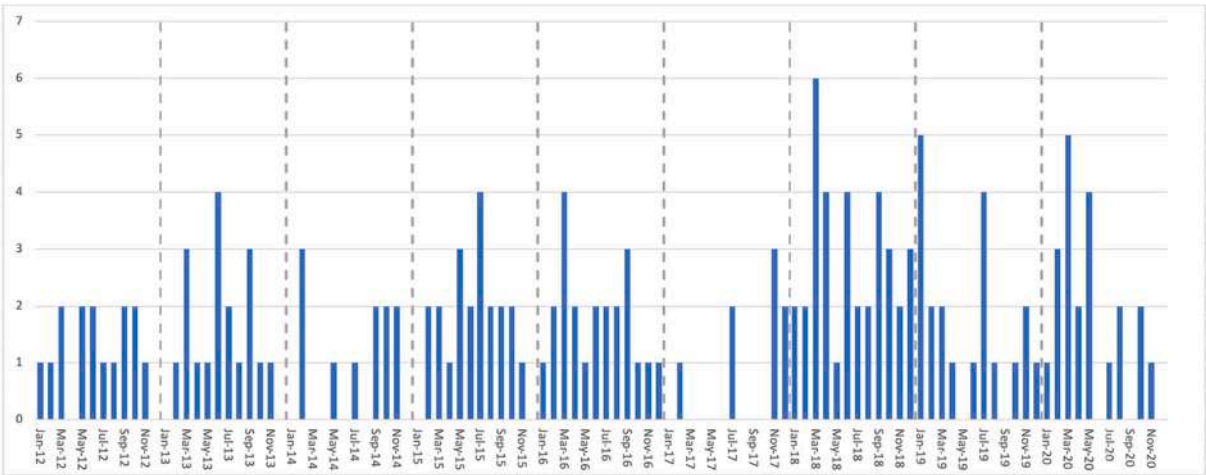

Fig. 3. Contagion incidence for the stock market co-movements between China and developed trading partners.
Notes: A positive and statistically significant coefficient at 5% level for δ_m in $\overline{\rho}_{ij,t} = \lambda_0 + \lambda_1 \overline{\rho}_{ij,t-1} + \delta_m Dum_m + \varepsilon_{ij,t}$ is interpreted as a contagion episode. Each episode takes the value of one. All estimates are computed separately and sequentially for each pairwise DCC. The vertical axis denotes the number of contagion episodes summed up across country pairs for a particular month (i.e., contagion incidence). Vertical dashed lines separate different years.

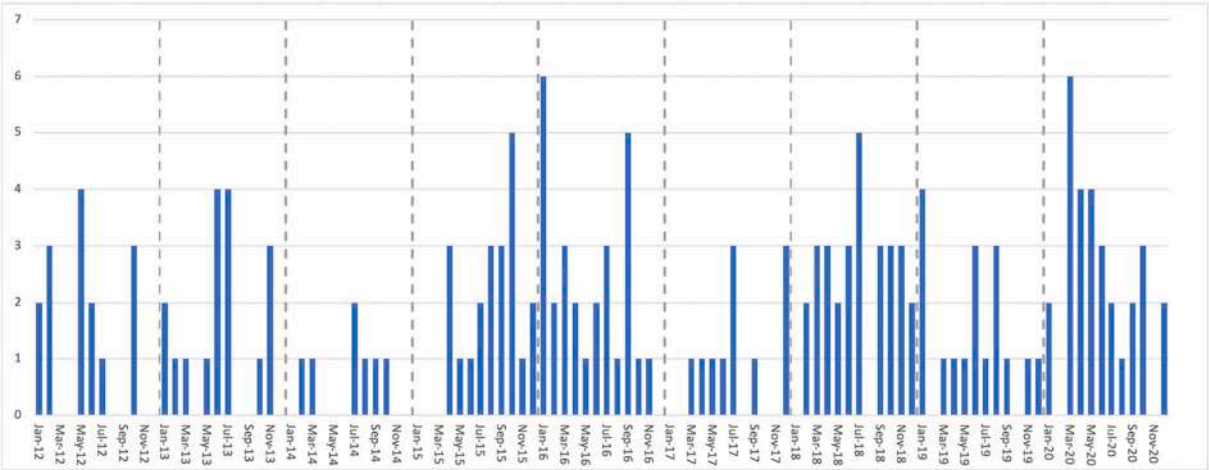

Fig. 4. Contagion incidence for the stock market co-movements between China and emerging trading partners.
Notes: A positive and statistically significant coefficient at 5% level for δ_m in $\overline{\rho}_{ij,t} = \lambda_0 + \lambda_1 \overline{\rho}_{ij,t-1} + \delta_m Dum_m + \varepsilon_{ij,t}$ is interpreted as a contagion episode. Each episode takes the value of one. All estimates are computed separately and sequentially for each pairwise DCC. The vertical axis denotes the number of contagion episodes summed up across country pairs for a particular month (i.e., contagion incidence). Vertical dashed lines separate different years.

Table 5A
Influencing factors for stock market co-movement between China and its developed trading partners.

Dependent variable: pairwise DCC-MIDAS	Full sampleEstimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
China VXFXI Index	−0.0009		−0.0116***	
	(0.0012)		(0.0014)	
China Term Spread	0.0814***		0.0768***	
	(0.0103)		(0.0190)	
Culture	0.1433***		0.2423***	
	(0.0136)		(0.0186)	
Trade	1.4848***	0.7206**	1.8508***	1.0910**
	(0.1007)	(0.3623)	(0.1548)	(0.5122)
Production	0.2859*	0.4787***	0.6581***	0.3199**
	(0.1642)	(0.1198)	(0.1686)	(0.1457)
Money Supply	−1.4161***	−0.1766	−1.1009**	−0.3623
	(0.3675)	(0.3123)	(0.5227)	(0.4596)
Inflation	0.8459	1.2442	0.1402	−2.8824
	(1.5462)	(1.4311)	(1.9041)	(1.9898)
Cross-Border Position	−0.0465	−0.0484	−0.5526***	−0.4597***
	(0.0858)	(0.0810)	(0.1315)	(0.1242)
Size	−0.0415***	−0.0317***	−0.0313***	−0.0730***
	(0.0037)	(0.0057)	(0.0072)	(0.0181)
Turnover	−0.0331***	−0.0340***	−0.0103	−0.0454***
	(0.0046)	(0.0038)	(0.0077)	(0.0072)
Constant	0.2113***	0.1904***	0.3646***	0.3695***
	(0.0324)	(0.0660)	(0.0443)	(0.1104)
Country-Pair Fixed	NO	YES	NO	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.6518	0.6868	0.8076	0.8163
F statistics	55.81***	59.48***	47.17***	45.20***

