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International trade network and stock market connectedness: Evidence from eleven major economies

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A B S T R A C T

Depth of cross-country international trade engagement is an important source of (the strength of) stock-market connectedness, depicting how directional attributes of trade determine the magnitude of spillover of stock returns across economies. We premise and test this hypothesis for a group of eleven major economies during 2000 m1-2021 m6 using both system-wide and directional evidence. We exploit the input–output network of Bilgin and Yilmaz (2018) to construct a trade-network, and use Diebold and Yilmaz's (2009, 2012, 2014) Connectedness Index to proxy for stock-market connectedness among economies. We reveal China's instrumental role in the trade-network and its rising influence in stock markets dominated by the US. Motivated by the fact that shocks on an economy's imports and exports may lead to different magnitude of stock market spillover to its trade partner, we further carry out a pairwise directional level investigation. Once the directional dimensions of both the trade flows and the stock market influences are considered, we find that an economy's stock return spillover to its trade partner is generated from its position as an importer and exporter. More importantly, being an importer is found to be a stronger source of such spillover than being an exporter.

1. Introduction

In a highly internationalised world, cross-country stock markets appear to be highly connected amounting to spillover of informational inefficiency and regressive response of various national economies. However, the propensity for international stock markets to be connected to one another can vary measurably (e.g., Longin and Solnik, 1995; Forbes and Rigobon, 2002; Kim et al., 2005; Morana and Beltratti, 2008; He et al., 2014,2015; Zhang et al., 2017). A number of factors have been used in the extant literature as potential predictors of stock market interdependencies, such as the changes in national outputs (e.g., Dumas et al., 2003), perceived market risk and uncertainty (e.g., Connolly et al.,2007; Cai et al., 2009), price and exchange rate indices (e.g., Kiviaho et al., 2014) and oil prices movements (e.g., McMillan et al., 2021). In this paper, we introduce the role of a country's depth of international trade engagement as a primary source of stock-market connectedness. An empirical investigation for major eleven economies leads us to conclude that the depth of international trade among countries significantly explain cross-economy spillover of stock returns. In particular, we find that the very position of a country as an importer has a greater explanatory power for positive spillover of stock

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returns.

Why is international trade an important determinant of stock-market connectedness across countries? Among other reasons, which we will present shortly, international trade is one of the most important aspects of the real economy that connects nations globally. A foremost feature of international trade is that a country's import and export directions and depth capture the dynamic effects of national output growth (i.e., excess growth can generate greater income through trade), ability to embed price and exchange rate risks (depending on the urgency of the need to earn foreign currencies and pump-prime the country's economic growth), and oil price movements (which almost every country is experiencing its volatile effects of price changes). Furthermore, increasing international trade has made countries more vulnerable to adverse foreign demand and supply shocks, which may affect the local financial markets via weakened returns on assets due to reduced demand for exports or uncertainty in imports (Chen and Zhang, 1997; Bracker et al., 1999; Pretorius, 2002; Shinagawa, 2014). For instance, Fung et al. (1995) and He et al. (2021) argue that stock markets often react strongly to trade news. Further studies have explored the relationship between bilateral trade and stock market interdependence (e.g., Johnsen and Soenen (2003), Wälti (2005, 2011), Liu et al. (2006), Chambet and Gibson (2008), Tavares (2009), Liu (2013), Balli, et al. (2015), Vithessonthi and Kumarasinghe (2016), Dhanaraj et al (2017), Nguyen and Lam (2017)). Yet, there remains some key gaps in the current literature.

Firstly, at an aggregate level, literature on the interdependence between a trade-network and stock-market connectedness among economies, is nascent. This could provide a useful indicator for international organisations to monitor intensifying or weakening global trade-network and its potential impact on the stock market interdependence over time. To fill this gap in the literature, we build an import–export network following the input–output network of Bilgin and Yılmaz (2018) and adopt the Diebold-Yilmaz Connectedness Index (DYCI) framework (Diebold and Yilmaz, 2009, 2012, 2014), to present static and dynamic system-wide indicators for trade and stock-market connectedness. We thereby examine the hypothesis of whether the network of international trade influences stock market connectedness for a group of economies as a whole.

Secondly, previous studies on the trade-stock market interdependence relationship often do not incorporate the *directional dimension* in their analysis. More specifically, the widely used stock market correlation and integration measures do not distinguish if an economy is the giver or receiver of stock return spillover between a pair of economies; the conventional bilateral trade measures overlook the directional element of trade flows. As elaborated in Section 2.1 and further demonstrated in Appendix A, a shock to an economy's imports and exports may transmit to its trade partner's stock market in different magnitude. Specifically, an economy's position as an importer could be a stronger generator of stock return spillover to its trade partner than being an exporter. Therefore, underneath the trade-network, we differentiate between these two directions of trade flows (with their relative importance to the economies accounted for) in order to investigate their individual effect in generating stock-market connectedness. Combining the pairwise directional trade information with the corresponding pairwise directional stock return spillover produced in the DYCI framework, we are able to reveal the directional impact of trade flows on stock market spillover. More importantly, we are able to examine the hypothesis that an economy's position as an importer leads to stronger stock market spillover to its trade partner than the spillover generated by its position as an exporter. As such, our work provides an important extension to the existing studies on the relationship between stock-market connectedness and trade flows. We posit that this study would further provide valuable information for investors and policy makers in assessing the directional impact of changes in trade flows on stock market interdependence.

Our empirical analysis includes eleven major international players in trade and stock markets, namely the ASEAN 5, Australia, Brazil, China, Euro Area, Hong Kong (China), India, Japan, South Africa, UK and the US. Combinedly, they cover 68.2 % of world's total exports and over 90 % of global market capitalisation in 2020. They also present a sound geographic inclusion, covering Asia, Africa, North America, South America, Europe, and Australia. Our estimation uses a monthly data for the period between Jan 2000 and June 2021, that includes the ongoing Covid-19 pandemic period.

The rest of the paper is organised as follows. Section 2 presents the theoretical link and the directional dimension of the trade-stock market relationship, reviews relevant empirical literature and discusses our contributions. Section 3 outlines Diebold-Yilmaz Connectedness Index framework and describes the data. Section 4 presents results of both static and dynamic system-wide connectedness of the stock markets and the import–export network. Section 5 formally examines the system-wide and pairwise directional level evidence. Finally, Section 6 concludes with some implications for policy.

2. Literature review

2.1. International trade-network and stock-market connectedness – The theoretical link and the directional dimension

International trade is known to be an important macroeconomic determinant of global stock market integration (Chen and Zhang, 1997; Johnson and Soenen, 2002; Forbes and Chinn, 2004, Joyo and Lefen, 2019; Caporale et al., 2019). Trade activities link the cash flows of the trading partners and make their equity markets more connected (Chen and Zhang, 1997). Also, supply chain implications—represented by the distribution of manufacturing processes over more than one country—might accelerate financial market spillover (Shinagawa, 2014).

While many studies have shown that stronger trade ties amongst economics leads to closer co-movement in their stock markets (e.g., Bekaert and Harvey, 1997; Wälti, 2005; Amstad et al., 2021; He et al., 2021), literature on the interdependence between a system-wide trade-network and stock-market connectedness among economies is scarce. Building an import–export network following the input–output network of Bilgin and Yılmaz (2018) and employing the DYCI framework, this paper presents static and dynamic system-wide indicators for trade and stock-market connectedness. It allows us to investigate any patterns and trends in these two aggregate level indicators and examines whether the former affects the latter for a group of economies as a whole.

H_1: A tighter international trade-network leads to stronger stock market connectedness at a system-wide level amongst economies

Furthermore, we extend existing literature in this area by distinguishing the directions in both trade and stock market spillover. Choosing *j* as our country and *i* its trade partner, we examine how *j*'s imports from *i* affect *j*'s stock market spillover to *i* comparing to how *j*'s exports to *i* affect *j*'s stock market spillover to *i*. In the former case, *j* is an importer, and in the latter, *j* is an exporter. The same can be described about country *i*. If a substantial proportion of a source country's output is exported to one target country, then an economic boom in the target county will lead to an increase in its imports from the source country. Thus, a thriving target country's stock market, caused by its domestic economic upswing, will be associated to the rising in the source country's stock market given its increased exports to the target country (Pretorius, 2002; Shinagawa, 2014).

H_2: An economy's position as an importer leads to stock return spillover to its trade partner

While Pretorius (2002) and Shinagawa (2014) emphasise how one country may exert its influence on another country's stock market via its role as an importer, Bracker et al (1999) underline how such influence can be generated via a country's role as an exporter. Specifically, if there an adverse shock to the source country's production, the stock market of the target country would be negatively affected as there is uncertainty on target country's consumers and producers to be able to acquire imports from the source country at low cost.

H_3: An economy's position as an exporter creates stock return spillover to its trade partner

Finally and most importantly, our differentiation of a country's position as an importer and as an exporter in the context of its stock market spillover to its trade partner is motivated by the fact that shocks on an economy's imports may generate stronger magnitude of stock market spillover to its trade partner than the economy's exports.

First, we consider the shock transmission from an importing economy to its trade partner. Starting from a regime where trade is stable, exporting countries build up large capacities (De long Summers, 1984) which limits entry to the suppliers' market effectively, making the market a global oligopoly. These countries must have invested heavily in such capacity building. If importing countries face a negative demand shock resulting from an external factor, then exporters need to find another importer to sell their product which may result in a bargained down price, reducing profit. Such a phenomenon may reduce investment prospects in the market and hence will expose the exporting economy to the risk of break-even and a downward spiralling effect of multiple orders. If the shock to the importing economy is persistent in nature (even i.i.d shocks, for example), exporting investors may need to insure themselves against a possible fall in their earning which may pose a second order cost to the capacity builders. This may be reflected in a downward movement in stock market trends due to reduction in prospects and increase in risks. In addition, *a la* De Long and Summers (1984), when an exporter is operating at an optimal (profit maximising with respect to the trend) capacity, such percolation of a negative shock combined with the 'end of expansion' (Gordon, 1979) effect may lead to a sharp fall of labour productivity which may be reflected in the stock market due to fluctuation to the return on investments led by such fall in productivity. In addition, difference in macroeconomic stability between the importing economy and its trade partner may amplify the contagion of shocks via the above channel.

However, the shock transmission from an exporting economy to its trade partner may not have the same dynamics as above. If an exporting country faces a negative supply shock, then its trade partner may need to find another exporter to cater to its domestic demand. Since most exporting countries have built-in large capacities as state above, importing countries will not face a major challenge in finding a substitute exporter. Despite the fact that exporting countries enjoy an oligopolistic market structure due to large entry costs, strong competition among themselves may make it hard for these exporters to enjoy a strong bargaining position when their trade partners seek substitution. Hence it leaves very little room for an exporting country to pass on its shock to the importing country in a first-order basis. On a second-order consideration, one can imagine that a supply shock in the exporting countries may be viewed as a harbinger of reduction in some consumables (correlated shocks across the industry), thereby shifting the weight of propensity to consume to an alternative. This may reduce spending in that consumable sector (in the trade intermediary sense) and increase spending in an alternative sector. Owing to different levels of marginal productivity from the level of investment, a Slutsky balance may adjust investment differently to the status-quo, thereby transferring the supply shock of the exporting economy to its trade partner. However, the overall effect will be of second order.

Therefore, a shock to the demand of an importing country has both first and second order effect on its trade partner, while a supply shock to an exporting economy has mostly second order effect only on its trade partner. Given the asymmetric shock transmission process described above, we expect an economy's position as an importer leads to stronger stock market spillover to its trade partner than in the reverse case where its position is of an exporter. In addition, we present a simple two-country Keynesian model in Appendix A to demonstrate how such asymmetric shock transmission process could take place. We thereby propose the following hypothesis:

H_4: An economy's position as an importer is a stronger generator of stock return spillover to its trade partner than being an exporter

2.2. Overview of the empirical literature

For studies investigating how international trade affect stock market dependence, a number of them have confirmed a positive effect trade linkage has on stock market interdependence, although the magnitude of this effect various (e.g., Bracker et al.,1999; Wälti, 2005,2011; Chambet and Gibson, 2008; Johnsen and Soenen, 2003; Tavares, 2009; Liu, 2013; Balli et al., 2015; Paramati et al., 2015; Paramati et al., 2018). Some analyses have found international trade to be the most important contributing factors to stock market integration in all the factors considered in their studies (e.g., Forbes and Chinn, 2004; Pretorius, 2002). In contrast, two recent studies, Vithessonthi and Kumarasinghe (2016) and Nguyen and Lam (2017), find a country's international and bilateral trade integration is not related to its global and bilateral stock market integration, respectively. Liu et al (2006) and Dhanaraj et al (2017) also observe that trade relations cannot significantly explain difference in the stock market interdependence.

