The Diversification Benefits and Policy Risks of Accessing China's Stock Market *

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Abstract

Correlations of China's stock market with the global are the lowest among major markets and not increasing in the last two decades. Moreover, unlike other markets, China is not vulnerable to financial contagion of global market. Therefore, China's stock market can provide valuable diversification benefits for international investors. Using firm-level data, we find that A-share stocks are more connected with global market if they are held by Qualified Foreign Institutional Investors (QFII), more connected with real economy, and less policy-sensitive. Last, we show that disconnection with real economy and government intervention are more important than market openness in explaining the isolation of China's stock market.

JEL classification: F3; G01; G12; G15.
Keywords: China; Stock market; Contagion; International diversification; Policy sensitivity.

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1. Introduction

China's stock market has grown rapidly and become the second largest in the world with a market capitalization of about 55 trillion CNY (8 trillion USD) and more than 3000 firms listed as of December 2017. Moreover, since Chinese government has launched many new policies during the reform of financial system in the last two decades, China is a good laboratory for many financial studies. As a result, it has attracted much attention from academic in recent years. Carpenter and Whitelaw (2017) provide good review of studies in this area. In summary, there are four streams of research on China's stock market: the privatization of SOEs, political connections of firms, regulatory environment, and A-H cross-listed stocks. Although the literature is large, one important question is missing: the role of China's stock market in the global market. While the stake of China's stock market is still small for international investors, it will play a more important role in global market with the liberalization of financial market, especially after the inclusion of China A-share in the MSCI Emerging Market Index. Particularly, like other emerging markets, China can provide diversification benefits for international investors. And the benefits can be even larger since China's stock market has very low correlations with major developed markets as shown in Carpenter, Lu, and Whitelaw (2017). Therefore, this study tries to fill the gap by investigating the connectedness of China's stock market with global market.

The benefits of international diversification have relied largely on the existence of low cross-country correlations (Christoffersen, Errunza, Jacobs, and Langlois, 2012). However, some recent studies find that major stock markets are more correlated in the last few decades (e.g. Christoffersen, Errunza, Jacobs, and Jin, 2014), which leads to less potential diversification benefits. Moreover, studies show that stock markets are more correlated when market volatility is high, especially during market downturns. If correlations are higher than normal during bear markets in which investors are exposed to losses, then the gains of international diversification will be the weakest when these benefits are most needed. Therefore, many studies have turned to the unusual high correlations among markets during crisis period, or the so called “contagion”. Early studies find novel evidence of contagion in developed markets (DMs) (e.g., Ang and Bekaert, 2002; Longin and Solnik, 2001). Although the severity is much less, recent studies find that contagion also affects emerging markets (EMs) (e.g., Baur, 2012; Christoffersen et al., 2012). However, China may be an exception considering its specially features like small foreign ownership and frequent government intervention. Therefore, in this study, we examine whether China's stock market is also increasingly correlated with global market and vulnerable to financial contagion like other markets. If not, China would be a better choice for diversification and a safe haven for international investors during global shocks.

In order to examine the connectedness of major markets, we construct a sample that includes 9 DMs, 10 EMs, and the global market. The MSCI World Index (the Index), which includes 23 DMs, is used to proxy the performance of global market. The sample period is from January 1995 to December 2017. Consistent with previous studies, we find that EMs are overall less correlated with other markets than DMs. Particularly, China's correlations are the lowest among all markets. We also use dynamic conditional correlation (DCC) model of Engle (2002) and Tse and Tsui (2002) to analyze the time series change of correlations. The results show that the DCC of EMs increase more than DMs in the last two decades, probably because of market liberalization of EMs. Moreover, all markets except China have an uptrend DCC, suggesting that different from other markets, China is not increasingly correlated with the global market. Therefore, while diversification benefits from most EMs are decreasing, investing in China can provide as much diversification as twenty years ago for international investors.