Note: The full sample period is from Jan 2012 to Dec 2020, excluding two MIDAS years. The turmoil period contains two pieces of time (Jun 2015 - Feb 2016) and (Mar 2018 – Dec 2020). Developed trading partners are Australia, Hong Kong, Japan, New Zealand, Singapore, and United States. Numbers in parentheses are robust standard errors. The ***, **, and * indicate significance at the 1, 5, and 10% levels respectively. Trade represents the average dependency ratio of bilateral trade between country *i* and *j* (fixed to China); Production represents the absolute difference in the industrial production M-o-M growth rates; Money Supply represents the absolute difference in broad money (i.e., M2) M-o-M growth rates; Inflation represents the absolute difference in inflation rates; Cross-Border Position represents the absolute difference in cross-border banking position percent changes; Size represents the absolute difference in market capitalizations relative to Chinese market capitalization; Turnover represents the absolute difference in stock market turnover ratios.

frictions, as shown by the surge of contagion incidence in March 2018 when Trump signed the memorandum on proposed tariffs on China-specific goods. And it is noted that the temporary relief of US-China tensions around the start of 2019 and Trump's re-thinking of tariffs in July 2019 also stimulated the Chinese stock market (Shi et al., 2021). The subsequent increase of contagion episodes in March 2020 mainly relates to the spread of the COVID-19 pandemic since the US-China trade war entered a smoother stage after the official signing of the Phase One Deal in January 2020. There are also increases in the number of contagion episodes after mid-2015, but the considerable incidence for 2015 and 2016 does not surpass the highest level observed in previous years. Compared to the other two events, the Shanghai stock market crash has a slighter effect on stock market co-movement with China for the group of developed trading partners, consistent with the finding of Ahmed and Huo (2019) that some developed countries in the Asia-Pacific region are not affected by this crash. The distribution of contagion incidence in 2016 supports the argument that the influence of the Chinese stock market turbulence lasted after February 2016 until the end of 2016 (Qarni and Gulzar, 2018).

As for the group of emerging trading partners (see Fig. 4), there are several noteworthy observations: (1) The number of contagion episodes increased in the second half of the year 2015 and in the first half of the year 2020, with contagion incidence reaching their peaks in January 2016 and March 2020. This implies that stock market co-movement between China and its emerging partners were intensified by the Shanghai stock market crash and COVID-19 pandemic outbreak. (2) Since more contagion episodes were detected in 2018 than in 2017, and contagion incidences increased to their second-highest level in July 2018, we also find that the US-China trade wars influenced stock market co-movement for this group of markets. (3) The contagion episodes frequently observed in the second half of the year 2016 also suggested the impact of Shanghai stock market crash remained after February 2016. (4) Comparing the findings mentioned above with those observed in Fig. 3, we notice that emerging partners' volatility linkages with the Chinese stock market are more intensively influenced by the Shanghai stock market crash in 2015, showing a steeper increase of contagion incidence, while they are less sensitive to US-China trade frictions. Furthermore, the COVID-19 pandemic affects both groups of markets from early 2020, with contagion incidence surging in March 2020.

Table 5B
Influencing factors for stock market co-movement between China and its emerging trading partners.

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
China VXFXI Index	0.0015		−0.0063***	
	(0.0010)		(0.0011)	
China Term Spread	0.0518***		0.1177***	
	(0.0080)		(0.0144)	
Culture	0.0367***		0.0308**	
	(0.0092)		(0.0135)	
Trade	1.4077***	1.3659***	2.6257***	4.0544***
	(0.1331)	(0.4782)	(0.2202)	(0.6915)
Production	−0.0399	0.2628***	0.0989	0.1094
	(0.0775)	(0.0850)	(0.1004)	(0.1027)
Money Supply	−0.0440	0.0342	−0.6417*	−0.1570
	(0.1721)	(0.1713)	(0.3742)	(0.4510)
Inflation	0.4435	1.1956	−0.1714	−3.0583*
	(1.0406)	(1.0044)	(1.4379)	(1.7418)
Cross-Border Position	0.2109**	0.1342	−0.3316***	−0.5906***
	(0.0898)	(0.0895)	(0.1028)	(0.1204)
Size	−0.2034***	−0.3376**	−0.2195**	0.9497***
	(0.0501)	(0.1350)	(0.0930)	(0.3000)
Turnover	−0.0478***	−0.0400***	−0.0212***	−0.0405***
	(0.0038)	(0.0037)	(0.0057)	(0.0063)
Constant	0.3565***	0.4876***	0.4141***	−0.9359***
	(0.0512)	(0.1015)	(0.0742)	(0.2450)
Country-Pair Fixed	NO	YES	NO	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.4510	0.4140	0.6708	0.6212
F statistics	24.48***	19.17***	22.90***	16.68***

Note: The full sample period is from Jan 2012 to Dec 2020, excluding two MIDAS years. The turmoil period contains two pieces of time (Jun 2015 - Feb 2016) and (Mar 2018 – Dec 2020). Emerging trading partners are India, Indonesia, Malaysia, South Korea, Taiwan, and Thailand. Numbers in parentheses are robust standard errors. The ***, **, and * indicate significance at the 1, 5, and 10% levels respectively. Trade represents the average dependency ratio of bilateral trade between country *i* and *j* (fixed to China); Production represents the absolute difference in the industrial production M-o-M growth rates; Money Supply represents the absolute difference in broad money (i.e., M2) M-o-M growth rates; Inflation represents the absolute difference in inflation rates; Cross-Border Position represents the absolute difference in cross-border banking position percent changes; Size represents the absolute difference in market capitalizations relative to Chinese market capitalization; Turnover represents the absolute difference in stock market turnover ratios.

4.3. Influencing factors for stock market co-movements between China and its Asia-Pacific trading partners

After studying the evolving pattern of stock market co-movement between China and its 12 partners, we are further curious about factors driving those cross-border co-movements. For each group of trading partners, we first investigate drivers of stock market co-movement during the full period of the sample and during periods of turmoil and then test the hypotheses of contagion. There are two popular hypotheses regarding the contagion effect explored in empirical research: (1) Fundamental contagion hypothesis is that contagion is related to country-specific economic and financial factors (e.g., Bekaert et al., 2014); and (2) Pure contagion hypothesis argues that contagion is independent of the fundamentals (e.g., Shen et al., 2015).

4.3.1. Explaining stock market co-movements between Jan. 2012 to Dec. 2020 and during the turmoil period covering key events

We regress the estimated long-run dynamic conditional correlation (monthly) onto a set of variables which can be categorized as common factors, economic integration factors, and market similarity factors. As mentioned in the Section 4.2, the crisis period covering Shanghai stock market crash was from June 2015 to February 2016, while the outbreak of US-China tariff wars and COVID-19 pandemic occupied the period from March 2018 to December 2020. Regression results are presented in Table 5A and 5B for developed and emerging trading partners, respectively. In each table, specifications I and III consider the effect of mixed factors, while specifications II and IV introduce the country-pair fixed effect to test the robustness of findings regarding the time-and-country-pair varying variables.

Looking at the estimates in Table 5A, estimation results for the periods of turmoil are similar to those of the full sample. We notice that stock market co-movements are positively affected by China term spread (as a proxy for market stress from illiquidity in China) for

Table 6A
Factors influencing of stock market co-movement during contagion times (China vs. developed trading partners).