Different ways of measuring stock market co-movement and trade linkage have been adopted in previous studies examining the influence of trade on stock market independence. One of the most widely used measurements for stock market interdependence is the correlation coefficients between stock market returns (e.g., Chen and Zhang, 1997; Pretorius, 2002; Wälti, 2005, 2011; Liu et al., 2006; Tavares, 2009; Gupta and Guidi, 2012; Liu, 2013; Shinagawa, 2014; Paramati et al., 2015; Paramati et al., 2018). In Forbes and Chinn (2004), stock market interdependence is based on cross-factor loadings that measure the effect of asset return between two countries after controlling for global and/or sector shocks. Dhanaraj et al. (2017) adopt Forecast Error Variance Decomposition (FEVD) analysis obtained by vector autoregressive (VAR) modelling of stock returns to investigate the extend of stock market interdependence.

On the other hand, stock market integration is measured as the explanatory power (or the R-square) of the returns of the global or another specific stock market on the returns of the stock market of interest by for instance Vithessonthi and Kumarasinghe (2016) and Nguyen and Lam (2017). Bracker et al. (1999) and Johnsen and Soenen (2003) employ the Geweke measures of international stock market integration. Chambet and Gibson (2008) estimates the level of financial integration using a multivariate GARCH (1,1)-M return generating model allowing for partial market integration as well as for the pricing of systematic market risks. Balli et al. (2015) employ AR-GARCH models to obtain return and volatility spillover. There is also a strand of studies which examine the extend of stock market integration of a particular country and its major trading partners without explicitly investigating whether international trade has enhanced such stock market integration (e.g., Karim and Karim (2008) for Malaysia, Elyasiani et al (1998) for Sri Lanka, Joyo and Lefen (2019) for Pakistan).

Some recent studies have employed the DYCI measurement of stock return spillover (e.g., Chevallier et al., 2018; Abbas et al., 2019; Charfeddine and Refai, 2019; Su and Liu, 2021; Youssef et al., 2021); they are discussed further in Section 2.3.

In terms of the measurement of the trade linkage, often bilateral trade (exports or/and imports) between two countries adjusted by national exports or/and imports (e.g., Bracker et al. (1999), Pretorius (2002), Johnson and Soenen (2003), Paramati et al. (2015), Paramati et al. (2018), Vithessonthi and Kumarasinghe (2016), Nguyen and Lam (2017)), sum of exports and imports of a country adjusted by its GDP (e.g., Chen and Zhang (1997), Gupta and Guidi (2012)) or the predicted value of this ratio (e.g., Chambet and Gibson (2008)), sum of exports and imports of a country with its trade partner adjusted by this country's GDP (e.g., Dhanaraj et al. (2017)), sum of exports and imports of a country adjusted by regional total exports and imports (e.g., Chen and Zhang (1997)) and the average of two bilateral-export-to-GDP ratios for each pairs of countries (e.g., Tavares (2009)) are employed.

Forbes and Chinn (2004) measure bilateral trade linkage between country c and i using 'trade competition' that is weighted sum of two factors. The first factor is exports from country c in a given industry as a share of world exports in that industry. The second is the total exports from country i in the same industry, as a share of country i's GDP. Wälti (2005, 2011) first measures the bilateral trade intensity as the sum of bilateral exports and imports between two countries divided by the sum of total exports and imports of each country. Then the paper uses the predicted value of bilateral trade intensity based on a regression on the variable on distance between the main business centre of each country, GDP and three dummies for a common border, common language, and EU membership.

2.3. Our contributions

While previous analyses have examined how bilateral trade affect the correlation of stock returns of countries pairs (e.g., Chen and Zhang (1997), Bekaert and Harvey (1997), Bracker et al. (1999), Pretorius (2002)), or have used trade tension to explain stock market volatility (e.g., Amstad et al. (2021), He et al. (2021)), they often operate without analysing the directional nature of the influence. Such directional nature has two folds. First, the strong correlation between two countries' stock returns does not inform in terms of the magnitude of each of the bi-directional influence between these two countries' stock markets. Second, bilateral trade does not show the direction of trade flows. For instance, large bilateral trade maybe generated by substantial exports of A to B (or trade flows from A to B) alone. As such, without these two important pieces of information, it would be unclear that how much of the directional influence between two nations' stock markets is generated by the respective directional trade between these two economies. When the directional dimension is incorporated, it offers deeper understanding and clearer evidence on how the flows of international trade affect the stock markets interdependence among economies.

Our paper makes two important contributions to the research on relationship between international trade and stock market interdependence. First, we start from system-wide level evidence. We construct an import–export network where a system-wide connectedness of the network is provided to measure overall trade linkage for a group of economies of interest. The import–export network is built adapting the input–output network of Bilgin and Yılmaz (2018) and is used for the first time analysing trade-stock market relationship. To assess the system-wide stock-market connectedness, we adopt the Diebold-Yilmaz Connectedness Index (DYCI) framework (Diebold and Yilmaz, 2009, 2012, 2014) which fully utilises the information in generalised variance decompositions from vector. These two system-wide indicators would provide static and dynamic information on the trade and stock-market connectedness, allowing us to first analyse the relationship between them for our group of economies as a whole.

Second, in addition to the above aggregate level investigation, our study incorporates pairwise directional dimension in our further examination on the relationship between the trade-network and stock market interdependence where the direction of both the stock market return spillover and the trade flows matter. As discussed in Section 2.1 and also demonstrated in Appendix A, the directional assessment is motivated by how a shock on an economy's imports and exports could lead to different magnitude of stock market spillover to its trade partner, with imports being the stronger generator of such spillover. Thus, compared with previous measures of trade linkage that are of bilateral nature or capture trade openness in the broad sense (e.g., sum of exports and imports divided by GDP), we would provide new insights on how the import and export flows of a country from and to, respectively, the other would affect the influence goes from its stock market to the other's. This is also possible as the DYCI framework, compared with the correlation or integration measure widely used in the literature, has the advantage of providing information on pairwise directional linkages, or the net stock return spillover from one economy to the other. Although some previous studies have applied the DYCI measurement on stock market returns (e.g., Chevallier et al., 2018; Abbas et al., 2019; Charfeddine and Refai, 2019; Su and Liu, 2021; Youssef et al.,2021), they have not fully utilised the pairwise directional stock market interdependence information generated by DYCI to explore the deeper relationship between trade and stock market spillover.

For instance, Chevallier et al (2018) employ the DYCI measurement of stock return spillover to study whether the interdependence of emerging ASEAN stock markets is driven by their high exposure to the US and Japan shocks. A number of financial integration and economic openness indicators are reported but the relationship between financing integration and trade is not empirically examined. Charfeddine and Refai (2019) and Youssef et al. (2021) also mention the importance of trade to stock market interdependence (which is measured using DYCI method) but the relationship between the two is not further analysed. Abbas et al. (2019) adopt the DYCI measurement for the G-7 but without the cross-country element. In other words, they examine the connectedness between stock market and trade of each individual country and the stock-market connectedness between two countries is not explored. Focusing on 10 industries in China, Su and Liu (2021) estimate total and net inter-sectoral stock return spillover using DYCI method and examine how they are influenced by economic policy uncertainty indices. The pairwise sectoral level stock return spillover is reported but not utilised in the main analysis. Therefore, to our knowledge, no previous studies has fully exploited the pairwise directional stock market spillover information generated by DYCI to consider direction evidence on the relationship between trade and stock market spillover.

Therefore, by providing both system-wide and pairwise directional level of evidence, our study would offer insights on the broader issue of whether the real economy (e.g., trade) has an impact on the stock markets. It also in practice presents more relevant information for policy makers and investors in monitoring international trade flows and their potential impact on stock market interdependence globally and between certain country pairs.

For the empirical context, we select ASEAN 5 (i.e., Indonesia, Malaysia, the Philippines, Singapore, and Thailand), China, Euro Area, Hong Kong (China), Japan, UK and the US after considering the world's largest trading partners and major stock markets. According to the Direction of Trade Statistics of the IMF, these eleven markets account for 68.2 % of the world's exports in 2020, and 69.7 % of the world's export during the period 2000–2020. Their market capitalisation makes up over 90 % of the global stock market in 2020 (based on the World Bank data on Market Capitalisation of listed domestic companies). Also, although it is not the first time that China is included in trade-stock market relationship studies (e.g., Pretorius, 2002; Forbes and Chinn, 2004; Chambet and Gibson, 2008; Paramati et al., 2015; Paramati et al., 2018), we include China in our study as an important global player[1] with more updated data goes up to first half of 2021.

3. Methodology and data

3.1. Diebold-Yilmaz connectedness index (DYCI) framework

In our work, we exploit the generalised variance decomposition approach developed by Diebold and Yilmaz (2012), which uses the available information from variance decomposition. It is now commonly known that this methodology provides both static and dynamic measures of spillovers and a plethora of research in finance and many other disciplines have routinely applied to understand dynamics of interconnectedness among agents (be it in the trade network as in our case, or in the financial markets – as the extant literature in the subject shows).

The Diebold-Yilmaz (2012) mechanism exploits variance decomposition and structure the same with Cholesky factorisation methods. This strategy produces orthogonal innovations as is typically required for variance decompositions in Vector Auto-Regressive (VAR) models, with the main drawback of being sensitive to variable ordering. However, Diebold-Yilmaz (2012) offers a generalised variance decomposition (GVD) that allows them to alleviate the orthogonality condition altogether and to account for correlated innovations, hence improving on their previous effort by making their measure of spillovers invariant to the order of the variables in the system. Considering our case of investigation, the estimates of spillover are based on the following covariance-stationary VAR model, such as a VAR(1) presentation:

$$z_t = \phi z_{t-1} + \omega_t, \tag{1}$$

where z_t denotes an $N \times 1$ vector of time series variables and ω_t is a $N \times 1$ white noise vector process. Its moving average representation is:

$$z_t = \sum_{i=0}^{\infty} \phi^i \omega_{t-i}. \tag{2}$$

In general, the components of ω_t are correlated and the error variance and covariance matrix $\Omega = E\left[\omega_t \omega_t^{'}\right]$ is non-orthogonal. However, using Cholesky decomposition, it is always possible to find a lower triangular matrix A so that $\Omega = AA^{'}$. This decomposition facilitates an error vector $\widetilde{\omega}_t = A^{-1}\omega_t$. It can be verified that the covariance matrix $E\left[\widetilde{\omega}_t \widetilde{\omega}_t^{'}\right]$ is orthogonal. Using the orthogonal

[1] According to the World Bank, China's stock market capitalisation has grown from 2.7% of the US' in 2004 to 30.0% in 2020. China's account for 14.7% and 11.8% of the world's exports and imports, respectively, in 2020, placing China as the largest exporter and second largest importer (only after the US) globally.

error, the following structural form of the VAR can drive us to prepare a predictive model:

$$z_t = (1-\phi L)^{-1} A \widetilde{\omega}_t \tag{3}$$

$$z_t = B(L)\widetilde{\omega}_t, where B(L) = (1-\phi L)^{-1} A \tag{4}$$

$$z_t = \left(B_0 + B_1 L + B_2 L^2 + \cdots\right)\widetilde{\omega}_t. \tag{5}$$

Here, (i,j) element of B_k measures the response of i^{th} variable to the forecasting error of j^{th} variable ($\widetilde{\omega}_t^j$) after k time-steps. That means that the totality of connectedness among the components of z_t is encapsulated in $\{B_0, B_1, B_2, \cdots\}$. Variance decompositions transform the encapsulated information in $\{B_0, B_1, B_2, \cdots\}$ and better reveal the connectedness (Diebold and Yilmaz, 2009). The error in 1-step-ahead forecast at time t is $z_{t+1} - z_{t+1,t}$, where $z_{t+1,t}$ is the forecast at time t and z_{t+1} is the realised one at time $t+1$. The corresponding error vector of 1-step-ahead forecast (Diebold and Yilmaz, 2009) is $e_{t+1,t} = z_{t+1} - z_{t+1,1} = B_0 \widetilde{\omega}_{t+1}$.

Under the properties of the covariance matrix $E\left[\widetilde{\omega}_{t+1,t}\widetilde{\omega}'_{t+1,t}\right], E\left[\widetilde{\omega}_{t+1,t}\widetilde{\omega}'_{t+1,t}\right] = B_0 B_0^1$.