Next, we investigate financial contagion of sample markets. As in Longin and Solnik (2001), testing contagion is a difficult exercise because of the spurious relationship between correlation and volatility. Therefore, various measures of financial contagion have been proposed. We use three methods to measure financial contagion in this study. First, we simply test cumulative market returns (CR) of EMs around global index shocks. The results suggest that all EMs except China have significantly negative CR around global shocks. Second, in the spirit of Chae (2005) and Schiller (2017), we measure financial contagion of EMs using *abnormal DCC* (ADCC) of EMs with the Index around global index shocks. ADCC is calculated as the difference between DCC in the index shock week and the average DCC over an estimation window from 30 to 5 weeks prior to the shock week. We find that all EMs except China have large and significantly positive ADCC around global shocks. Third, following Bae, Karolyi, and Stulz (2003), we use *coexceedance* to measure financial contagion. We define bottom coexceedance as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. Our results suggest that most EMs have lower bottom coexceedance than DMs. However, some EMs like South Africa, Brazil, and Mexico have even higher coexceedance than DMs, suggesting that although they have low correlations with the global market, they may be even more vulnerable to financial contagion than DMs. In contrast, China has the lowest coexceedance among all markets. Therefore, the results from all three methods suggest that China is not vulnerable to financial contagion, which makes China a safe haven for international investors during global shocks. At last, we directly examine the diversification benefits of EMs by constructing optimal portfolios that contain the Index and each of the ten EMs and comparing Sharpe ratios (SR) of the optimal portfolios. We show that adding China to the Index can increase its Sharpe ratio (SR) more than other EMs.

The isolation of China's market can potentially be explained by its special features. First, Bartram, Griffin, Lim, and Ng (2015) show that common ownership is as important as traditional country and industry factors in explaining international stock returns. China's stock market has very low foreign ownership because of capital control. Therefore, it potentially has low comovement with other markets and can withstand the "common ownership" channel of financial contagion documented in existing studies (e.g., Elliott, Golub, and Jackson, 2014). Second, as the largest exporter and second largest importer, China's economy is highly correlated with the global economy. And Lin and Ye (2017) find that Chinese manufacturing firms are affected by global shocks though trade credit of foreign direct investment. However, the stock market may fail to incorporate this information as China's stock market is disconnected with the real economy (Allen, Qian, Shan, and Zhu, 2018). Therefore, the stock market may be less connected with the global economy and not vulnerable to the "international trade" channel of contagion in the literature (Bekaert, Ehrmann, Fratzscher, and Mehl, 2014). Third, since Chinese government has larger control over financial market than other governments, stock market performance is more dependent on government policy. The government tends to intervene whenever the market is extremely volatile. While government intervention may bring more country-specific risk, it makes China less correlated with global market. And it also prevents China from the "wake-up call" channel of contagion documented in the literature (e.g., Goldstein, 1998).

Next, we use firm-level data to test the three potential explanations. Our sample includes all non-financial A-share firms listed in Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) from 1995 to 2017. We use two methods to measure connectedness of stocks with the global market. The first measure is correlation of the stock with the Index based on weekly USD return (*Correlation*). The second measure is global beta of the stock, which is defined as the loading of weekly excess return of the stock on excess return of the Index (*Global beta*). We exploit the Qualified Foreign Institutional Investors (QFII) holding data to test the effect of foreign ownership on stock's connectedness. As expected, A-share stocks with QFII holdings are more connected with the global market. Specifically, the correlation of QFII held stocks are 0.006 higher than that of other stocks. This difference is economically large as the average correlation is only 0.046. Therefore, the low foreign ownership in A-share market can partly explain its low connectedness with global market. This has important implication for international investors that investing on A-share stocks with less foreign ownership may provide more diversification benefits. Then we investigate whether disconnection between stock return and real economy affects stock's connectedness with the global market. In the spirit of Allen et al. (2018), we rely on correlation of stock return with GDP growth rate to measure stock's connection with real economy (*Economy connection*). We show that stocks more connected with the real economy are also more correlated with the global market. Thus, the disconnection of A-share market with the real economy may also explain the isolation of China's market.