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
Trade	0.7367*	0.7312*	1.3127**	1.0328*
	(0.4302)	(0.4265)	(0.6078)	(0.5880)
Production	0.7173***	0.5076***	0.4912**	0.3871***
	(0.2126)	(0.1305)	(0.2171)	(0.1318)
Money Supply	−0.3823	−0.1434	−0.8323	−0.2883
	(0.4183)	(0.3602)	(0.6333)	(0.5477)
Inflation	1.0384	1.1775	−3.9956*	−3.6659*
	(1.3094)	(1.1966)	(1.7702)	(1.5925)
Cross-Border Position	−0.0407	−0.0636	−0.4665***	−0.5463***
	(0.1142)	(0.1029)	(0.1735)	(0.1588)
Size	−0.0318**	−0.0317**	−0.0766**	−0.0832***
	(0.0134)	(0.0133)	(0.0307)	(0.0310)
Turnover	−0.0343***	−0.0306***	−0.0481***	−0.0333***
	(0.0044)	(0.0047)	(0.0064)	(0.0067)
Trade*Contagion	−0.1266	–	−0.5132***	–
	(0.1285)		(0.1771)	
Production*Contagion	−0.3549	–	−0.1809	–
	(0.2646)		(0.2640)	
Money*Contagion	0.7412	–	1.4432	–
	(0.7021)		(1.0667)	
Inflation*Contagion	1.4189	–	0.6512	–
	(2.8925)		(4.0609)	
Position*Contagion	−0.0319	–	−0.1235	–
	(0.2009)		(0.3111)	
Size*Contagion	–	0.0063	–	0.0190
		(0.0098)		(0.0139)
Turnover*Contagion	–	−0.0116***	–	−0.0337***
		(0.0059)		(0.0072)
Constant	0.1911**	0.1802**	0.3678***	0.3840***
	(0.0824)	(0.0825)	(0.1374)	(0.1350)
Country-Pair Fixed	YES	YES	YES	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.6887	0.6889	0.8309	0.8345
F statistics	48.91***	55.09***	40.19***	46.81***

Note: The full sample period is from Jan 2012 to Dec 2020, excluding two MIDAS years. The turmoil period contains two pieces of time (Jun 2015 - Feb 2016) and (Mar 2018 – Dec 2020). Contagion represents the contagion indicator, a monthly dummy variable taking values 1 when contagion is detected during a certain month, 0 otherwise. The interaction terms: Trade*Contagion, Production*Contagion, Money*Contagion, Inflation*Contagion, Position*Contagion are included in the regression Eq.(11) to examine the effects of economic integration variables during the contagion times. The interaction terms: Size*Contagion and Turnover*Contagion are included in the regression Eq.(11) to examine the effects of market similarity variables during the contagion times. The ***, **, and * indicate significance at the 1, 5, and 10% levels respectively.

both total sample and sub-sample. The result is similar to the finding of Niţoi and Pochea (2019) that Euribor-Eonia spread has a positive impact on EU stock market co-movement. Estimates for culture are also positive and significant for both samples. The impact of cultural similarity is related to transaction frictions caused by cultural differences, suggesting the preference of allocating investments across markets under similar cultures. By comparison, estimates for China VXFXI index are only negative and significant during turmoil period. Intuitively, the Chinese market expectation of greater volatility (proxied by the VXFXI index) is linked to higher risk aversion, reducing stock market co-movements between China and other economies significantly during crises. This finding is similar to Bekaert et al.'s (2014) finding that the increase in the VIX index decreases co-movements between US and international stock markets. This is potentially consistent with evidence in Bekaert et al. (2011) that global markets are more segmented in times of heightened risk aversion.

Regarding the country-pair explanatory variables, trade dependency is positively related to stock market co-movement for both the sample and turmoil periods. The results are robust when introducing the country-pair fixed effect. This finding is consistent with previous studies that stronger trade ties enhance stock market co-movement (e.g., Alotaibi and Mishra, 2015; Forbes and Chinn, 2004; Wälti, 2011; etc.). There are also clues of a positive relationship between the industrial production growth rate differential and stock market correlations. A possible reason for this lies in the portfolio strategy whereby international investors diversify their assets across high-growth and high-quality markets (Thomas et al., 2019). Besides, the money supply growth differential negatively affects stock market co-movements, while the inflation rate differential is irrelevant to co-movements. At the same time, differences in cross-border banking position growth are negatively related to stock market correlations. The results for banking position are only significant during the turmoil period and robust when controlling the country-pair fixed effect. Most of these findings support a popular point that similarities in economic development contribute to stock market co-movements. Moreover, estimates for size and turnover

Table 6B
Factors influencing stock market co-movement during contagion times (China vs. emerging trading partners).

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
Trade	1.5031***	1.4735***	4.3603***	3.9636***
	(0.4642)	(0.4624)	(0.6958)	(0.6882)
Production	0.6635***	0.2956***	0.6953***	0.1811**
	(0.1710)	(0.0806)	(0.2138)	(0.0909)
Money Supply	−0.0557	0.0529	−0.6499	0.0199
	(0.2807)	(0.2337)	(0.6443)	(0.4628)
Inflation	1.5413	1.1861	−3.0803	−3.3993*
	(1.2202)	(1.0878)	(2.2403)	(1.8222)
Cross-Border Position	0.1926*	0.1618*	−0.5968***	−0.5124***
	(0.1059)	(0.0893)	(0.1911)	(0.1351)
Size	−0.3034**	−0.3109**	0.9247***	0.9740***
	(0.1392)	(0.1398)	(0.3554)	(0.3537)
Turnover	−0.0406***	−0.0403***	−0.0416***	−0.0472***
	(0.0040)	(0.0045)	(0.0061)	(0.0069)
Trade*Contagion	−0.0690	–	−0.5074**	–
	(0.1505)		(0.2049)	
Production*Contagion	−0.4454**	–	−0.6027**	–
	(0.1884)		(0.2330)	
Money*Contagion	0.3364	–	1.0294	–
	(0.4529)		(0.8315)	
Inflation*Contagion	−1.0536	–	−0.8345	–
	(2.2230)		(3.3056)	
Position*Contagion	−0.1156	–	0.1587	–
	(0.1734)		(0.2490)	
Size*Contagion	–	−0.0313	–	−0.0999***
		(0.0213)		(0.0290)
Turnover*Contagion	–	0.0006	–	0.0153
		(0.0075)		(0.0095)
Constant	0.4377***	0.4553***	−0.9316***	−0.9258***
	(0.1102)	(0.1102)	(0.3153)	(0.3128)
Country-Pair Fixed	YES	YES	YES	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.4288	0.4205	0.6591	0.6474
F statistics	16.59***	18.05***	15.81***	17.04***

Note: The full sample period is from Jan 2012 to Dec 2020, excluding two MIDAS years. The turmoil period contains two pieces of time (Jun 2015 - Feb 2016) and (Mar 2018 – Dec 2020). Contagion represents the contagion indicator, a monthly dummy variable taking values 1 when contagion is detected during a certain month, 0 otherwise. The interaction terms: Trade*Contagion, Production*Contagion, Money*Contagion, Inflation*Contagion, Position*Contagion are included in the regression Eq. (11) to examine the effects of economic integration variables during the contagion times. The interaction terms: Size*Contagion and Turnover*Contagion are included in the regression Eq. (11) to examine the effects of market similarity variables during the contagion times. The ***, **, and * indicate significance at the 1, 5, and 10% levels respectively.

differentials are significant and negative over the full sample period and for periods of turmoil, except that the estimate for Turnover is insignificant in the column III. These findings indicate that more similar market sizes and turnover ratios enhance stock market co-movement, consistent with previous arguments (e.g., Bracker et al., 1999; Pretorius, 2002).