Let

$$B_0 = \begin{bmatrix} b_{0,11} & b_{0,12} & \cdots & b_{0,1N} \\ \vdots & & \ddots & \vdots \\ b_{0,N1} & b_{0,N2} & \cdots & b_{0,NN} \end{bmatrix}. \tag{6}$$

Diebold and Yilmaz (2009) propose the Spillover Index (S) that as a ratio (percentage) of the total spillover variance to total forecast error variance as

$$S = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \left(b_{0,ij}\right)^2}{trace\left(B_0 B_0'\right)} \times 100. \tag{7}$$

The proposed Spillover Index can be generalised for a p^{th}-order N-variate VAR, H-step-ahead forecasts as well. According to Diebold and Yilmaz (2009), the Spillover Index can be defined as

$$S = \frac{\sum_{h=0}^{H-1}\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \left(b_{0,ij}\right)^2}{\sum_{h=0}^{H-1} trace\left(B_h B_h'\right)} \times 100. \tag{8}$$

As noted earlier, the generalised variance decomposition approach does not require orthogonalized shocks, hence the forecast error variance decompositions are expressed by

$$\theta_{ij}^G(H) = \frac{\sigma_{ii}^{-1}\sum_{h=0}^{H-1}\left(e_i' C_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' C_h \Sigma C_h' e_i\right)}. \tag{9}$$

Where Σ represents the variance matrix for error ω_t. Note that here we need to assume that ω_t are independent and identically distributed. σ_{ii} represents the i^{th} diagonal element of Σ and e_i is the unit vector with one as the i^{th} element and zeros otherwise. We normalise $\theta_{ij}^G(H)$ as

$$\widetilde{\theta}_{ij}^G(H) = \frac{\theta_{ij}^G(H)}{\sum_{j=1}^{N}\theta_{ij}^G(H)}. \tag{10}$$

We use Diebold-Yilmaz connectedness index framework (Diebold and Yilmaz, 2012) to define system wide spillover connectedness index ($S^G(H)$) based on the generalised VAR framework (Koop et al., 1996; Pesaran and Shin, 1998) that is analogue of Cholesky factor-based index earlier discussed as

$$S^G(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N}\widetilde{\theta}_{ij}^G(H)}{N} \times 100. \tag{11}$$

Similarly, pairwise spillover, directed spillover from others to i ($S_{i\leftarrow\bullet}^G(H)$), and directed spillover from i to others ($S_{\bullet\leftarrow i}^G(H)$) are defined as shown below.

$$S^G_{i\leftarrow\cdot}(H) = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \widetilde{\theta}^G_{ij}(H)}{\sum_{j=1}^{N} \widetilde{\theta}^G_{ij}(H)} \times 100 \tag{12}$$

$$S^G_{\cdot\leftarrow i}(H) = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \widetilde{\theta}^G_{ji}(H)}{\sum_{j=1}^{N} \widetilde{\theta}^G_{ji}(H)} \times 100 \tag{13}$$

In our empirical analysis, we consider 2nd order multivariate VARs with 12-step-ahead forecasts.

Compared with previous studies employing alternative ways of measuring stock market independence (see detail in Section 2.2), the DYCI method ensures that the results are not affected by the sequence of variables and by using a generalised impulse response function it eliminates the need for Cholesky decomposition. Variable order invariance is important in the prediction power of trade in explaining stock-market connectedness as it would be hard to justify a particular ordering of variables in a multivariate VAR setting. Additionally, Diebold and Yilmaz (2012) introduce directional indices, which results in a more comprehensive single spillover measure.[2] We are also aware of the recent Cesa-Bianchi et al. (2019) approach which uses principal component analysis and VAR to distinguish business cycles due to common shock and idiosyncratic shock. Despite the merit of their method, the focus of this paper is system-wide connectedness and pairwise directional spillover, and hence we consider Diebold-Yilmaz Connectedness Index framework (Diebold and Yilmaz, 2009, 2012, 2014) a more suitable method for our analysis.

3.2. Data

For our empirical exercise, we have obtained stock market price index from various sources, such as the Shanghai Stock Exchange Composite Index for China, S&P 500 Index for the US, EURO STOXX Index for the Euro Zone, FTSE 100 for the UK, Hang Seng Composite Index for Hong Kong (China), Nikkei 225 for Japan, MSCI International AC ASEAN Index for ASEAN 5, S&P/ASX 200 Index for Australia, FTSE/JSE Africa All Share Index for South Africa, Bovespa Index for Brazil, and Nifty 50 for India. They are collected from Datastream. The EURO STOXX Index is a broad yet liquid subset of the STOXX Europe 600 Index representing large, mid and small capitalisation companies of 11 Eurozone countries: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain[3] For market capitalisation, the total market values of the total market indices (which captures all the stocks trading in an economy's stock market) are also collected from Datastream. We employ the total market value of the EU to approximate the market capitalisation of the Eurozone, and the total market capitalisation of the ASEAN 5 is the sum of each individual country (i.e., Indonesia, Malaysia, Philippine, Singapore and Thailand). These stock indices are chosen as they are the main benchmark indices from the largest stock exchange in each economy (e.g., Shanghai Stock Exchange in China, New York Stock Exchange in the US, Sao Paulo Stock Exchange in Brazil) or widely used regional indices (e.g., EURO STOXX and MSCI International AC ASEAN Index). The monthly sample period is Jan 2000-June 2021. As discussed in Section 1, these economies are included not only because they are the major players in international trade and stock markets, but also due to that as a group they present a sound geographic coverage.

As for the international trade data, we have used the Direction of Trade Statistics of the IMF. The GDP (in constant price) and exchange rate (domestic currency per USD) data are from the International Financial Statistics of the IMF. All data are available at monthly interval. The only exception is the GDP data that is only available at quarterly which was interpolated into monthly data using linear interpolation. The data span is 2000 m1-2021 m6. As the Euro Stoxx Index represents companies of the above mentioned 11 Eurozone countries, to be consistent with this stock price index, for all data below for the Eurozone, these 11 countries are included. Similarly, the five ASEAN core countries mentioned above are included in the ASEAN 5 region. We provide below a summary description of the key variables/concepts which we will use frequently throughout our empirical analyses.

System-wide stock-market connectedness index: This index is calculated following the methodology mentioned in Section 3.1 (Equation (11) using stock returns of all eleven stock market indices. The index starts from 2005 m1. That is due to the window length (60) that we used for parameter estimation in spillover connectedness index. So, the first estimation starts from the 61st step. Between 2000 m1 to 2004 m12 there are 60 months, and the first forecast error variance decomposition starts from 2005 m1. A higher value indicates stock markets in the eleven regions are more connected.

System-wide import–export network index: This index is calculated following the input–output network by Bilgin and Yillmaz (2018) as sum of all off-diagonal elements of the import–export matrix (as shown in Table 2) for each month. A higher value indicates stronger trade-network amongst the eleven regions.

Pairwise directional stock return spillover indices $i \leftarrow j$ (Stock Market Spillover$_{i\leftarrow j}$): This index is calculated following the methodology mentioned in Section 3.1 (Equation (10). All indices are measured between two economies i and j, where the stock return spillover go from j to i. However, a negative value would suggest a negative spillover from j to i, i.e., it in fact goes from i to j.

Pairwise directional imports $i \rightarrow j$ (Import$_{i\rightarrow j}$): j's imports from i divided by GDP of i. It measures the importance of j to economy i

[2] For example, as mentioned in Section 2.2, Dhanaraj et al (2017) explore the relationship between bilateral (but not directional) trade and stock market interdependence using generalized FEVD analysis of Pesaran and Shin (1998). We employ the DYCI method which has advantages over Pesaran and Shin (1998) approach and provides information on directional stock market spillover as discussed above.

[3] For more description of the data please see https://www.stoxx.com/index-details?symbol=SXXGT.

Table 1
Descriptive statistics and correlation matrix.

Variables	No. of obs	Mean	Std. dev.	Min	Max			
System-wide stock-market connectedness index	198	72.5983	4.8902	64.3248	81.5842			
System-wide import–export network index	198	24.7119	2.3485	19.2459	32.4510			
Correlation: System-wide stock-market connectedness index and import–export network index	0.3461							
Variables	No. of obs	Mean	Std. dev.	Min	Max			
Pairwise directional stock return spillover indices $i \leftarrow j$	21,780	0	1.1985	−5.5866	5.5866			
Pairwise directional exports $i \leftarrow j$	21,780	2.5258	9.6107	0.0128	213.8600			
Pairwise direction imports $i \rightarrow j$	21,780	1.3826	1.8555	0.0025	19.9639			
Relative GDP	21,780	4.6746	10.1333	0.0133	75.2587			
Relative size of the stock market	21,780	3.6138	7.6830	0.0085	118.3050			
Relative P/E ratios	21,780	1.0717	0.6417	−3.3824	22.3965			
Geographical distance	21,780	8.9920	1.9970	3.1844	13.7896			
Exchange rate risk	21,780	8.3466	10.8920	0.0040	371.8650			
Correlation Matrix								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)Pairwise directional stock return spillover indices $i \leftarrow j$	1.0000							
(2)Pairwise directional exports $i \leftarrow j$	0.1519	1.0000						
(3)Pairwise direction imports $i \rightarrow j$	0.2456	0.3325	1.0000					
(4)Relative GDP	0.3039	0.3795	0.3529	1.0000				
(5)Relative size of the stock market	0.3602	0.0239	0.3245	0.6081	1.0000			
(6)Relative P/E ratios	0.0608	0.0774	0.0888	0.1374	0.1008	1.0000		
(7)Geographical distance	−0.4336	−0.4127	−0.5744	−0.6227	−0.4616	−0.1900	1.0000	
(8)Exchange rate risk	0.0079	−0.0986	−0.1208	0.0182	0.1138	0.0061	0.0543	1.0000

Note: Although our full sample period is 2000 m1-2021 m6, all variables above start from 2005 m1 due to the window length of 60. See Section 3.2 for variable definition and measurement. The Geographical distance is in natural logarithm.

as i's export destination. A larger value suggests a higher level of importance to i. It is employed to examine j's influence on i's stock market via j's role as an importer (as described in Section 2.1).

Pairwise directional exports $i \leftarrow j$ (Export$_{i \leftarrow j}$): j's exports to i divided by GDP of i. It measures the importance of j to economy i as i's source of imports. A larger value suggests a higher level of importance to i. It is used to evaluate j's influence on i's stock market via j's role as an exporter (as described in Section 2.1).

Relative GDP: the real GDP (in constant price) of j divided by that of i.

Relative size of the stock market: the ratio of stock market capitalisation of j to that of i.

Relative Price to Earnings (P/E) ratio of the stock indices: the P/E ratio of stock market index of j to that of i.

Geographical distance: the distance (in Kilometres) between the two chosen stock exchanges adjusted by the ratio of j's real GDP to i's real GDP to filter out the impact of the relative GDP.

Exchange rate risk: the exchange rate (number of currency j per unit of currency i) volatility is derived using a GARCH model (see Caporale et al (2019) and Narayan et al (2014) for a similar treatment).

The descriptive statistics and correlation matrix of variables discussed above is summarised in Table 1. Although our full sample period is 2000 m1-2021 m6, the two system-wide indices start from 2005 m1 due to the window length (60) explained above and hence there are 198 observations. All other variables are panel with 110 cross sections (eleven regions) and hence there are 21,780 observations. There are clear variations of the values of variables across the sample set. Note that the sum of pairwise directional stock return spillover indices is zero as the two values between two economies always comes to a zero sum. The highest and lowest pairwise directional exports $i \leftarrow j$ is 213.8600 (exports from China to Hong Kong (China) adjusted by the GDP of the latter in 2013 m3) and 0.0128 (exports from China to India adjusted by India's GDP in 2016 m3), respectively. It shows the importance of China to Hong Kong (China) as the latter's source of imports. The Chinese mainland has indeed been Hong Kong (China)'s largest supplier in goods since 1982 (Trade and Industry Department, 2022). It also implies that being the two of the largest developing economies, China and India do not seem to have a strong trade tie between them as reflected in the low pairwise directional exports from China to India.

On the other hand, the highest and lowest pairwise direction imports $i \rightarrow j$ is 19.9639 (China imports from South Africa adjusted by the latter's GDP in 2013 m3) and 0.0025 (Japan's imports from the UK adjusted by UK's GDP in 2020 m6), respectively. It highlights the importance of China as South Africa's source of imports and the much smaller magnitude of UK as Japan's supplier of imports relative to Japan's GDP. It also illustrates the advantage of adopting the directional element in trade, as it clearly demonstrates the importance of an economy's trade partner from the distinctive exports and imports perspectives. Specifically, economy j could be i's top export destination, but not necessary be i's top source of imports. This information would not have been revealed by the sum of exports and imports which is widely used to gauge trade relationships in previous studies mentioned in Section 2.2 (e.g., Chen and Zhang, 1997; Gupta and Guidi, 2012; Dhanaraj et al., 2017).