Last, we examine whether stock's policy sensitivity affects its connectedness with the global market. We use two different variables to measure stock's policy sensitivity. In the spirit of Baker, Bloom, and Davis (2016), our first measure, *Policy sensitivity*1, is based on correlation of stock return with China's Economic Policy Uncertainty Index (EPUI). As the main regulatory body of China's stock market, China Securities Regulatory Commission (CSRC) has a huge impact on market performance (e.g., Chen, Firth, Gao, and Rui, 2005). In the spirit of Liu, Shu, and Wei (2017), our second measure, *Policy sensitivity*2, is based on absolute three-day cumulative abnormal return (CAR) of stocks around announcements of new regulatory documents issued by CSRC. The regression results suggest that correlation with global market of the most policy-sensitive firms is 0.013 lower than that of the least sensitive firms, which is equivalent to 28.26% of the average correlation. Thus, consistent with our expectation, stocks less sensitive to policy are more correlated with the global market, because their performance are less affected by government intervention. So the frequent government intervention can also partly explain the isolation of A-share market. Although policy-sensitive stocks are less connected with the global market, one concern is that they may have more policy risk, which can decrease realized return. To address this concern, we examine the effect of policy sensitivity on A-share stock performance. We find that policy-sensitive stocks have higher ROE, Tobin's q, stock return, and SR than other stocks. Therefore, they not only provide more diversification benefits to international investors, but also perform better than other stocks.

Another concern is that the low correlation may not persist when the A-share market has more international investors with the reform and open of Chinese financial market. To address this issue, we exploit the introduction of Shanghai-Hong Kong Stock Connect Program (SH-

HK) and Shenzhen-Hong Kong Stock Connect Program (SZ-HK). Since the connected stocks are more open to international investors, they should be more correlated with the global market according to the argument. However, our DCC analysis shows that connected stocks and the other stocks in both exchanges have similar trend. We also perform a difference-in-difference (DID) regression analysis using the connected stocks as the treatment group. The results suggest that connected stocks do not increase in connectedness with the global market overall. However, we find that the change of SH/SZ-HK stocks' connectedness depends on their connection with real economy and policy sensitivity. Stocks with high connection with real economy or low policy sensitive tend to increase in connectedness, while stocks with low connection with real economy or high policy sensitive tend to decrease in connectedness. It suggest that disconnection with real economy and government intervention may be more important than market access in explaining the isolation of China's stock market.

The rest of this paper is organized as follows. Section two provides institutional background of China's stock market. Section three presents the data and summary statistics. The empirical results are reported in section four. Section five contains some discussion and conclusions.

2. China's Stock Market

First opened in 1990 with only 8 firms listed, China's stock market has grown rapidly and become the second largest in the world with a market capitalization of about 55 trillion CNY (8 trillion USD) and more than 3000 firms listed as of December 2017. China's stock market is shaped by several key features.

First, China's stock market is dominated by domestic retail investors. In China, listed firms can issue three classes of tradable shares: A-shares priced in RMB and held by domestic investors, B-shares priced in USD or HKD and held by foreign investors, and H-shares traded in Hong Kong Exchanges. Some Chinese firms are A-H cross-listed by issuing both A-shares on SSE or SZSE and H-shares on Hong Kong Exchange. Before 2002, foreign investors could only trade B-shares in Mainland China, which represent only very small fraction of the total market capitalization. In 2002, the Chinese government introduced the QFII program that allows foreign institutional investors to trade A-shares directly. In 2011, the Chinese government launched the Renminbi Qualified Foreign Institutional Investors (RQFII) program, which further relaxes restrictions on currency settlement and expands investor eligibility. However, QFII and RQFII are not ideal for most international investors due to licensing requirement, quotas, and repatriation restrictions (Carpenter and Whitelaw, 2017). To further open the financial market, Chinese government launched the Shanghai-Hong Kong Stock Connect Program in November 2014 and Shenzhen-Hong Kong Stock Connect Program in December 2016. The stock connect allows international and Mainland Chinese investors to trade securities in each other's markets through the trading and clearing facilities of their home exchange.[1] However, the stock connect still restricts stocks and volume can be traded. Therefore, foreign investment still represents a small fraction of China's stock market until now. Moreover, China's stock market is dominated by retail investors, which is different from DMs where institutional investors play a major role. According to Jia, Wang, and Xiong (2015), retail investors hold 58% of the market.