Moving on to Table 5B, we find similar findings as for the group of developed markets: the term spread, cultural closeness and bilateral trade are positively related to stock market co-movement, while turnover differentials have adverse effects for both periods. Moreover, the China ETF volatility index also has a negative impact on correlations, reflecting the effect of higher risk aversion under turbulence. However, apart from a weak sign that the inflation differential is negatively associated with correlations during the turmoil period, there are three findings specific to emerging markets: (1) The relation between industrial production growth and stock market co-movement is not significant under turbulence. Investors prefer rising economic growth rate differentials between developed and emerging markets because of signals that emerging markets will outperform developed markets ("Why Growth Matters In EM, Now More Than Ever," 2015). Compared to the emerging markets in this group, China does not have an absolute advantage over them in terms of growth rate. (2) The estimates for the differences in percent changes in cross-border banking position are significant and positive in the column I for the full sample although the estimates are negative during the turmoil period. The Chinese government maintains many restrictions on its external exposure and controls over its banking sector, featuring high-level macroprudential policies within Chinese financial system (Chang et al., 2015; Klingelhöfer and Sun, 2019). This finding indicates the benefit of prudential policies for emerging economies, as synchronizing with China in terms of expanding or shrinking cross-border banking linkages may reduce stock market co-movements with China in normal times. (3) The size differential is positively associated to stock market correlations in the column IV after controlling the country-pair fixed effect. This implies that for each emerging partner, correlations with Chinese market are higher when its market capitalization diverge more from Chinese market cap during the turmoil period. Since all emerging partners considered in this study have a smaller stock market compared to China, it indicates that smaller markets are more influenced by turbulences.

4.3.2. Explaining stock market co-movements during contagion times

To investigate whether there are some channels of propagating shocks when contagion occurs, we include the interaction terms of contagion indicators and time-and-country-pair variables into the panel data regression. Given that it is unwise to include too many interaction terms when computational power is limited for a short-horizon sample and 'blanket testing' may lead to spurious effects (Yan et al., 2009), we examine the effects of two groups of variables (i.e., economic integration and market similarity) separately. The results are reported in Table 6A and Table 6B for developed markets and emerging markets respectively.

We obtain several interesting findings from Table 6A: (1) All interactions of economic integration variables and contagion are irrelevant in explaining pairwise co-movement for the entire sample, while the Trade*Contagion yields significant and negative results for the turmoil period. The findings are a sign for the pure contagion hypothesis, which cannot be explained by fundamentals. We can notice that the estimates for Position*Contagion are negative but not significant, complementing previous studies. Niţoi and Pochea (2019) report that cross-border banking inflows differential is negatively associated with stock market co-movements within the European Union when contagion occurs and regard this as a flag of wake-up call in the banking sector. In this study, we can't observe a significant flag in percent changes in cross-border banking position. (2) For both the whole sample period and the turmoil period, the turnover ratio differential negatively affects stock market co-movement during contagion episodes. This result indicates that shocks are more easily spread across Chinese and developed stock markets that have comparative turnover ratios.

Looking at Table 6B, for both full and sub-samples, the estimate for the interaction of contagion indicator and the industrial production differential is negative and significant, indicating that divergence in economic growth rates reduces stock market co-movement during contagion episodes. The possible reason for this is that industrial production growth influences the stock market through the cash flow model, and the similarity of growth rates between two economies enhances their stock market co-movement (Pretorius, 2002). Moreover, there is no indication that stock market characteristics affect co-movement during the episodes of contagion for the full sample. If we distinguish the turmoil period from the full period, we find that the estimate for Trade*Contagion is negative and significant, indicating that trade negatively affects stock market co-movements between China and emerging partners during the contagion episodes. This finding is similar to the negative trade impact Mobarek et al. (2016) find among emerging stock markets during the Global Financial Crisis, which might be due to portfolio rebalancing (or flight to quality). Moreover, the estimate for the interaction term between the contagion indicator and market size is negative and significant, implying that divergence in market size reduces stock market co-movement under the effect of contagion during the turmoil period. Gkillas et al. (2019) suggest that changes in market capitalization contribute to contagion in international equity markets via portfolio selection.

Finally, let us discuss the nature of contagion. On the one hand, for developed trading partners (see Table 6A), estimates for interactions are primarily insignificant. Especially for the full sample, all macroeconomic variables are irrelevant to stock market co-movements during periods of contagion, which suggests the pure contagion phenomenon i.e. that macroeconomic fundamentals do not drive contagion. The interaction of the contagion indicator and turnover ratio also supports this phenomenon since when investors' behaviour is reflected by relative turnover velocity between two markets, this is defined as herding. On the other hand, emerging trading partners also receive estimation results that most interactions are irrelevant in stock market co-movements (see Table 6B). By contrast, the estimate for industrial production growth rate interaction suggests the wake-up call hypothesis (i.e. fundamental contagion hypothesis) for the entire sample. Furthermore, the negative impact of trade and market size differential may reflect portfolio selection of investors. These findings suggest that the intensification of stock market co-movement is explained in part by fundamental and pure contagion hypotheses, consistent with the study of Leung et al. (2017) on volatility spillover.

5. Robustness test

To the best of our knowledge, there are no other commonly accepted methods to derive the long-run component of Dynamic Conditional Correlation apart from the DCC-MIDAS approach. In this part, we conduct the regression analysis of Eq. (9) and Eq. (10), using alternative DCC-MIDAS estimates (or explanatory variables). First, we re-treated the dataset to estimate pairwise monthly DCC-MIDAS by excluding all common holidays and replacing the returns corresponding to non-common holidays with zeros. The fixed-span period N is chosen for each pair of China and trading partners separately, according to principle that obtained monthly DCC-MIDAS estimates cover at least $9*12 = 108$ months after excluding the first two years. We regard the estimate first occurring in a particular month as monthly DCC for this month. The regression of re-estimated monthly DCC yields similar results as presented in Section 4.3.1 (see Table C1 and Table C2 in Appendix). We also calculate the differential between the Y-o-Y growth rate in industrial production and M2 supply to gauge the economic and monetary convergences between two economies. Then, we replace the M-o-M growth rate differentials with Y-o-Y growth rate differentials in regression analysis and obtain similar findings (see Table D1 and Table D2 in Appendix). Finally, the cross-border banking position is quarterly-frequent, and the method of converting quarterly data to monthly data has little influence on results (see Table E1 and Table E2 in Appendix).