In terms of the relative GDP, the US was 75.2587 fold of Hong Kong (China) in 2006 m6 (the inverse gives the lowest value 0.0133). The relative size of the stock market of the US was 118.3054 times of South Africa in 2020 m4 (the inverse gives the lowest value of 0.0085). The most volatile periods of exchange rate risk gather around the 2008–2009 period led by the exchange rate between South

Table 2

Stock-market connectedness (2005 m1-2021 m6).

i j	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	Sum	**FROM**
(1)China	91.89	0.61	3.11	0.08	0.50	0.62	0.90	0.51	0.73	0.73	0.34	100	8.13
(2)US	7.99	87.69	0.15	0.71	0.82	0.35	0.57	0.86	0.49	0.24	0.12	100	12.30
(3)Euro Area	7.49	69.03	19.91	0.25	0.60	0.27	0.33	0.26	1.49	0.15	0.22	100	80.09
(4)UK	5.17	68.80	7.46	14.84	0.55	0.53	0.71	0.49	1.05	0.16	0.24	100	85.16
(5)Hong Kong (China)	18.39	35.09	3.86	1.80	35.74	0.78	1.98	0.27	0.43	1.52	0.15	100	64.27
(6)Japan	6.71	47.51	4.41	0.29	0.38	35.03	1.78	0.61	2.11	0.08	1.10	100	64.98
(7)ASEAN	7.30	39.64	1.52	3.37	10.47	1.15	33.33	0.55	0.92	1.61	0.15	100	66.68
(8)Australia	8.05	53.20	5.60	3.05	0.97	1.03	1.41	22.55	3.36	0.42	0.36	100	77.45
(9)South Africa	5.34	44.52	4.40	2.67	5.54	1.15	1.81	2.28	31.48	0.74	0.07	100	68.52
(10)Brazil	8.05	35.30	3.76	2.02	6.99	1.59	2.94	1.06	1.61	36.43	0.25	100	63.57
(11)India	5.97	34.74	3.86	1.06	12.65	1.61	5.07	0.91	0.98	1.71	31.42	100	68.56
To Others	80.46	428.44	38.13	15.30	39.47	9.08	17.50	7.80	13.17	7.36	3.00		**59.97**
Net	72.33	416.14	−41.96	−69.86	−24.80	−55.90	−49.18	−69.65	−55.35	−56.21	−65.56		

Note: The *ij*th item represents the pairwise connectedness, i.e., the percent of the 12-month-ahead forecast error variance of economy *i* due to stock price changes in economy *j*. The From/To Others column/row is the row/column sum excluding the diagonal elements. The former shows the total directional connectedness from all other economies to economy *i*, and the latter reports the total directional connectedness generated from the stock market of economy *j* to others. The difference between To Others and From is the net connectedness. In the bottom-right corner is the mean of To others connectedness between all eleven economies and is identical to the mean of the From connectedness.

Africa and Japan in 2008 m11 with a value of 371.865, whilst the exchange rate between the Hong Kong dollar the US dollar remained most stable due to its currency board regime of the Hong Kong dollar. The overall values of correlation coefficients also do not raise any concern in the dataset.

4. Static and dynamic analysis

4.1. Static analysis

Table 2 presents the static stock-market connectedness across the eleven economies using the DYCI method discussed above over period 2000 m1-2021 m6. Specifically, it is obtained from the estimation of 2nd order multivariate VARs with 12-step-ahead forecasts. The off-diagonal ij^{th} element shows the proportion of forecast error variance of stock market *i* which are explained by shocks originated in market *j*. Thus, a higher/lower off diagonal ij^{th} entry indicates stronger/limited stock market interdependence from market *j* to *i* and vice versa. The diagonal elements are the own connectedness measures. The sum of each row presents the total influence on market *i* originated from other markets in the system as well as market *i* itself and hence equals to 100.

The final column of Table 2 named “From” reports the sum of all off-diagonal elements of each row capturing the total impact on stock market *i* due to all other stock markets in the system. The final row of Table 2 named “To Others” presents the sum of all off-diagonal elements of each column demonstrating influence of stock market *j* on each stock market *i*. Correspondingly, the final row of Table 1 named “Net” is the results of “To Others” subtracting “From” of each market, with a positive value indicating this stock market to be a net transmitter of stock return shocks to other markets and a negative value suggesting a net receives of shocks from others.

As the largest economy in the world, the US is the largest transmitter of price shocks to other countries judged by the high value of in the US column “Net” row (i.e., 416.14). The US stock markets also has strong own connectedness (i.e., 87.69). However, the US seems to have exerted quite small influence on the stock market of China (i.e., 0.61). Other markets (e.g., UK, Japan, Hong Kong (China) and ASEAN) have also had limited impact on the Chinese stock markets. The economy whose stock market has had the largest effect on China is the Euro area (i.e., 3.11), although the magnitude of such effect is relatively modest. Chinese stock market seemed to be responding largely to domestic price shocks given a high diagonal entry of 91.89. China, as the largest developing country, its influence on other markets seems to have surpassed the Euro area except in the case of the UK.

China has also exceeded that of the Euro area, UK, Hong Kong (China), Japan, ASEAN 5, Australia, South Africa, Brazil and India with the exceptions of Hong Kong’s (China) influence on ASEAN 5 and South Africa, India and Euro area’s influence on the UK. The Chinese stock market has much stronger influence on the US market (7.99) than the reversed influence (0.61). China has the most effect on the US than any other markets. Other economies (i.e., UK, Hong Kong (China), Japan, ASEAN 5, Australia, South Africa, Brazil and India) have limited cross country impact, except in the four cases mentioned above. Their negative values in the “Net” rows suggest that they are net receiver of return spillover in the system. The Euro area also has overall negative net influence large due to the large impact it receives from the US. The UK has the highest “From” connectedness (-69.86), implying it receives the largest return spillover from other markets (especially the US). It is followed by Australia (-69.65), India (-65.56), Brazil (-56.21), Japan (-55.90), South Africa (-55.35), ASEAN 5 (-49.18), the Euro area (-41.96) and Hong Kong (China) (-24.80).

Table 3
Import-export network table (2005 m1-2021 m6).

i j	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	**FROM**
(1)China		1.62	2.10	0.20	0.31	2.65	2.07	0.73	0.22	0.47	0.24	10.61
(2)US	1.67		1.75	0.34	0.05	0.90	0.66	0.06	0.05	0.17	0.20	5.85
(3)Euro Area	1.54	1.55		1.71	0.07	0.58	0.60	0.07	0.14	0.25	0.23	6.74
(4)UK	1.44	1.97	10.83		0.21	0.54	0.58	0.21	0.31	0.14	0.27	16.49
(5)Hong Kong (China)	81.25	10.43	9.55	2.95		14.28	21.26	1.18	0.47	0.67	3.04	145.07
(6)Japan	2.22	1.27	0.97	0.14	0.69		1.53	0.69	0.11	0.14	0.09	7.85
(7)ASEAN	6.66	4.47	3.81	0.68	1.42	6.09		1.06	0.14	0.33	0.89	25.55
(8)Australia	2.26	2.10	2.31	0.55	0.42	1.40	2.51		0.10	0.06	0.19	11.88
(9)South Africa	2.79	1.58	5.96	1.09	0.26	0.95	1.14	0.40		0.41	0.78	15.35
(10)Brazil	1.11	1.96	1.87	0.17	0.10	0.27	0.24	0.05	0.03		0.19	5.97
(11)India	2.01	1.10	1.99	0.42	0.50	0.46	1.74	0.53	0.14	0.15		9.03
TO Others	102.94	28.05	41.12	8.25	4.02	28.12	32.33	4.98	1.71	2.78	6.10	
Net to Others	92.33	22.20	34.38	−8.24	−141.05	20.27	6.78	−6.90	−13.65	−3.19	−2.93	

Note: The *ij*th term shows that trade flows from *j* to *i* adjusted by *i*’s (the destinations) GDP. The From column and To others row are calculated in the same way as in Table 2. The former shows the total imports of each economy from other economies, while the latter reports the total exports of each economy to other economies. The Net to Others row is the difference between To Others and From.

Table 3 presents our import–export network. Adapting from the input–output network of Bilgin and Yillmaz (2018), the import–export network illustrates the flow of international trade among a group of countries. Specifically, Table 3 reports the edge weights for the import–export network over 2005 m1-2021 m6 period. The values are the average of the entries of the monthly tables from 2005 m1 through 2021 m6. Values in each column present trade flow from economy *j* (i.e., the source) to other economies.

Correspondingly, values in each row denote trade flow to economy *i* (i.e., the destination) that is generated from economy *j*. Each value *ij* of the static import–export Table 3 donate trade flow from economy *j* to *i* after being normalised by the GDP of destination market.[4]

To be compatible with the stock-market connectedness, we also construct "From", "To others" and "Net" measures of flows. The sum of each row reports the total amount of imports purchased by each economy *i* from other economies and is named as column "From". The sum of each column presents the number of exports supplied by economy *i* to other markets and is named as row "To Others". Naturally the diagonal elements are excluded from column "From" and row "To Others". Note that different from the stock-market connectedness Table 2, the sum of each row or column in Table 3 does not add to 100.[5] The difference between the row "To Others" and the column "From" present a "Net to others" effect of each economy.

The economy with the highest "To" and "Net" connectedness is China (102.94 and 92.33 respectively), suggesting it is a main exporter in this group of country. A large proportion of China's high value of net connectedness is due to China's close trade connection with Hong Kong (81.25). Other countries with relatively high "To" entries include Euro area, ASEAN, Japan and the US. The South Africa and Brazil are two economies with the lowest destination GDP normalised exports in the group reflected in the low "To" connectedness. The "Net" connectedness of these two economies, Hong Kong (China), UK, Australia and India are negative whilst that of China, US, Euro area, Japan and ASEAN are positive, implying that in the latter group their destination GDP normalised exports exceeded its own GDP normalised imports from other countries.

Looking at Table 2 and 3 together, in both tables there are some instances where the values are quite small, suggesting very limited pairwise connectedness, while in other cases the entries are quite large, implying very strong pairwise connectedness across these economies. Some countries have positive "Net" values in both tables (e.g., China and the US), suggesting that they are transmitters of stock market returns, and at the same time there are net trade flows from China and the US to other countries with the size of the destination economies taken into account. In contrast, Hong Kong (China), UK, Australia, South Africa, Brazil and India have negative net values in both tables. On the other hand, the net values of Euro area, Japan and ASEAN have opposite signs in Table 2 and 3.

In addition to Table 2 and 3, we present the corresponding trade-network and stock-market connectedness graphically in Figs. 1 and 2, respectively. To visualise networks, the open-source Gephi software is considered. Layout algorithms like ForceAtlas2 algorithm (Jacomy et al., 2014) in Gephi detects node locations and sets the graph shape. The objective of the algorithm is identifying the final layout of nodes and edges that minimises the energy of the system. This involves computing the repulsive forces of each node to the other nodes while edges among the nodes provide spring like attractive forces. The approach identifies a stable state in which repelling and attractive forces are perfectly balanced: nodes repel each other as if they were comparable poles of two magnets, while edges between nodes attract their nodes as if they were springs. The average pairwise directional link between the two nodes determines the edge's attractive force, which also effects the edge's thickness.

While plotting the stock-market connectedness network and the trade network, the layout algorithm helps in visualising the structural proximities into visual proximities. In Fig. 1, the repulsive force between any pair of nodes is proportional to the average total stock market values (sizes of the nodes) and the attractive force between the nodes is proportional to "To Others" values between the pair of nodes. These attractive and repulsive forces are used to disperse groups (clusters of nodes) and give space around the dominating nodes. We can clearly see that the US is the most dominating node as shown in the stock-market connectedness network in Fig. 1. Similarly, in Fig. 2, the attractive and repulsive forces are due to the "Average size of the economies" (node sizes) and the "difference between the trade flows" (edge thickness). That means, we disperse the nodes using the repulsive forces proportional to the sizes of the economies while pulling them together using the forces that are proportional to the associated differences between the trade flows. In Fig. 2, we can see the domination of US, Euro area and China in the context of import–export network.

In Fig. 1, the colour of the node, ranging from light to dark green, indicates the total directional stock connectedness of "To others" from weak to strong. The size of the node represents the average total stock market value throughout 2005 m1-2021 m6. The thickness of the edge and the size of the arrow are decided by the value of "To other" from *j* to *i* connectedness between each pair of markets in Table 2. The colour of the edge follows the colour of the node of country *j*. The US stock market has the darkest colour compared with other stock market and it occupies the central spot, surrounded by all other stock markets. It clearly highlights the global importance of the US stock market. Thick edges and arrows shoot out from the US to all other economies. The only exception is the case of China where the arrow goes from China to the US (7.99) dominates the arrow in the opposite direction (0.61).