Second, IPO process in China is very different from other markets, as the access to equity market is often a politically determined process. A quota system for IPO was used before 1999 and a channel system was adopted during 2000-2004. After 2005, a sponsor system is adopted where sponsors recommend its client firms to CSRC for an IPO. Because CSRC has been tightly restricting the number of IPOs every year, firms normally need to wait for years to be listed on A-share market. SOEs usually have priority for an IPO because of their political connections. Moreover, because firms are required to have at least three years of positive earnings to gain approval for an IPO, they may conduct more earnings management before IPO and pursue short-term profits at the cost of sacrificing long-term growth (Allen

[1] For more information about the stock connect, see the official website of Hong Kong Exchange: https://www.hkex.com.hk/Mutual-Market/Stock-Connect.

et al., 2018).

Third, since China has a less developed legal and financial system (Allen, Qian, and Qian, 2005) but a strong government, government policy has a huge impact on market performance. For example, Chen et al. (2005) find that enforcement actions of CSRC have a negative impact on stock prices with most firms suffering wealth losses of around 1-2% in the five-days window surrounding the event. With the aim of stabilizing financial market, Chinese government tends to intervene whenever the market is extremely volatile. For instance, the government took much action to stimulate the market during market crash in late 2015. Moreover, as part of the reform and open of the financial market, Chinese government frequently perform some regulatory experiments that also affect market performance. While regulatory reforms are a necessary and welcome part of the development of the market, a permanent policy or heavy-handed intervention seems counterproductive (Carpenter and Whitelaw, 2017).

3. Data and Descriptive Statistics

We start to construct our market-level sample with the G20 countries, which accounts for 85% of global economic output and 80% of global investment.[2] Then we drop the European Union (EU) since the largest four markets of EU (UK, France, Germany, and Italy) are already in the sample. Saudi Arabia is also dropped because the available data period is short and different from all other markets. We add Hong Kong stock market into the sample as it is closely connected with China's A-share market and many Chinese firms are listed on Hong Kong Exchange. We collect data of China's market from the China Stock Market and Accounting Research Database (CSMAR) maintained by GTA Information Technology. Then we use MSCI market index collected from DATASTREAM to measure the performance of other markets. At last, we use MSCI World Index (the Index), which includes 23 DMs, to proxy the performance of global market. Therefore, our market-level sample includes 9

[2]More information about G20 countries can be found on the official website: https://www.g20.org/en/g20/what-is-the-g20.

DMs: US (USA), Japan (JPN), Hong Kong (HKG), UK (GBR), Germany (DEU), France (FRA), Canada (CAN), Italy (ITA), and Australia (AUS); 10 EMs: China (CHN), South Africa (ZAF), South Korea (KOR), India (IND), Indonesia (IDN), Brazil (BRA), Mexico (MEX), Russia (RUS), Turkey (TUR), and Argentina (ARG); and the global market. The 19 stock markets accounts for more than 90% of global market capitalization according to the World Bank.[3] Our full sample period is from January 1995 to December 2017. We also have a more recent sub-period from January 2006 to December 2017 for comparison.