6. Conclusion

This paper investigates the dynamics of, and influencing factors for, stock market co-movements between China and its Asia-Pacific trading partners from January 2012 to December 2020. The DCC-MIDAS approach is employed to evaluate time-varying co-movement between stock markets on a long-run basis: weekly DCCs for contagion tests and monthly DCCs for regression analyses. Our empirical results are summarized as follows:

First, we obtain a considerable range of values for the pairwise co-movements. The results reveal that the Chinese stock market is more correlated to Asian markets than Pacific markets for the group of developed partners and more integrated with East Asian markets for the group of emerging partners. Although different pairwise correlations reveal different evolving patterns, increasing trends are commonly observed in most pairwise co-movements in mid-2015 and early-2018.

Second, contagion episodes suggest that stock market co-movements are mainly intensified by turbulent events, with a rise in levels of contagion frequency during the Shanghai stock market crash, US-China tariff wars, and COVID-19 pandemic. However, the findings for developed economies and emerging economies are slightly different. There are indications that stock market co-movement between China and its developed partners are more sensitive to US-China trade frictions, while those between China and its emerging partners are more influenced by the Shanghai stock market crash.

Third, regarding drivers of stock market co-movement, the regression results present several regularities: (1) Among common factors, excess illiquidity pressure in financial markets leads to increasing co-movements for both the whole and turmoil periods. In contrast, an increase in the China ETF volatility index has a negative impact on pairwise DCCs under turbulences. Culture proximity is also relevant to co-movements for both groups of trading partners. (2) For both groups, bilateral trade plays an essential role in driving the pairwise dynamic correlations, showing that stronger trade connections lead to enhanced co-movement in normal and turmoil times. The stock market co-movement between China and its developed partners are positively affected by industrial production differential for the whole and turmoil periods, and negatively affected by differences in cross-border banking position (% changes) during the periods of turmoil. By comparison, the industrial production differential is irrelevant to stock market co-movement between China and emerging partners during the turmoil period. (3) Similarities in terms of market size and turnover ratio are positively associated with stock market co-movement between China and its trading partners in both normal and turmoil times. (4) The results for factors influencing stock market co-movement during episodes of contagion are mixed. For one thing, stock market co-movements between China and partners are irrelevant to most economic fundamentals, indicating pure contagion. For another thing, stock markets co-movements between China and its emerging partners are negatively affected by differences in industrial production growth and market sizes.

Financial integration among international stock markets requires attention due to its impact on portfolio diversification, assets allocation and risk management. Our findings on stock market co-movement between China and its trading partners in the Asia-Pacific region have some important implications for policymakers and investors participating in capital flows in this region. The evolving patterns, the co-movement drivers, and the propagation of contagion provide policymakers with insights on the timing of shocks transmitted from the Chinese stock market and potential measures to reduce stock market co-movements. And the positive relationship between bilateral trade and stock market co-movement suggests that China's position in international trade contributes to the rise of its financial power. The dynamic correlations are also important for international investors who diversify investments across markets to manage their overall risk portfolio.

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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Appendix A. Appendix

Table A
Variables description.

Variable	Description	Source
Pairwise dynamic conditional correlation	The weekly and monthly conditional correlations are estimated by the DCC-MIDAS model and then Fisher-Z transformed to adjust for potential non-normality issue in this study. Related references: Colacito et al. (2011)	Authors' estimates
Contagion indicator	Dummy variable is equal to 1 if contagion is detected during a certain month, 0 otherwise. Related references: Buchholz and Tonzer (2016), Niţoi and Pochea (2019)	Authors' estimates
Common Variables		
China volatility index	The Chicago Board Options Exchange China ETF Volatility Index (VXFXI). Index prices are collected on monthly basis. All pairwise conditional correlations investigated in this study are exposed to the volatility risk of Chinese stock markets since the co-movements are all involved with China. Related references: Lehkonen (2015)	*Investing.com*
China illiquidity risk	The term spread (unit: %) affecting each pairwise conditional correlation is the spread between China's long-term 10-year government bond yield and China's the 3-month interbank rate, a proxy for Chinese market stress from illiquidity. Related references: Christoffersen et al. (2012), Mobarek et al. (2016)	CEIC database
Culture Proximity	Dummy variable takes value 1 if the country/region has a closer culture distance with China, belonging to the bottom 50% in the group when all economies in the group are ranked by culture distances from high to low. The culture distance is estimated by the following equation using the six-dimension cultural scores provided by the Hosftede Insights. $CultureDistance_i = (\sum_1{}^6[(Score_{fi} - Score_{fchina})^2/Var(Score_f)])/6$ where $Score_{fi}$ and $Score_{fchina}$ denote the value of *f_th* cultural dimension of country *i* and China respectively, $Var(Score_f)$ is the variance of values of *f_th* cultural dimension in our all sample (i.e China and its 12 trading partners). Related references: Hofstede (1994), Mobarek et al. (2016)	Website: https://www.hofstede-insights.com/country-comparison/
Economic integration variables		
Bilateral Trade [1]	Average bilateral trade between country *i* and *j* (fixed to China). The calculated equation: $[(X_{ij}/X_i) + (M_{ij}/M_i) + (X_{ji}/X_j) + (M_{ji}/M_j)]/4$ where X is exports, M is imports, ij refers to monthly trading flows from country *i* to country *j*, *ji* is trade flow from country *j* to country *i*, X_i and X_j are total exports of country *i* and country *j* respectively, while M_i and M_j are total imports of country *i* and country *j* respectively. Related references: Bracker et al. (1999), Mobarek et al. (2016)	*TradingEconomics.com* *CSMAR database (only for monthly imports/exports data of China)*
Industrial Production M-o-M Growth Rate Differential [2]	$\lvert\Delta Industrial\ Production_{it} - \Delta Industrial\ Production_{jt}\rvert$, where *i, j* stands for country *i* and country *j* (fixed to China) during time *t*. $\Delta Industrial\ Production_{it}$ is calculated by monthly Industrial Production Index: $\Delta Industrial\ Production_{it} = (IPI_{it} - IPI_{it-1})/IPI_{it-1}$. Related references: Pretorius (2002)	*TradingEconomics.com*
M2 M-o-M Growth Rate Differential	$\lvert\Delta M2_{it} - \Delta M2_{jt}\rvert$, where *i, j* stands for country *i* and country *j* (fixed to China) during time *t*. $\Delta M2_{it}$ is computed by monthly M2: $\Delta M2_{it} = (M2_{it} - M2_{it-1})/M2_{it-1}$. Related references: Brada et al. (2005)	CEIC database
Inflation Differential	$\lvert InflationRate_{it} - InflationRate_{jt}\rvert$, where *i, j* stands for country *i* and country *j* (fixed to China) during time *t*. $InflationRate_{it}$ is calculated by monthly Consumer Price Index: $InflationRate_{it} = (CPI_{it} - CPI_{it-1})/CPI_{it-1}$. Related references: Brada et al. (2005)	*TradingEconomics.com*
Cross-Border Banking Position Differential	$\lvert\Delta GrossPosition_{it} - \Delta GrossPosition_{jt}\rvert$, where *i, j* stands for country *i* and country *j* (fixed to China) during time *t*. Gross position is the sum of liability and claim in banking sector, and $\Delta GrossPosition_{it} = (GrossPosition_{it} - GrossPosition_{it-1})/GrossPosition_{it-1}$. Related references: Tonzer (2015)	Bank for International Settlements Database
Stock market similarity variables		
Stock Market Size Differential [3]	$\lvert MCap_{it} - MCap_{jt}\rvert/MCap_{jt}$, where *i, j* stands for country *i* and country *j* (fixed to China) during time *t*, where $Mcap_{it}$ is the monthly stock market capitalization of country *i* . Related references: Johnson and Soenen (2002), Mobarek et al. (2016)	The World Federation of Exchanges (WFE) World Development Indicators (world cap)
Stock Market Turnover Ratio Differential [4]	$\lvert turnover_{it} - turnover_{jt}\rvert$, where *i, j* stands for country *i* and country *j* (fixed to China) during time *t*. $turnover_t$ is the monthly turnover ratio of total equity market, representing the liquidity of stock market. Related references: Thomas et al. (2019)	The World Federation of Exchanges (WFE)