With regard to the trade-network illustrated in Fig. 2, the size of the node represents the average size of the economy during 2005 m1-2021 m6. The colour (darkness) of the node reflects the value of "To others" where bigger value shows darker colour. There is one arrow between two counterparties. The direction of the arrow points at the economy that has a larger value of GDP normalised exports between the two. The colour of the edge follows that of the dominate market between the two, and the thickness of the edge and the size of the arrow represent the gap of these two values. For instance, Euro area to UK (10.83) is larger than from the UK to Euro area (1.71) by 9.12, and hence the arrow points from the Euro area to the UK, and the thickness of the edge (and size of the arrow) reflect the gap (9.12) and adopt the colour of the dominate economy, i.e., Euro area. China has the largest value of "To" and "Net" connectedness, although a considerable proportion of it was due to China's trade linkage with Hong Kong (China) relative to Hong Kong's GDP. The arrows shoot out from China to all other economies except Japan in which case the arrow is pointed at China. In contrast to Fig. 1, there does not seem to be a central economy around which other economies cluster, with markets such as China, US, Euro area and Japan all

[4] The diagonal elements are not reported here as they are not relevant for analysis of relationship between trade and stock market interdependence. They are available upon request.

[5] Similar to Bilgin and Yillmaz (2018), our analysis in this and the follow sections were not affected if we normalise the number in Table 3 making each row add up to 100.

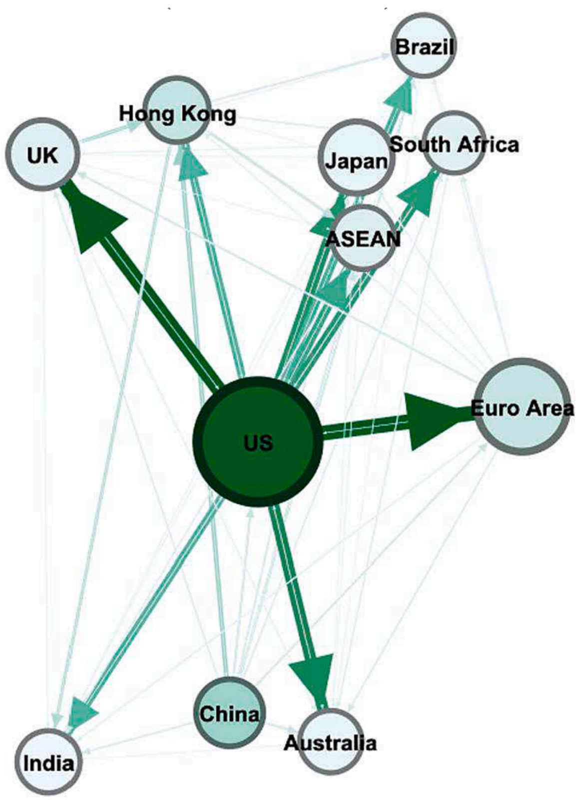

Fig. 1. Stock-market connectedness (2004 m3-2021 m6).

pulling the edges towards themselves.

4.2. Dynamic analysis

(a) System-wide connectedness

Section 4.1 provides a static representation of the relationship between trade-network and stock-market connectedness. In this section, the dynamic system-wide stock-market connectedness index from 2005 m1 to 2021 m6 is calculated following Section 3.1. The system-wide connectedness is embedded within the global view that the pairwise connections deliver optimal dynamic interdependence among each pair of countries trade engagement. Similar to the stock-market connectedness, the import–export connectedness index for each month is the sum of all off-diagonal elements of the import–export matrix (see Bilgin and Yılmaz (2018) for a similar calculation for the system-wide input-export connectedness).

Over our sample period, a visual inspection of Fig. 3 shows that the stock-market connectedness has been rising since 2007, when the 2007/8 global financial crisis started to break out and peaked at the height of the crisis towards the end of 2008. It remained relatively high until 2012 amidst the European debt crisis period. There was also another jump in 2015, coincide with the episode of China's stock market crash between June 2015 and February 2016, which had sent a shock wave to major stock markets across the world. A number of studies have found that intensified stock return spillover during volatile periods (e.g., Forbes and Rigobon (2002), Aloui et al. (2011), Chevallier et al. (2018)). The index has since gradually picked up until towards the end of 2019 and beginning of 2020 when the index has first soared, then declined quickly, and finally gradually adjusted downwards, echoing the global adverse impact of the outbreak of the Covid-19 pandemic and then the uplifting effect of unprecedented stimulus measures and vaccine breakthroughs. There had been overall albeit modest rising in the index since the mid-2020.

On the other hand, as a result of globalisation, trade connectedness has been gradually growing prior to 2008. After that, there had been a considerable drop in the trade connectedness due to the severely damped global trade after the financial crisis. The global trade has been gradually recovering until it reached the peak in 2013, when the trade connectedness index started to decline again towards the end of 2018. Several reasons could cause this recent reverse of trend. The first explanation lies within the structural change in the long-term relationship between trade and income. In a recent study by Constantinescu et al. (2015), they find that long-run elasticities of gross trade to GDP decreased over time approaching around 2012–2013 the lower and subsequently more stable estimates of the trade elasticities in value added terms. Using data from the 1990 s to 2013, they find that US and China both experienced significant declines in the elasticity of trade to growth (from 3.7 to 1.0 for the US, and from 1.5 to 1.1 for China). In the case of China, they find progressive substitution of domestic inputs for foreign inputs by Chinese firms, echoing the increasing domestic value added in Chinese

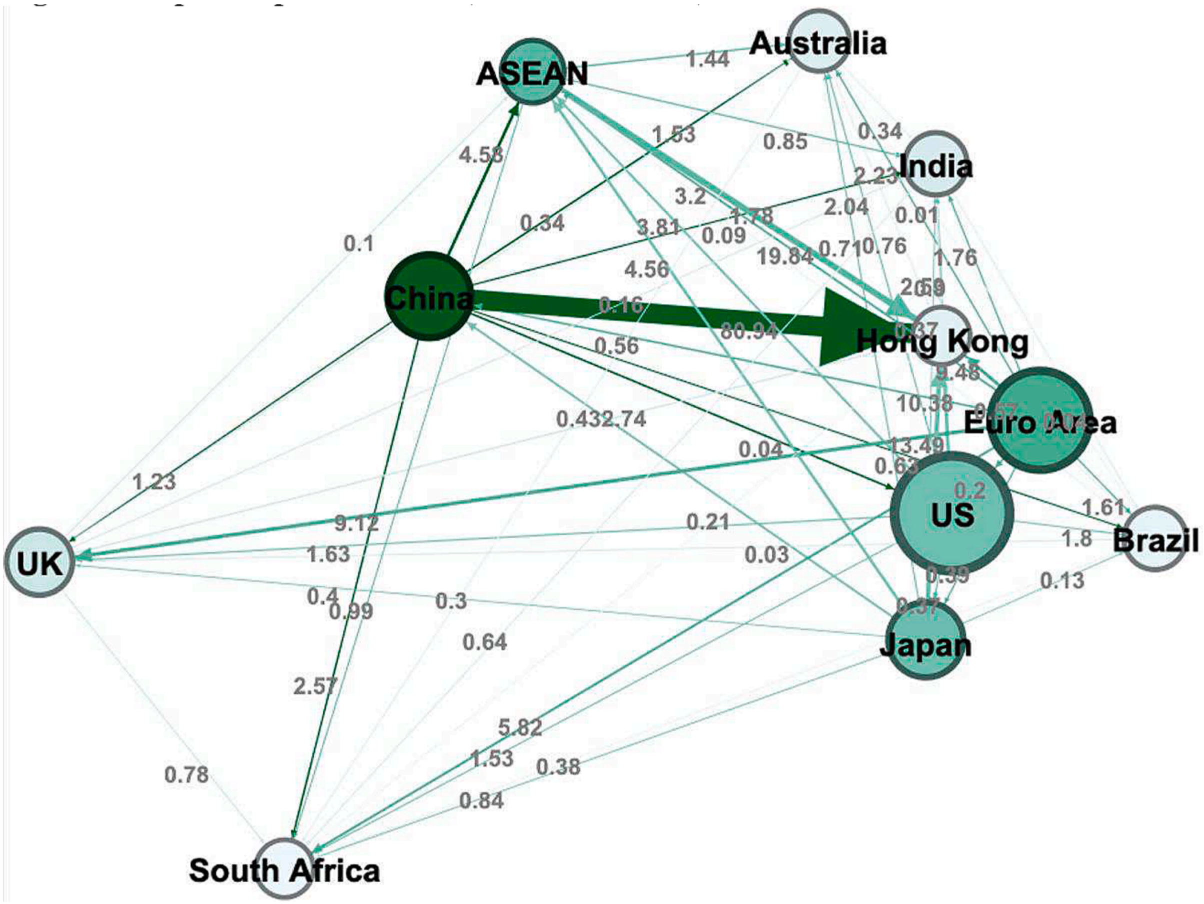

Fig. 2. Import-export network (2004 m3-2021 m6) *Note:* The thickness of the edges is based on numbers in Table 3. For instance, the edge goes from Euro area to UK is based on that 10.83 in row (4) column (3) in Table 3 is larger than 1.71 in row (3) column (4)) by 9.12.

Fig. 3. System-wide stock-market connectedness and export–import network.

firms found by Kee and Tang (2016).

The second explanation is related to the rising traditional protectionism in recent years which has created barriers for international trade and removal of trade agreements. For instance, Mattoo et al. (2017) argue that undoing US trade agreements would result in a decline in US exports by up to 4.3 percentage points and exports of the US's trading partners by 0.1–7.2 percentage points. Noland et al. (2016) and Bouet and Laborde (2017) analyse the impacts of different trade war scenarios between the US and China/Mexico. They find that trade war would have substantial damaging effect on the US economy and subsequently reducing US' demand for imports. Toward the end of 2018 the import–export trade-network index has been in decline, reflecting the negative impact of US trade war with China and other countries. This has continued until the first half of 2020 when the outbreak of Covid-19 has further exacerbated the situation. However, since mid-2020 the index has been gradually recovering. Driven by the strong export performance of East Asian economies, the world trade's recovery from the COVID-19 crisis hit a record high in the first quarter of 2021, increasing by 10 % year-over-year and 4 % quarter-over-quarter (UNCTAD's Global Trade Update, 2021).

Our visual inspection of the trade with the stock-market connectedness highlights that there is evidence of similar trend between these two indices, especially in the years after the 2008 financial crisis and after the initial outbreak of Covid-19 pandemic. As they present the system-wide connectedness in the stock markets and trade-network, we further examine in Section 5.1 the relationship between these two indices to test H_1 that the international trade-network influences stock market connectedness at a system-wide level amongst economies.

(b) Pairwise directional stock-market connectedness.

As part of the dynamic demonstration of the stock market interdependence, we further present the net spillover indices of each market over time (calculated following Equation (13) in Section 3.1) in Fig. 4. Both US and China have net spillover indices that are positive, implying that they are net transmitter of shocks to the other stock markets. In contrast, all other nine economies have negative net spillover suggesting their stock markets are receiver of shocks.

Focusing on the US and China, while the influence of the US stock market has hiked at the onset of 2008 financial crisis as indicated by the peak in October 2008 in Fig. 4, it has since been declining gradually but spiked in early 2020 following the Covid-19 outbreak. In contrast, the Chinese stock market has become more influential since 2008, although there was a declined in 2012, probably due to raised net spillover from Japan. We observe a moderate rise in 2015 July following the Chinese market crash that lasted until around from Feb to June 2015, following which the net spillover from China to other market has been gradually rising in most months but overall stable until second half of 2018 when the trade war between China and the US had started and China's net spillover had seen modest decline. Similar to the US, the net spillover of Chinese stock market also seen a spike in early 2020, although with a smaller magnitude compared with the US, and has been rising until the end of our sample period.

Fig. 5 further illustrates the pairwise stock market return spillover of the eleven markets. 55 graphs are presented as we have eleven economies and the results of the net directional spillover from A to B would be the mirror image of that from B to A. China-US (ij) indicates the spillover that runs form the US(j) to China(i). The values could be positive or negative. A positive value suggests between the pair of ij, the spillover goes from j to i, while a negative value suggest i is receiving negative spillover of j, or in other words, the spillover runs from i to j.

The first ten panels in Fig. 5 shows the spillover China have received from the other ten markets. The values of the directional spillover are mostly negative for all ten markets, although the magnitude is relatively small. The average of spillover during the period of 2005 m1 and 2021 m6 is between the range of −1.57 (between China-HK) and −0.42 (between China-UK) for the ten pairs. It implies that overall, China is not a net receiver but a net giver of stock markets spillover. The top two receivers of China's stock market influence are Hong Kong (China) (-1.57) and Brazil (-0.89) followed by India and Japan (both −0.69), highlighting China's growing influence on Asian (as suggested by Arslanalp et al (2016)) and South American financial markets. It is also interesting to observe that despite having the largest and most developed stock market in the world, the US seems to be a net receiver of spillover from China.