Our initial firm-level sample includes all A-share firms listed in SSE and SZSE from 1995 to 2017. Financial firms are excluded because their financial statements are complied under different accounting standards. To construct the measures of policy sensitivity, we collect China's monthly EPUI during 1995 to 2017 from the EPUI website. [4] And we hand-collect the announcement dates of new regulatory documents issued by CSRC from their official website for the period from 2001 to 2017 since the first document is issued in 2001.[5] 137 regulatory documents are issued by CSRC during this period. We also investigate change of connectedness of stocks with global market in the SH-HK and SZ-HK. The SH-HK includes constituent stocks in the SSE 180 Index and SSE 380 Index and all A-H cross-listed stocks. The SZ-HK includes constituent stocks with market capitalization greater than 6 billion CNY in the SZSE Component Index and SZSE Small/Mid Cap Innovation Index and all A-H cross-listed stocks. Since the stocks in both programs are adjusted every few months, we only include stocks that are in the programs throughout the sample period. This leaves us 546 stocks in the SH-HK and 833 stocks in the SZ-HK. All the other firm-level data and macroeconomic data of China are also obtained from CSMAR.

Panel A of Table 1 reports summary statistics of annualized weekly returns in USD for our sample markets. Consistent with previous studies, EMs have much higher return and volatility than DMs. Hong Kong has the highest return and volatility among DMs and

[3]See https://data.worldbank.org/indicator/CM.MKT.LCAP.CD.

[4]http://www.policyuncertainty.com/, which is developed by Scott Baker, Nicholas Bloom, and Steven J. Davis based on Baker et al. (2016).

[5]See http://www.csrc.gov.cn/pub/zjhpublic/index.htm?channel=3300/3311.

Russia has the highest return and volatility among EMs. In contrast, Japan has the lowest return among all markets. The average return of China is 15.132%, which is higher than all DMs and most EMs. Although Russia and Turkey have higher return than China, their volatility is almost one time higher than that of China. EMs like South Africa, India, and Mexico have similar volatility with China, but their returns are much lower. Therefore, from the perspective of an international investor, China provides very attractive return compared to other markets. However, the common knowledge holds that the portfolio risk of a well-diversified investor depends not only on the volatility of each asset, but also on the correlation of the assets. Therefore, it is necessary to examine the connectedness of our sample markets.

Panel B reports summary statistics of firm-level variables used in this study. Variable definitions are summarized in Appendix A and all variables are winsorized at 1% to 99% except dummy variables. As expected, the average correlation of A-share stocks with the Index is only 0.046. The average $QFII$ is 0.131, suggesting that only very small part of A-share stocks have QFII holdings. Since our measures of connection with real economy and policy sensitivity are based on rankings from 0 to 1, their means are all around 0.5. Most of the statistics of firm characteristics are comparable to those in other studies (e.g. Giannetti, Liao, and Yu, 2015; Liu et al., 2017). Our sample has more SOEs than recent studies because our sample period is long and most Chinese listed firms are SOEs before the Split-Share Structure Reform in 2005.

4. Connectedness of Global Stock Market

4.1. Correlations of Sample Markets

4.1.1. Unconditional Correlations

Some recent studies show that international diversification benefit is decreasing because markets are more correlated over time (e.g., Christoffersen et al., 2012) and financial contagion makes international investors more vulnerable to global shocks. However, Bekaert, Hodrick, and Zhang (2009) conclude that there is no clear upward trend in international stock return correlations from 1980 to 2005. Therefore, in this section, we use different methods to measure correlation and contagion of the sample markets to further investigate this issue. Particularly, we try to compare China with other markets. Our first measure of connectedness is unconditional correlation. Although unconditional correlation can be biased when market is volatile, it remains to be a popular measurement for the long-term connectedness of assets. We report cross-market correlations based on weekly USD returns in Panel A of Table 2. All correlations are significant at 1% significance level. Consistent with previous studies, correlations of DMs are generally higher than those of EMs. Japan has the lowest correlations among DMs. Markets in the EU have high correlations with each other as EU economies are closely connected. Correlations of EMs vary a lot across markets. South Africa, Brazil, and Mexico have the highest correlations, while China has the lowest correlations, especially with DMs. For example, the correlation of China with US is only 0.038. It is worth to note that China has higher correlation with Hong Kong than with most other DMs, as China's financial market is more connected with Hong Kong market. We also report the correlations for the period from 2006 to 2017 in Panel A of Table IA1 in the Internet Appendix. It shows that correlations of all 19 markets have increased in the last 23 years, but the pattern does not change, with China still has the lowest correlations. The unconditional correlations suggest that compared with the other markets, China can potentially provide more diversification benefits for international investors.