Note: [1] We collect monthly trade data of country *i* from the *TradingEconomics.com* and replenish the incomplete data from its official statistics website the *TradingEconomics*.com refers to. The values are presented in the local currency and following the local customs criteria. Meanwhile, the exports/imports data (total & by partner) for China is collected from CSMAR database, a comprehensive database for Chinese business research. For

Indonesia and Malaysia, data are replenished by CEIC dataset since their official website cannot provide complete historical records. And from 2020, the monthly trade data of China will not be available for January and February, and instead the accumulated amount of the first two months of year will be released by the end of February. We divide the accumulated values evenly for January and February. [2] Australia, Hong Kong and New Zealand release the industrial production index quarterly. With the assumption that industrial production increases/decreases with the same rate in each month for a certain quarter (i.e. $(1+r_m)^3 = (1+r_q)$), we convert the industrial production Q-o-Q growth rate to industrial production M-o-M growth rate. Data for Hong Kong, Indonesia and New Zealand are replenished by Census and Statistics, CEIC database and OECD database. [3] The stock market capitalization for China is the sum of capitalizations of Shanghai and Shenzhen stock exchanges. The stock market capitalization for the United States is the sum of capitalization of New York and Nasdaq stock exchanges. [4] The turnover ratio is also known as turnover velocity. We collect data mostly from the WFE database, along with monthly stock market reports from Singapore and Nasdaq (USA) stock exchanges and CSMAR database. Chinese stock market turnover ratio is the average of monthly turnover ratio for Shanghai and Shenzhen stock exchanges. Due to data availability, US stock market turnover ratio is approximated by New York & Nasdaq EOB domestic shares and market capitalizations according to the equation provided by the WFE Statistics Definitions Manual 2021.

Table B1
Parameter estimates for the DCC-MIDAS approach (China v.s. developed partners).

	CN-AU		CN-HK		CN-JP		CN-NZ		CN-SG		CN-US	
Step 1: univariate volatility process												
	CN	AU	CN	HK	CN	JP	CN	NZ	CN	SG	CN	US
μ	0.0004	0.0003	0.0004	0.0002	0.0004	0.0007	0.0004	0.0006	0.0004	0.0001	0.0004	0.0007
	(0.034)	(0.028)	(0.029)	(0.215)	(0.063)	(0.000)	(0.038)	(0.000)	(0.052)	(0.271)	(0.042)	(0.000)
α	0.0547	0.1321	0.0516	0.0532	0.0448	0.1987	0.0588	0.1522	0.0571	0.0975	0.0497	0.1822
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	0.9286	0.8081	0.9423	0.9110	0.9499	0.6819	0.9160	0.6638	0.9277	0.8671	0.9475	0.7685
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
θ	0.1635	0.1079	0.1628	0.1165	0.1400	0.1376	0.1789	0.1275	0.1619	0.0995	0.1481	0.1023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\bar{z}$	0.0087	0.0070	0.0113	0.0085	0.0115	0.0094	0.0072	0.0044	0.0091	0.0066	0.0156	0.0080
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ω_{v1}	Set to 1	Set to 1	1.0819	6.9923	5.6992	19.138	Set to 1	Set to 1	Set to 1	Set to 1	11.434	4.3617
			(0.000)	(0.100)	(0.006)	(0.008)					(0.037)	(0.075)
ω_{v2}	1.0010	1.0953	9.8385	5.9990	18.021	6.0705	1.0367	2.8632	1.1207	1.0010	24.411	17.724
	(0.000)	(0.000)	(0.000)	(0.093)	(0.009)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.043)	(0.080)
Constraint1 Satisfied?	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constraint2 Satisfied?	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Step 2: dynamic conditional correlation												
a	0.0201		0.0189		0.0459		0.0187		0.0271		0.0181	
	(0.118)		(0.063)		(0.011)		(0.097)		(0.020)		(0.228)	
b	0.5963		0.5588		0.4621		0.8499		0.6990		0.7007	
	(0.086)		(0.055)		(0.057)		(0.000)		(0.000)		(0.045)	
ω_{c1}	Set to 1		9.7071		9.4346		Set to 1		Set to 1		1.0230	
			(0.000)		(0.011)						(0.000)	
ω_{c2}	1.0294		2.8482		2.4998		1.0010		3.0524		1.1878	
	(0.000)		(0.000)		(0.007)		(0.000)		(0.000)		(0.020)	

Note: CN, AU, HK, JP, NZ, SG, and US denote China, Australia, Hong Kong, Japan, New Zealand, Singapore and United States respectively. The sample covers 2010-01-04 until 2020-12-31. When calculating dynamic conditional correlations between Chinese and a partner's stock markets, we exclude the trading days on which either of the two markets is closed. And ω_{v1} & ω_{c1} are set to one when two-parameter beta weights are not suitable and replaced by one-parameter beta weights. For more details, please refer to the Methodology. $\mu, \alpha, \beta, \theta, \bar{z}, \omega_{v1}, \omega_{v2}$ are parameters of Eq. (3)-Eq. (5). a, b, ω_{c1}, ω_{c2} are parameters of Eq. (6)-Eq. (7). The GARCH-MIDAS process in the first step has a form of GARCH(1,1) in Eq. (4), and α and β may satisfy the moment conditions of GARCH(1,1). Constraint1: $\alpha + \beta < 1$, the condition for existence of second moment of GARCH(1,1); Constraint2: $3\alpha^2 + 2\alpha\beta + \beta^2 < 1$, the condition for existence of fourth moment of GARCH(1,1) (Reference: Ling and McAleer, 2002; Ng and McAleer, 2004). The numbers in the parenthesis are P-values of t-statistics.

Table B2
Parameter estimates for the DCC-MIDAS approach (China v.s. emerging partners).