While previous studies examine and confirm the bilateral spillover between the China and US stock markets or these two stock markets being cointegrated in the long run (e.g., Mei and McNown (2019), Uludag and Khurshid (2019) and Song et al (2021)), our study provides further evidence in terms which countries is the net giver of spillover and does so in a dynamic manner. Our evidence shows the net giver of influence is China to the US. Although it is at odds with the conventional view, it is consistent with some recent papers that observe the increasing leading role of the Chinese stock market (e.g., Ahmed et al (2019), Hung (2021), Shi (2021)). Furthermore, although China's influence on the US would seem to be with modest magnitude overall, we observe that during the Covid-19 outbreak in end of 2019 and beginning of 2020, there had been significant increase in China's spillover to other economies (i.e., the value in the first 10 panel becomes much more negative). In contrast, during the 2007/2008 global financial crisis, China-US turned from negative to positive, suggesting the impact of stock market spillover from the US to China.

In terms of the US (panels 11–19 in Fig. 5), it is a strong giver of spillover for all markets except China (which would be the mirror image of panel 1 which is not shown here to save space). The biggest receivers are UK (with an average value of −3.39 during 2005 m1-2021 m6), Euro Area (-3.34), Australia (-2.60), followed by Japan (-2.48), South Africa (-2.32) and India (-1.91). The 2007/8 global financial crisis and 2020 Covid-19 outbreak have seen dips in the net spillover (becoming more negative) of the US in panels 11–19, implying heightened spillover from the US to these economies during these two disruptive events.

For the other economies, overall, the Eurozone is a net receiver from the US and China, although at a much lower magnitude from the latter, and a net giver at very moderate level to all other eight economies. During the peak of the European debt crisis around 2012, the net spillover of CH-EU (panel 2) turned to positive for a few months, US-EU (panel 11) became less negative, and the mirror image of EU to the other eight economies (panel 20–27) became less negative or turned positive, implying the global impact of the crisis. UK is a net giver to all regions apart from being a net receiver from US, China and the Euro Area (panels 3, 12 and 20) although at a much smaller magnitude in the case of the latter two economies. The mirror images of panels 28–35 showed the rising impact of the UK

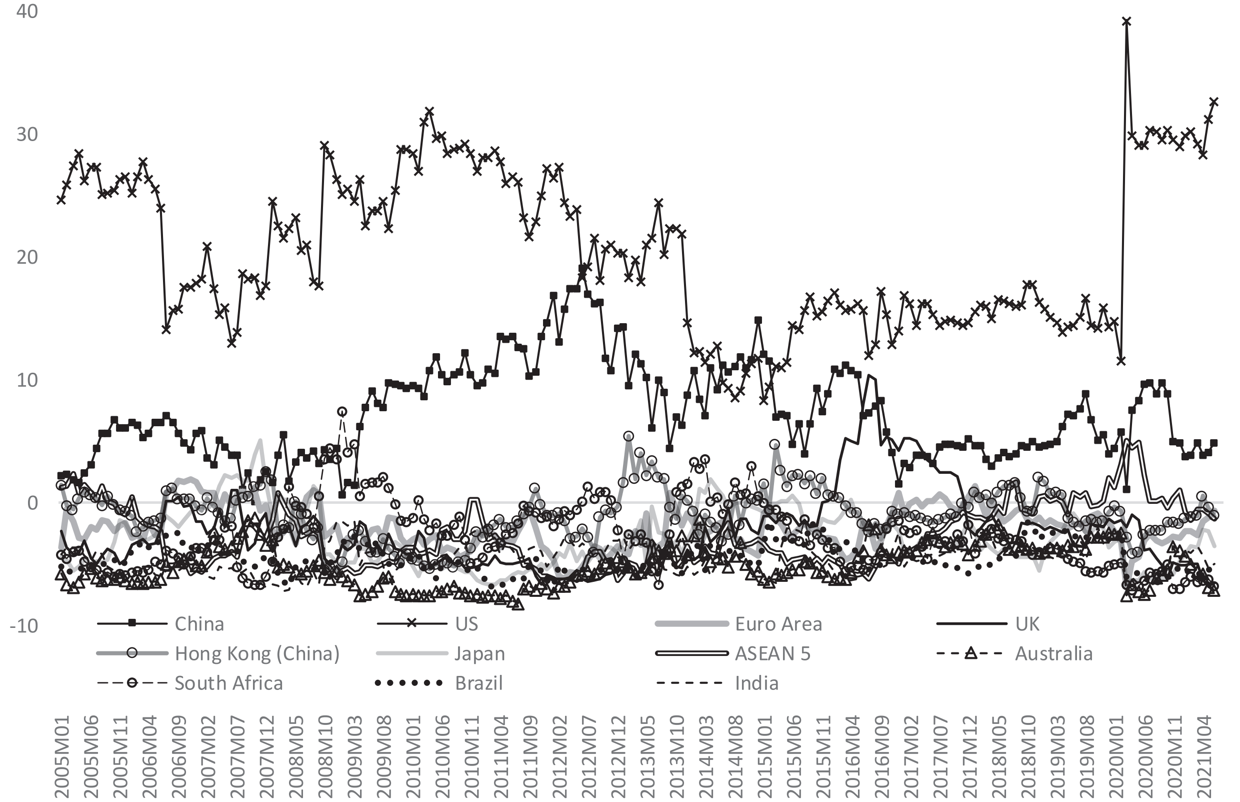

Fig. 4. Net directional stock market return spillover.

during the Brexit referendum period June 2016 as the net spillover became less negative or turned to positive to these economies. Its impact was less evident in the case of CH-UK (panel 3), suggesting a much-limited impact of the Brexit event on China. For Hong Kong (China), Japan and ASEAN 5, they are net receiver from China, US, Euro area and the UK although the influence is much smaller from the latter two countries. They are net giver to the rest of the six markets except Japan is a net receiver (of very small magnitude) from Hong Kong (China), ASEAN 5 and South Africa and ASEAN5 is a net receiver from Hong Kong (China). For Australia, on average it is a net receiver from all other economies although the impact from South Africa, Brazil and India is negligible (panels 49–51). South Africa, Brazil and India are net receivers from other economies except they are all net givers to Australia and South Africa is also a net giver to Japan, Brazil and India.

Looking at the trend of the panels in Fig. 5, since the aftermath of the 2007/8 global financial crisis, there had been gradually rising in the US-Eur, -UK, -HK, -ASE, -AU, SA and -BR (panels 11–13 and 15–18, respectively) (becoming less negative) until the outbreak of Covid-19 in 2020. Such rising seems to be less consistent in the cases of China (mirror image of panel 1), Japan (panel 14) and India (panel 19). It suggests that Eurozone, UK, Hong Kong (China), ASEAN 5, Australia, South Africa and Brazil have been gradually under less net influence of the US market.

5 International trade linkage and stock market interdependence

In Section 4, we have discussed in depth static and dynamic patterns and for the latter, we have studied both the system-wide, net and pairwise directional connectedness. In this section, we formally examine whether and how the trade linkage has influenced the stock market interdependence for our eleven markets. First, we analyse at aggregate level where the effect of system-wide trade on the stock-market connectedness are going to be investigated, examining H_1. Then we investigate the pairwise directional relationship between trade flows and stock return spillover. We assess separately how economy *j*'s importance to *i* as an exporter and as an importer would influence stock spillover that runs from *j* to *i*, evaluating H_2 and H_3, respectively. Finally, we examine H_4 by analysing whether *j*'s position as an importer creates stronger stock return spillover to *i* than being an exporter.

5.1. Relationship between system wide trade and stock-market connectedness

We examine the relationship between the system-wide stock-market connectedness and trade-network presented in Fig. 3. The results are summarised in Table 4. We first test for the stationarity of these two variables using the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) unit root tests which show that both series follow an $I(1)$ process. Given this, we employ Johansen

Fig. 5. Pairwise directional stock market return spillover *Note:* US = United States, Eur = Eurozone, UK = United Kingdom, HK = Hong Kong (China), JA = Japan, ASE = ASEAN 5, AU = Australia, SA = South Africa, BR = Brazil and IN = India. Ching_US indicates the spillover that runs from the US to China. US_China would be the reverse of China and not shown here to save space.

cointegration test to examine whether there is any long-term relationship between these two indices. Both trace and maximum eigenvalue statistics are lower than the 5 % critical values, suggesting that there is no cointegrating relationship.[6] Therefore, we do not find any system-wide evidence for the long run relationship between the trade-network and stock-market connectedness for these eleven economies as a whole.[7] In other words, our results do not support H_1.

However, the missing of trade-stock market relationship at aggregate level does not necessarily mean the same when the directions of trade flow and stock returns transmission are considered. We thereby employ the directional net stock market return spillover and trade flows in the following section to carry out further analysis on their relationship to examine H_2, H_3 and H_4.

5.2. Evidence based on pairwise directional trade and stock-market connectedness

We investigate the relationship between pairwise directional connectedness of stock market and trade in this section. The measurement of both has been discussed in Section 3.2 and the former is also presented in Fig. 5. In terms of the directional trade flows, as discussed in Section 2, we employ both export and import aspects of the international trade between economy *i* and *j*. Since we expect both exports and imports play important roles in inducing stock market spillover that goes from *j* to *i* and more importantly, imports could play a more dominate part (see discussion in Section 2.1 and Appendix A).

We first examine the stationarity of the pairwise directional series panels employing Levin et al. (2002) test, Im et al. (2003) test and Fisher-ADF and Fisher-PP tests define by Maddala and Wu (1999). The results are summarised in Table 5. The Levin et al. (2002) method tests the null hypothesis of unit root (assuming common unit root process across the cross-sections) against the alternative hypothesis of no unit root. The latter three methods test the null of unit root (assuming individual unit root process across the cross-sections) against the alternative hypothesis of some cross-sections do not have a unit root. All tests have confirmed that the pairwise

[6] We have also employed the Engle and Granger cointegration test for the two system wide indices. However, the residuals were non-stationary, which confirming that there is no cointegrating relationship between the two indices.

[7] Granger causality test on the first difference of these two systemwide variables (which are *I*(0)) suggests that there is no Granger causality in either direction.

Table 4
ADF unit root and Johansen cointegration tests for the system wide indices.

ADF Unit root test			
Variables	Lag length	ADF stats	
		Level	1st difference
System wide stock-market connectedness	1	−2.01	−16.68***
System wide trade connectedness	1	−2.09	−18.27***
Johansen cointegration test			
No. of cointegrating equation(s)	Trace stats	Maximum eigenvalue stats	
None	8.26(15.49)	5.89(14.26)	
At most 1	2.37 (3.84)	2.27(3.84)	

Notes: For the ADF unit root test, we set a maximum lag length of 12. Lag length is chosen by the Schwarz information criterion (SIC). *** indicates 1% significance level. For the Johansen cointegration test, the critical values at 5% significance level are in parentheses.

directional stock market and trade variables follow an $I(0)$ process.

Given that all three series are stationary, we further examine the causal relationship between trade and stock market return spillover. We first apply the standard Granger Causality test (Granger, 1969) to our panel data. As this method assumes that all coefficients are the same across all cross-sections, we further employ the Dumitrescu and Hurlin (2012) panel causality tests where all coefficients are allowed to be different across cross-sections. The results are reported in Table 6. The Granger Causality test with up to four lags suggests that for the panel as a whole, the null is rejected at 1 % significance level for all lag length 1–4 in the direction from Export$_{i\leftarrow j}$ to Stock Market Spillover$_{i\leftarrow j}$ and for all lag length 1–4 in the direction from Import$_{i\rightarrow j}$ to Stock Market Spillover$_{i\leftarrow j}$. The Dumitrescu and Hurlin (2012) panel causality tests also reject the null of no causality in both cases at least at 5 % significance level. Therefore, it confirms that the causality goes from exports and imports to stock market spillover.

On the other hand, for the causality goes from stock market spillover to exports and imports, the null of no causality cannot be rejected for any lag length in the case of Stock Market Spillover$_{i\leftarrow j}$ → Export$_{i\leftarrow j}$ using the Granger Causality test despite it is rejected by the Dumitrescu and Hurlin (2012) test; the null is rejected in the case of Stock Market Spillover$_{i\leftarrow j}$ → Import$_{i\rightarrow j}$ but with decaying significance level as lag increases from 1 to 4 and it is not rejected by the Dumitrescu and Hurlin (2012) test. As such, we do not find convincing evidence that the causality goes from stock market spillover to exports and imports. Therefore, we conclude that there is uni-directional causality goes from exports and imports to stock market spillover but not the other way around.