	CN-IN		CN-ID		CN-KR		CN-MY		CN-TW		CN-TH	
Step 1: univariate volatility process												
	CN	IN	CN	ID	CN	KR	CN	MY	CN	TW	CN	TH
μ	0.0002	0.0006	0.0005	0.0004	0.0004	0.0003	0.0003	0.0001	0.0002	0.0005	0.0004	0.0004
	(0.209)	(0.000)	(0.011)	(0.002)	(0.060)	(0.018)	(0.062)	(0.299)	(0.321)	(0.002)	(0.036)	(0.004)
α	0.0567	0.1677	0.0616	0.2155	0.0613	0.1359	0.0698	0.1152	0.0409	0.1350	0.0504	0.1050
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	0.9294	0.6545	0.9228	0.6637	0.9146	0.7252	0.9142	0.8163	0.9497	0.7094	0.9466	0.8829
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
θ	0.1552	0.1381	0.1759	0.1589	0.1797	0.1391	0.2096	0.1627	0.0761	0.1322	0.1496	0.1450
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.138)	(0.000)	(0.000)	(0.000)

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Table B2 (*continued*)

	CN-IN		CN-ID		CN-KR		CN-MY		CN-TW		CN-TH	
$\bar{z}$	0.0095	0.0071	0.0082	0.0069	0.0072	0.0062	0.0060	0.0037	0.0125	0.0064	0.0149	0.0088
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ω_{v1}	Set to 1	Set to 1	Set to 1	Set to 1	Set to 1	Set to 1	Set to 1	Set to 1	Set to 1	Set to 1	16.853	1.0429
											(0.009)	(0.000)
ω_{v2}	1.1119	13.984	1.0010	4.3568	1.0862	3.1704	1.1589	1.0010	1.0712	2.3140	34.311	8.9765
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.012)	(0.002)
Constraint1 Satisfied?	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constraint2 Satisfied?	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Step 2: dynamic conditional correlation												
a	0.0281		0.0187		0.0490		0.0121		0.0055		0.0197	
	(0.007)		(0.049)		(0.002)		(0.082)		(0.172)		(0.025)	
b	0.8599		0.8795		0.6928		0.9306		0.9533		0.8586	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
ω_{c1}	Set to 1		Set to 1		Set to 1		Set to 1		Set to 1		1.7766	
											(0.075)	
ω_{c2}	1.0010		2.1396		3.0559		1.9960		1.2438		1.0870	
	(0.000)		(0.001)		(0.000)		(0.002)		(0.000)		(0.083)	

Note: CN, IN, ID, KR, MY, TW and TH denote China, India, Indonesia, South Korea, Malaysia, Taiwan and Thailand respectively. The sample covers 2010-01-04 until 2020-12-31. When calculating dynamic conditional correlations between Chinese and a partner's stock markets, we exclude the trading days on which either of the two markets is closed. And ω_{v1} & ω_{c1} are set to one when two-parameter beta weights are not suitable and replaced by one-parameter beta weights. For more details, please refer to the Methodology. $\mu, \alpha, \beta, \theta, \bar{z}, \omega_{v1}, \omega_{v2}$ are parameters of Eq. (3)-Eq. (5). a, b, ω_{c1}, ω_{c2} are parameters of Eq. (6)-Eq. (7). The GARCH-MIDAS process in the first step has a form of GARCH(1,1) in Eq. (4), and α and β may satisfy the moment conditions of GARCH(1,1). Constraint1: $\alpha + \beta < 1$, the condition for existence of second moment of GARCH(1,1); Constraint2: $3\alpha^2 + 2\alpha\beta + \beta^2 < 1$, the condition for existence of fourth moment of GARCH(1,1) (Reference: Ling and McAleer, 2002; Ng and McAleer, 2004). The numbers in the parenthesis are P-values of t-statistics.

Table C1
Influencing factors of stock market co-movement between China and its developed trading partners (based on re-estimated DCC-MIDAS).

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
China VXFXI Index	−0.0012		−0.0102***	
	(0.0011)		(0.0014)	
China Term Spread	0.0839***		0.0992***	
	(0.0098)		(0.0181)	
Culture	0.1420***		0.2283***	
	(0.0124)		(0.0179)	
Trade	1.4762***	0.4104*	2.0345***	1.4619***
	(0.0932)	(0.3697)	(0.1547)	(0.4950)
Production	0.2798*	0.4719***	0.4887***	0.2675*
	(0.1615)	(0.1275)	(0.1628)	(0.1445)
Money Supply	−1.3373**	−0.1221	−1.1100**	−0.3975
	(0.3406)	(0.2875)	(0.4404)	(0.4122)
Inflation	1.9401	2.3121	1.4193	−1.1892
	(1.5325)	(1.4497)	(1.9334)	(2.1511)
Cross-Border Position	−0.0297	−0.0287	−0.5918***	−0.5092***
	(0.0812)	(0.0778)	(0.1254)	(0.1277)
Size	−0.0417***	−0.0489***	−0.0197***	−0.0629***
	(0.0037)	(0.0077)	(0.0069)	(0.0193)
Turnover	−0.0304***	−0.0316***	−0.0050	−0.0356***
	(0.0041)	(0.0034)	(0.0072)	(0.0071)
Constant	0.2088***	0.2863***	0.2781***	0.2919***
	(0.0308)	(0.0692)	(0.0440)	(0.1128)
Country-Pair Fixed	NO	YES	NO	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.6798	0.7118	0.8163	0.8075
F statistics	63.30***	67.00***	49.95***	42.68***

Table C2
Influencing factors of stock market co-movement between China and its emerging trading partners (based on re-estimated DCC-MIDAS).

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)	Turmoil period Estimates (std error)

(*continued on next page*)

Table C2 (*continued*)

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
	I	II	III	IV
China VXFXI Index	0.0016		−0.0044***	
	(0.0010)		(0.0013)	
China Term Spread	0.0497***		0.1064***	
	(0.0077)		(0.0156)	
Culture	0.0248***		0.0136*	
	(0.0090)		(0.0151)	
Trade	1.4423***	1.6236***	2.6000***	4.1262***
	(0.1404)	(0.4868)	(0.2515)	(0.6971)
Production	−0.0135	0.2854***	0.0873	0.1372
	(0.0715)	(0.0777)	(0.0908)	(0.0883)
Money Supply	−0.1660	−0.0739	−0.6465	−0.0329
	(0.1829)	(0.1866)	(0.4002)	(0.4603)
Inflation	0.8525	1.4843	0.2486	−2.6807
	(1.0424)	(1.0136)	(1.5794)	(1.7178)
Cross-Border Position	0.1999**	0.1196	−0.3168***	−0.5423***
	(0.0902)	(0.0908)	(0.1135)	(0.1276)
Size	−0.2248***	−0.4438***	−0.1425*	0.9602***
	(0.0497)	(0.1337)	(0.1035)	(0.3102)
Turnover	−0.0472***	−0.0390***	−0.0280***	−0.0431***
	(0.0037)	(0.0038)	(0.0062)	(0.0067)
Constant	0.3744***	0.5736***	0.3206***	−0.9384***
	(0.0522)	(0.0995)	(0.0819)	(0.2500)
Country-Pair Fixed	NO	YES	NO	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.4558	0.4302	0.6250	0.6281
F statistics	24.97***	20.48***	18.73***	17.18***

Table D1
Influencing factors of stock market co-movement between China and its developed trading partners (Note: Y-o-Y growth rate differentials in Production and Money Supply).