We subsequently move on to examine the individual influence of directional exports and imports on the stock market return spillover. To obtain information on the nature (i.e., positive or negative) and magnitude of such influence, we employ the panel regression:

$$\mathbf{Stockreturnspillovers_{i\leftarrow j,t}} = \boldsymbol{\alpha} + \boldsymbol{\beta}\mathbf{Export_{i\leftarrow j,t}} + \boldsymbol{\gamma}\mathbf{Import_{i\rightarrow j,t}} + \boldsymbol{x}^{'}_{i,t}\boldsymbol{\delta} + \boldsymbol{\varepsilon}_{i,t} \tag{14}$$

where the Stock return spillover$_{i\leftarrow j,t}$ denotes the pairwise directional stock return spillover from economy j to i at time t. Time t includes months from Jan 2000 (t = 1) to June 2021 (t = 258) although the analysis starts from Jan 2005 (t = 61) due to the 60 rolling windows, j denotes the eleven economies discussed in Section 1 and i denote j's corresponding trade partners. Export$_{i\leftarrow j,t}$ refers to the exports from j to i adjusted by i's GDP. It measures the importance of economy j as an exporter to i (or in other words, how important j is to i as i's source of imports). Import$_{i\rightarrow j,t}$ denotes j's imports from i adjusted by i's GDP. It measures the importance of economy j as an importer to i (or in other words, how important j is to i as i's destination of exports). α, β and γ are the coefficients of the above three variables, respectively. $\boldsymbol{x}$ is a column vector of control variables, which includes relative size of GDP, relative development of financial markets and exchange rate risk as discussed below, δ is a row vector of correspondingly parameters, and ε is the error term.

The relative GDP variable (the ratio of j's real GDP to i's) is included to control for the relative size of GDP (as discussed in Dumas et al., 2003). We also include the relative size and relative P/E ratio of the stock markets to capture stock market characteristics. Countries with larger stock market capitalisation attract foreign investments (e.g., the higher proportion of foreign holdings of bonds and/or equities), which subsequently increases the level of integration of local financial markets into world financial markets (Vithessonthi and Kumarasinghe, 2016). The higher the P/E ratio, the more that the market is willing to pay for each dollar of income earned. As a higher P/E ratio is associated with risky assets (Narayan et al., 2014), we expect it to reduce stock market connectedness. We thereby employ the relative form of these two variables to capture stock market influence from j to i generated by the relative size and P/E ratio of the stock market of j to i. We also include exchange rate risk and geographic distance as additional two control variables. Exchange rate risk is an important consideration in international portfolio management as it is seen as a source of uncertainty for investors. Great exchange rate risk often hinders international market correlations (Büttner and Hayo, 2011). Hence we expect higher relative exchange rate risk of j's currency would have a negative impact on j's influence on i's stock market. Grinblatt and Keloharju (2001) explain that information friction is the primary reason why distance matters as the geographical distance between two markets is often considered as the proxy for information costs. Following Flavin et al (2002) and Chong et al (2011), we include geographic distance as one of the control variables. As noted in Section 3.2, we adjust geographic distance between i and j by the ratio of j's real GDP to i's real GDP to filter out the impact of the relative GDP.

The results of panel regression analysis of Equation (14) are reported in Table 7. In model (1) and model (2) only Export$_{i\leftarrow j}$ and Import$_{i\rightarrow j}$ is included, respectively, and in model (3) both are incorporated in the panel regression. We control for country and time

Table 5
Panel unit root tests for the pairwise directional indices.

	Stock Market Spillover$_{i\leftarrow j}$	Export$_{i\leftarrow j}$	Import$_{i\rightarrow j}$
Levin, Lin and Chu adjusted t	−7.86***	−11.53***	−11.41***
Im, Pesaran and Shin W-stat	−19.41***	−17.58***	−14.64***
ADF - Fisher Chi-square	852.50***	996.28***	833.19***
PP - Fisher Chi-square	912.43***	2625.38***	2052.67***

Notes: Stock Market Spillover$_{i\leftarrow j}$ denotes the pairwise directional stock market spillover from *j* to *i*, Export$_{i\leftarrow j}$ denotes pairwise importance of *j* to *i* as an exporter (or as *i*'s source of import), and Import$_{i\rightarrow j}$ denotes pairwise importance of *j* to *i* as an importer (or as *i*'s export destination). The measurements of these variables are discussed in Section 3.2. The maximum lag length for the unit root tests is set at 12. Lag length is chosen based on SIC. *** indicates 1 % significance level. Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Table 6
Panel causality between the directional stock market return spillover and the export and import aspects of international trade.

	Granger causality test stats				Dumitrescu and Hurlin (2012) non-causality tests	
	Lag = 1	Lag = 2	Lag = 3	Lag = 4	Lag length	Stats ($\widetilde{Z}^{b}$)
Export$_{i\leftarrow j}$ →Stock Market Spillover$_{i\leftarrow j}$	13.8067***	5.8207***	3.6553**	3.5393***	2	2.0977**
	(0.0002)	(0.0030)	(0.0119)	(0.0068)		(0.0359)
Import$_{i\rightarrow j}$ →Stock Market Spillover$_{i\leftarrow j}$	27.1302***	13.8884***	8.5510***	7.5775***	2	3.1288***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)		(0.0018)
Stock market Spillover$_{i\leftarrow j}$ → Export$_{i\leftarrow j}$	0.5434	0.5921	0.4163	0.2484	2	5.3830***
	(0.4610)	(0.5532)	(0.7413)	(0.9108)		(0.000)
Stock Market Spillover$_{i\leftarrow j}$ → Impors$_{i\rightarrow j}$	11.2458***	4.7251***	3.0705**	2.3072*	1	0.7376
	(0.0001)	(0.0089)	(0.0266)	(0.0557)		(0.4607)

Note: See Section 3.2 for variable definition and measurement. P-values are in parentheses. The optimum lag length in the Dumitrescu and Hurlin (2012) non-causality tests is chosen based on SIC. *, ** and *** indicate 10%, 5% and 1% significance level, respectively.

fixed effects in all three models. In model (1), the directional exports factor has a positive sign and is significant at 5 % level, suggesting that exports from *j* to *i* (adjusted by *i*'s GDP) has a positive impact on directional stock market influence from *j* to *i*. This supports H_2. The controls variables of relative GDP and the relative size of stock market also have positive signs and significant at 1 % level, implying that the bigger size of *j*'s GDP and more developed is *j*'s financial markets, the stronger is *j*'s spillover to *i*'s stock market. The GDP adjusted geographical distance has a negative sign and significant at 5 %, suggesting that longer distance reduces stock market connectedness. On the other hand, the exchange rate risk does not seem to play a role in affecting stock market spillover.

In model (2), the directional imports factor is also positive and highly significant at 1 % significance level. It shows that the more *j* imports from *i* (adjusted by *i*'s GDP), the more influence *j*'s stock market would have on *i*'s. It thereby firmly confirms H_3. The three

Table 7
Panel regression results: Pairwise directional stock market return spillover and pairwise exports and imports.

Dependent variable: Stock Market Spillover$_{i\leftarrow j}$			
	(1) including Export$_{i\leftarrow j}$	(2) including Import$_{i\rightarrow j}$	(3) including both Export$_{i\leftarrow j}$ and Import$_{i\rightarrow j}$
Export$_{i\leftarrow j}$	0.0044**		0.0033*
	(0.0018)		(0.0018)
Import$_{i\rightarrow j}$		0.0374***	0.0361***
		(0.0063)	(0.0063)
Relative GDP	0.0063***	0.0065***	0.0058***
	(0.0022)	(0.0021)	(0.0022)
Relative size of the stock market	0.0069***	0.0043**	0.0047***
	(0.0017)	(0.0017)	(0.0018)
Relative P/E ratio	−0.0092	−0.0072	−0.0074
	(0.0074)	(0.0073)	(0.0074)
Geographical distance	−0.0429**	−0.0130	−0.0123
	(0.0167)	(0.1756)	(0.0176)
Exchange rate risk	−0.0005	−0.0004	−0.0004
	(0.0005)	(0.0005)	(0.0005)
Constant	0.2228	−0.0949	−0.1055
	(0.1684)	(0.1778)	(0.1779)
Cross-sections included	110	110	110
No. of observations	21,780	21,780	21,780
R^2	0.7786	0.6928	0.6788

Note: See Section 3.2 for variable definition and measurement. Standard errors are in parentheses. ** and *** indicate 5% and 1% significance level, respectively. In all three cases, we account for country- and time-fixed effect.

control variables in model (2) have very similar results as in model (1) except the geographical distance turns insignificant.

In model (3) we include both directional exports and imports factors. Both factors remain positive and significant at 10 % and 1 % level, respectively. Therefore, our results confirm the relationship between trade and stock market spillover described by Bracker et al. (1999), Pretorius (2002) and Shinagawa (2014) with specific directional evidence. The results on the three control variables in model (3) are consistent with model (2) except the level of significance increased from 5 % to 1 % for the relative size of the stock market. The values of R^2 suggest overall a good fit of the models.

Model (3) shows a most interesting finding that the magnitude of impact of $Import_{i \rightarrow j}$ (0.0374) is much bigger than $Export_{i \leftarrow j}$ (0.0044). It highlights that, whilst *j* exerts its stock market spillover via its imports from and exports to *i*, the former seems to play a more important role in generating the return spillover from *j* to *i*. In other words, being an importer of trade flows (or the exports destination of other economies) generates stronger impact on stock market spillover than being an exporter (or source of imports for other economies). It firmly corroborates the expected stronger impact of being an importer laid out in H_4 in Section 2 and illustrated in Appendix A.

To further explain this in the context of current global trade environment, many countries have experienced overcapacity - too much product (and too much production capability) chasing too few buyers - in a range of industrial sectors in the past few decades and it has become a globally recognised phenomenon (Erturk, 2001; Doner et al., 2004; OECD, 2015; National Association of Manufacturers 2016). Many economies such as China have turned to exporting as a strategy to absorb the domestic excess capacity (Yari and Duncan, 2007; IMF, 2016; Dai and Zhao, 2021). Given the overcapacity in production, and amidst the general weaker external demand from trade partners since the 2008 global financial crisis, a decline in the importing country's demand would have more devastating effects on its trade partner (the exporting country) than the effects of a decline in the exporting country's supply on the importing country, for while the importer could manage uncertainty caused by any adverse supply shock that has happened to its trade partner by organising and planning for an alternative exporter who is also keen to supply, it would be relatively harder for the exporter to cope with any adverse demand shock that has occurred to its trade partner due to the overall weak global demand and competition from other suppliers. The exporter may need to offer a significantly bargained down price to attract another importer, reducing profit and dampening investment prospects of the exporting firms which may further have ripple effects of multiple orders. In other words, in bilateral trade, the exporter is more dependent on its importer than inversely. Therefore, being an importer, the status of its economy and stock market would have a stronger spillover effect on the stock market of its trade partner than being an exporter, as described in Section 2.1 and Appendix A and found above. This finding also underlines the importance of employing pairwise directional trade in understanding the trade-stock market spillover relationship.

To summarise, at aggregate level we find no evidence of trade-network having any impact on stock-market connectedness using system-wide information. In this respect, our study is in line with Liu et al (2006), Shinagawa (2014) and Dhanaraj et al (2017). However, once we examine the pairwise directional evidence, we find that an economy's role both as an exporter and importer are channels which generate its influence on the stock market of its trade partner, and that being an importer (or the export destination of your trade partner) is more effective in generating such influence. It suggests that an adverse demand shock to *j* could have a far-reaching impact on the stock market of *i* than an adverse supply shock to *j*. Therefore, compared with previous studies (e.g.,

Table 8
Robustness checks.

Dependent variable: Stock Market $Spillover_{i \leftarrow j}$				
	(4) Using seasonally adjusted $Export_{i \leftarrow j}$ and $Import_{i \rightarrow j}$	(5) Using an alternative rolling window of 48	(6) Focusing on the global and Euro crisis period 2007 m1-2012 m12	(7) Including a lag of the dependent variable using system GMM (two-step)
L.Stock Market $Spillover_{i \leftarrow j}$				0.8770*** (0.0091)
$Export_{i \leftarrow j}$	0.0034** (0.0016)	0.0054*** (0.009)	0.0161*** (0.0032)	0.0067* (0.0035)
$Import_{i \rightarrow j}$	0.0324*** (0.0060)	0.01221** (0.0061)	0.0497*** (0.0100)	0.0677*** (0.2345)
Relative GDP	0.0057*** (0.0021)	0.0032 (0.0022)	−0.0080 (0.0049)	0.0118 (0.0117)
Relative size of the stock market	0.0049*** (0.0018)	0.0034** (0.0014)	−0.0382*** (0.0052)	0.0119* (0.0071)
Relative P/E ratio	−0.0076 (0.0074)	0.0221*** (0.0070)	−0.2108*** (0.0161)	−0.0611** (0.0281)
Geographical distance	−0.0015 (0.0175)	0.0314** (0.0156)	−0.4270*** (0.0337)	0.1572*** (0.0578)
Exchange rate risk	−0.0004 (0.0005)	−0.0006 (0.0005)	−0.0002 (0.0004)	−0.0030** (0.0013)
Constant	0.0714 (0.1769)	−0.3727 (0.1596)	4.1287*** (0.3157)	−1.5277*** (0.5709)
Cross-sections included	110	110	110	110
No. of observations	21,780	23,100	7920	21,670
R^2	0.6972	0.6700	0.5044	
ar1(p-value)				0.000
ar2(p-value)				0.110
Sargan(p-value)				0.197
Difference in Hansen tests (p-value)				0.356

Note: See Section 3.2 for variable definition and measurement. Standard errors are in parentheses. ** and *** indicate 5% and 1% significance level, respectively. We account for country- and time-fixed effect. The system GMM (two-step) in model (7) employs the Arellano-Bover/Blundell-Bond estimator.