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
China VXFXI Index	0.0007		−0.0083***	
	(0.0012)		(0.0013)	
China Term Spread	0.0823***		0.0931***	
	(0.0102)		(0.0192)	
Culture	0.1630***		0.2733***	
	(0.0140)		(0.0193)	
Trade	1.4077***	0.4290	1.8579***	0.4456*
	(0.1016)	(0.3470)	(0.1526)	(0.4522)
Production	0.1550	0.4459***	0.0760	0.4631***
	(0.1411)	(0.1307)	(0.1735)	(0.1508)
Money Supply	−1.1599***	−0.5351***	−1.1972***	−1.5652***
	(0.2045)	(0.2073)	(0.2619)	(0.2818)
Inflation	0.7759	1.5378	−0.5173	−3.4724**
	(1.4218)	(1.3540)	(1.7477)	(1.7349)
Cross-Border Position	0.0005	−0.0581	−0.4519***	−0.2292**
	(0.0876)	(0.0871)	(0.1313)	(−0.1163)
Size	−0.0365***	−0.0287***	−0.0215***	−0.1110***
	(0.0039)	(0.0059)	(0.0082)	(0.0177)
Turnover	−0.0379***	−0.0331***	−0.0117	−0.0428***
	(0.0048)	(0.0039)	(0.0081)	(0.0068)
Constant	0.2073***	0.2177***	0.3000***	0.6134***
	(0.0309)	(0.0639)	(0.0420)	(0.1004)
Country-Pair Fixed	NO	YES	NO	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.6606	0.6885	0.8046	0.8350
F statistics	11.60***	10.65***	46.29***	51.50***

Table D2
Influencing factors of stock market co-movement between China and its emerging trading partners (Note: Y-o-Y growth rate differentials in Production and Money Supply).

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
China VXFXI Index	0.0011		−0.0061***	
	(0.0010)		(0.0010)	
China Term Spread	0.0474***		0.1158***	
	(0.0076)		(0.0150)	
Culture	0.0376***		0.0338**	
	(0.0093)		(0.0136)	
Trade	1.4280***	1.4906***	2.5857***	4.0790***
	(0.1310)	(0.4692)	(0.2163)	(0.6879)
Production	0.2035**	0.3258***	0.1172	0.0754
	(0.0995)	(0.0972)	(0.1131)	(0.1159)
Money Supply	−0.1292	−0.3315***	−0.1480	−0.8500***
	(0.0861)	(0.1043)	(0.2034)	(0.2145)
Inflation	0.1742	0.8753	−0.6518	−2.7857
	(1.0662)	(1.0075)	(1.5532)	(1.8570)
Cross-Border Position	0.1809**	0.1094	−0.3323***	−0.5027***
	(0.0903)	(0.0897)	(0.1039)	(0.1250)
Size	−0.2132***	−0.3340**	−0.2107**	0.7122**
	(0.0493)	(0.1354)	(0.0942)	(0.2938)
Turnover	−0.0465***	−0.0401***	−0.0232***	−0.0366***
	(0.0037)	(0.0037)	(0.0055)	(0.0059)
Constant	0.3669***	0.4857***	0.4075***	−0.6954***
	(0.0512)	(0.1010)	(0.0767)	(0.2464)
Country-Pair Fixed	NO	YES	NO	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.4585	0.4282	0.6686	0.6336
F statistics	25.24***	20.32***	22.67***	17.59***

Table E1
Influencing factors of stock market co-movement between China and its developed trading partners (with an alternative method of converting quarterly to monthly frequency).

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
China VXFXI Index	−0.0010		−0.0123***	
	(0.0012)		(0.0014)	
China Term Spread	0.0818***		0.0752***	
	(0.0103)		(0.0190)	
Culture	0.1442***		0.2433***	
	(0.0137)		(0.0188)	
Trade	1.4870***	0.7338**	1.8530***	0.9838*
	(0.1007)	(0.3594)	(0.1545)	(0.5033)
Production	0.2867*	0.4779***	0.6903***	0.3096**
	(0.1644)	(0.1193)	(0.1691)	(0.1431)
Money Supply	−1.4246***	−0.1738	−1.0019*	−0.2378
	(0.3671)	(0.3125)	(0.5163)	(0.4657)
Inflation	0.8449	1.2412	0.2797	−2.8241
	(1.5509)	(1.4406)	(1.8583)	(1.9841)
Cross-Border Position	0.0037	0.0343	−0.4561***	−0.2777***
	(0.0704)	(0.0611)	(0.1037)	(0.0948)
Size	−0.0414***	−0.0324***	−0.0309***	−0.0719***
	(0.0037)	(0.0056)	(0.0072)	(0.0184)
Turnover	−0.0329***	−0.0337***	−0.0091	−0.0472***
	(0.0046)	(0.0038)	(0.0081)	(0.0073)
Constant	0.2079***	0.1841***	0.3678***	0.3666***
	(0.0329)	(0.0654)	(0.0449)	(0.1106)
Country-Pair Fixed	NO	YES	NO	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.6517	0.6867	0.8082	0.8138
F statistics	55.79***	59.48***	47.35***	44.47***

Table E2
Influencing factors of stock market co-movement between China and its emerging trading partners (with an alternative method of converting quarterly to monthly frequency).

Dependent variable: pairwise DCC-MIDAS	Full sample Estimates (std error)		Turmoil period Estimates (std error)	
	I	II	III	IV
China VXFXI Index	0.0017		−0.0068***	
	(0.0010)		(0.0011)	
China Term Spread	0.0527***		0.1117***	
	(0.0079)		(0.0145)	
Culture	0.0369***		0.0287**	
	(0.0091)		(0.0134)	
Trade	1.3963***	1.3603***	2.6667***	4.0351***
	(0.1333)	(0.4755)	(0.2190)	(0.6949)
Production	−0.0541	0.2598**	0.1374	0.1245
	(0.0798)	(0.0865)	(0.0979)	(0.0963)
Money Supply	−0.0443	0.0369	−0.6423*	−0.2143
	(0.1700)	(0.1701)	(0.3772)	(0.4408)
Inflation	0.4817	1.2284	−0.8004	−2.9387*
	(1.0399)	(1.0043)	(1.4349)	(1.7542)
Cross-Border Position	0.1973**	0.1107	−0.3120***	−0.4730***
	(0.0785)	(0.0775)	(0.0879)	(0.0970)
Size	−0.2033	−0.3418***	−0.2311***	0.8753***
	(0.0500)	(0.1344)	(0.0922)	(0.2967)
Turnover	−0.0485***	−0.0402**	−0.0192**	−0.0393***
	(0.0037)	(0.0037)	(0.0057)	(0.0064)
Constant	0.3573***	0.4940***	0.4251***	−0.8774***
	(0.0512)	(0.1011)	(0.0737)	(0.2408)
Country-Pair Fixed	NO	YES	NO	YES
Seasonal Time Fixed (Time Dummies)	YES	YES	YES	YES
No. of observations	648	648	258	258
R-squared	0.4525	0.4140	0.6735	0.6202
F statistics	24.64***	19.17***	23.18***	16.61***

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