Bracker et al.,1999; Wälti, 2005, 2011; Chambet and Gibson, 2008; Johnsen and Soenen, 2003; Tavares, 2009; Liu, 2013; Balli et al., 2015; Paramati et al., 2015; Paramati et al., 2018; Chevallier et al., 2018; Abbas et al., 2019; Charfeddine and Refai, 2019; Su and Liu, 2021; Youssef et al., 2021), our analysis highlights the vital importance of incorporating the directional element in studying the trade and stock market interdependence relationship. Furthermore, while most existing studies on spillover usually focus on the financial sector and often ignore the real economy or hardly employ any macroeconomic series of interest (Baur, 2012; Claessens et al., 2012; Dungey et al., 2013; Chevallier et al., 2018; Abbas et al., 2019; Charfeddine and Refai, 2019; Su and Liu, 2021; Youssef et al., 2021), our study present much-needed evidence showing how the trade side of real economy feedbacks into financial markets spillover.

5.3. Robustness checks on pairwise directional trade and stock-market connectedness

In this section we carry out a number of robustness checks in relation to the primary results in model (3) in Table 7. The results are summarised in Table 8. In models (4) and (5), we replace $\text{Export}_{i\leftarrow j}$ and $\text{Import}_{i\rightarrow j}$ by seasonally adjusted data and employ data using an alternative rolling window of 48, respectively, to evaluate whether our findings are sensitive to the choice of alternative trade data and rolling window. In model (6), we also check whether our results hold during the global and Euro crisis period of 2007 m1-2012 m12. In model (7) we consider the lag of the dependent variable Stock Market $\text{Spillover}_{i\leftarrow j}$ and subsequently we adopt the Generalised Method of Moments (GMM) for estimation. We employ the system GMM (two-step) estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) for our estimates. The Arellano-Bover/Blundell-Bond estimator is also referred to as the A–B–B estimator.

Across all investigations, the coefficients of $\text{Export}_{i\leftarrow j}$ are positive and significant at 1 % level in models (5) and (6), at 5 % in model (4), and at 1 % in model (7). It implies that *j* exports more to *i*, its stock market spillover onto *i* also strengthens. The coefficients of $\text{Import}_{i\rightarrow j}$ remain to be positive and significant at 1 % level (except at 5 % in Model (5)), suggesting that as *j* imports more from *i*, it has stronger spillover onto *i*'s stock market. Furthermore, the size of the coefficients of $\text{Import}_{i\rightarrow j}$ is consistently larger than that of the $\text{Export}_{i\leftarrow j}$ in all models, demonstrating that *j*'s position as an importer is a more powerful generator of stock market spillover that transmits from *j* to *i* than *j*'s position as an exporter. The above findings strongly corroborate with our primary results in model (3) in Table 7 and provide firm support to H_2, H_3 and H_4. Therefore, our key findings remain robust regardless of alternative trade data, alternative rolling window, being applied to the recent crisis period only and the inclusion of the lag of the dependent variable.[8]

For control variables, relative GDP is significant in model (4) where it also has the expected positive sign. Exchange rate risk is significant at 5 % in model (7) showing expected negative sign in all models. The coefficient of the relative size of the stock market is significant with expected positive sign in models (4), (5) and (7). However, during the sub-sample periods of global and euro crisis (2007 m1-2012 m12), its coefficient turned negative in model (6). Although the 2007/8 global financial crisis began from crisis in the banking sector, it was accompanied by a severe drop in stock prices (Boonman, 2023) and capital outflows from the stock market to safer assets such as the government bond (Bertaut and Pounder, 2009). Although the 2007/8 global financial crisis and the subsequently euro crisis started from developed economies, they sent the shockwave across the global stock markets. Therefore, there were capital outflows from the stock markets on the one hand and downward co-movement in global stock indices on the other, which explains the negative impact of the size of the stock markets on stock market spillover. The P/E ratio has expected negative sign in all models except model (5) when a shorter rolling window is employed. It seems that in a shorter time horizon, higher P/E ratio increases stock market spillover despite it may signify higher risk. Similar findings are also presented in Narayan et al (2014). Finally, geographical distance shows negative sign in models (4) and (6) and positive in models (5) and (7). Eckel et al (2011) find that beyond 50 miles geographical proximity is irrelevant for stock return correlations. Guo and Tu (2021) show that larger economic distance contributes to stock market connectedness due to the complementary effect between countries with greater economic distance. This could also apply to geographical distance as economies at similar development level often cluster in one area which explains the unexpected positive sign of geographical distance. Note that Sargen-Hansen tests and serial correlation tests for the GMM estimates in model (7) are reported at the bottom of the table. Both Sargan and Hansen tests suggest rejection of the overidentifying of restrictions, thus supporting the validity of the chosen instruments. The serial correlation tests show there are first order serial correlations, which is often expected, but no evidence of second-order serial correlation in the differenced error terms, implying that the GMM estimators are consistent in all models.

6. Conclusions and implications

Depth of international trade-network among countries can explain cross-country stock returns spillover and importantly, the direction of trade of a country (exporting or importing) largely drives the magnitude of spillover. This study premises and undertakes a comprehensive analysis on the impact of the international trade aspect of the real economy on stock-market connectedness with both system-wide and pairwise directional evidence. We have captured both export and import perspective between two economies in the latter analysis and examined whether imports induce stronger stock market spillover than exports. We consider a group of eleven economies: ASEAN 5 (Indonesia, Malaysia, the Philippines, Singapore, and Thailand), Australia, Brazil, China, Euro Area, Hong Kong (China), India, Japan, South Africa, UK and the US for period 2000 m1-2021 m6. We construct the import–export/trade-network which is adapted from the input–output network of Bilgin and Yilmaz (2018) and assess the stock-market connectedness employing the

[8] As the COVID pandemic started at the beginning of 2020, the COVID period alone is too short for any meaningful analysis. We exclude the COVID pandemic period (2020m1-2021m6) from our full sample and re-estimation model (3). The results are very similar to ones in model (3) and we omitted it here to save space. They are available upon request.

Diebold-Yilmaz Connectedness Index framework (Diebold and Yilmaz, 2009, 2012, 2014).

The static and time varying system wide and directional stock-market connectedness highlight the dominant role of the US and the rising role of China in the financial markets. The import–export network demonstrates China's importance in the world's trade system. Our examination shows that, first, at aggregate level, the system-wide linkage between trade and stock-market connectedness is missing. Second, however, the pairwise directional level of investigation demonstrates evidence that trade relationship granger-causes stock market spillover. Third, an economy's stock market spillover to its trade partner can be positively generated from its position as the importer (export destination of its partner economy) and the exporter (source of imports of its partner economy). Finally and most importantly, being an importer is a stronger producer of stock market spillover than being an exporter.

Compared with previous studies, this is a first analysis employing import–export network to evaluate the impact of trade (both exports and imports aspects) on stock returns connectedness and we incorporate the directional element into both trade and stock return spillover to reveal more accurate assessment on the relationship between the two. Imports create greater stock market spillover than exports. Our findings present supportive evidence on how trade side of the real economy feedbacks into financial markets interdependence, an important but under-studied area in exiting research, and have several important policy and investment implications.

First, trade agreement or trade policy adjustment could induce changes on the importance of one economy as another economy's export destination and/or source of import. Since both exports and imports aspects of the trade have a positive impact on stock return spillover, this information could be employed to assess possible future changes in magnitude or even direction in the spillover between two trade partners. It in turn has clear implications for investors seeking portfolio diversification as rising/declining return spillover due to trade dynamics would reduce/raise the opportunity for or benefit of diversification activities.

In addition, our dynamic pairwise and directional stock return spillover between China and other six major markets including the US (Section 4.2) suggest that, in contrast to the conventional view that China is a receiver (e.g., Mohammadi and Tan, 2015; Li and Giles, 2015; Zhang et al., 2021), China has showing increasing and clear signs of becoming a net giver of stock market influence (Ahmed et al., (2019), Hung (2019) and Shi (2021) show similar findings). Therefore, there needs to be a careful reconsideration of China's position and weights in certain financial modelling.

Furthermore, given the significant trade impact on stock market, for particular economies which have long been net exporters (e.g., China) or net importers (e.g., the US), certain domestic policy shifts may have consequences on global stock markets. For instance, China has set out its long-term plan to rely more on domestic consumption and less on exports as growth engine. The World Economic Outlook (2021) projects to 2026 that China's imports of goods and services will be growing at a faster pace than its exports. If China gradually reduces its importance as the world's source of imports but at the same time raises its significance as world exports destinations, it could have interesting dynamic impact on China's influence on the global stock market. On the other hand, in 2018, the US launched a trade war with China, an abrupt departure from its historical leadership in integrating global markets. Given US' long-standing role as a global importer (or export destination for many economies), such policy shift would have prolonged impact on its dominant role in the stock markets. All the above requires careful monitoring by policy makers in their evaluation and assessment of the evolving trade relationship and its impact on global financial influence and dominance.

CRediT authorship contribution statement

Kefei You: . **V.L. Raju Chinthalapati:** . **Tapas Mishra:** . **Ramakanta Patra:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing.

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.

Data availability

Data will be made available on request.

Appendix A

A Keynesian explanation for the formulation of H_4

Here we present a simple Keynesian model with external accounts and with fixed exchange and interest rate regime in order to demonstrate how an economy's position as an importer could be a stronger generator of stock return spillover to its trade partner than being an exporter.[9]

[9] We thank Professor Andrew Mountford for helpful discussions.

In line with discussion in Section 2.1, for the exporting country, we introduce an endogenous investment coefficient, i, and a fixed capacity investment of K which do not assume to be present in a net importing country (as only the exporting country makes investment to expand capacity which the importing country may not do). Now consider a standard two-country setting where $Y = C + I + (X - M) = A_0 + cY + I_0 + iY + K + m^* Y^* - mY$ is the output of the exporting country where C is consumption, I is investment, c is the marginal propensity to consume, K is the fixed investment cost for capacity building, i is the variable investment expenditure related to generating output and m, m^* are the marginal propensity to import by the exporting and importing country (* indicates macroeconomic variable of the importing country), respectively. The output for the importing country can be written as $Y^* = A_0 + c^* Y^* + I_0^* + mY - m^* Y^*$ Note that exports of any country in this model is the import of the trading partner.

Solving the above simultaneous equations we can deduce that, $Y^{Eq} = \frac{(1-c^*+m^*)(A_0+I_0+K)+m^*(A_0^*+I_0^*)}{(1-c-i+m)(1-c^*+m^*)-m^*m}$ and $Y^{*Eq} = \frac{(A_0^*+I_0^*)(1-c-i+m)+m(A_0+I_0+K)}{(1-c-i+m)(1-c^*+m^*)-m^*m}$. The denominator in both the equilibrium expressions can be simplified to $(1-c-i)(1-c^*+m^*)+m(1-c^*)$ (call it D) which is positive. We can observe that in both equations, Y is positively related to both its exports and its imports. However, note that the import propensity only appears in the denominator of both equations indicating that any increase in import will inversely impact the respective Y. Since the * indexed country is assumed to be a net importer, i.e., $m^* > m$, we can immediately see that the impact of a consumption shock in the importing country, i.e., a shock to A_0^*, on the exporting country will be higher than the impact of a supply shock in the exporting country to the importing country. This indicated $\frac{dY^{Eq}}{dA_0^*} = \frac{m^*}{D} > \frac{dY^{*Eq}}{dI_0} = \frac{m}{D}$. In addition, note that i enters Y^{*Eq} numerator negatively, indicating that such proportional investments undertaken by the exporting country may reduce only the A_0^* and I_0^* and would not be affecting any other variables in the importing economy, satisfying our arguments made in Section 2.1.

The point we wish to make here is that without resorting to much complex models to pin down the asymmetry of stock market shock spill overs, the above exposition illustrates that asymmetry in Y can be described simply with the help of propensities to import and export in a Keynesian model. Since more involved models in this literature (i.e., Acemoglu et al., 2012) have been engaged in intertemporal and optimizing models, aimed at explaining Keynesian predictions, our approach seems to yield results not too far off from the established message of the broad literature. However, our effort to fledge out the asymmetric impact that exogenous shocks in different directions of trade (i.e., exports and imports) seems to highlight a new dimension in the usage of Keynesian mechanics. In addition, although the approach to provide a theoretical justification of the relationship established above is simplistic, the authors are not aware of any other theoretical framework providing similar justifications even building up with microeconomic foundations. As such, this may open up interest in researching this relationship both from theoretical as well as empirical angle among economists in future.

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