4.1.2. Dynamic Conditional Correlations

The unconditional correlations provide an overall picture of long-term connectedness of the sample markets, but they cannot capture the pattern of connectedness over time. Therefore, we use a dynamic conditional correlation (DCC) model of Engle (2002) and Tse and Tsui (2002) to characterize time-varying connectedness in this subsection. In order to obtain white-noise innovations to model correlation dynamics, we fit univariate AR(2)-GARCH(1,1) models to the weekly returns of each sample market following Christoffersen et al. (2014). The autoregressive model of order two, AR(2), will pick up the potential return dependence of each market. And the GARCH(1,1) will pick up the second-moment dependence. The model specification and results of model estimates are summarized in Appendix B.

We first estimate the DCC for each pair of sample markets. Then for each market, at each week we calculate three average correlations with other markets: the average correlation with all other 18 markets; the average correlation with all 9 DMs (or the other 8 DMs for a DM); the average correlation with all 10 EMs (or the other 9 EMs for a EM). We plot the time series of average DCC with all other markets for each sample market in Figure 1. Consistent with Christoffersen et al. (2014), most sample markets have and upward trend DCC, suggesting that the global market is more correlated in the last two decades. Moreover, most EMs' DCC increase more than DMs', possibly because of market liberalization in EMs. However, the trend of China's DCC is not as clear as other markets, as the increase is only marginal. This suggests that although the global market is increasingly correlated, China is an exception. Therefore, investing in China can still provide as much diversification as two decades ago.

We then take time-series average of the three average correlations for each market and the results are reported in Panel B of Table 2. The average DCC with all markets in column 1 show similar pattern with unconditional correlation reported in Panel A, suggesting our DCC model estimates fit our data well. Most EMs have much lower DCC than DMs, especially China. Column 2 and 3 show that most markets have much higher DCC with DMs than with EMs, but China's DCC with DMs and EMs are comparable. This means that China should be particularly attractive to investors from DMs. To further investigate correlation of DMs with EMs, we plot average DCC for DMs and EMs in Figure 2. Specifically, at each week we take average of the DCC of all pairs of DMs to calculate correlations of DMs (DM-DM). The same method is used to calculate average DCC of EMs (EM-EM). And we take average of the DCC of all pairs of DM and EM to calculate average DCC of DMs with EMs (DM-EM).

It shows that the DCC of EM-EM and DM-EM increase much more than that of DM-DM, which again suggests that EMs increase more in correlation with global market than DMs in the last two decades. Last, we estimate DCC of the 10 EMs with the Index and the results are plotted in Figure 3. Consistent with Figure 1 and 2, DCC of most EMs with global market increase in the last two decades. However, unlike other EMs, the DCC of China with the Index does not have an upward trend. Therefore, Figure 2 and 3 conclude that the overall diversification benefit by investing in EMs is decreasing, with China as an exception.

4.2. Financial Contagion of Sample Markets

4.2.1. Market Returns around Global Index Shocks

In this subsection, we investigate whether sample markets are vulnerable to financial contagion of global market, which can further decrease international diversification. As in Longin and Solnik (2001), testing contagion is a difficult exercise because of the spurious relationship between correlation and volatility. Therefore, various measures of financial contagion have been proposed. We use three methods to measure contagion in this study. Since one would expect markets vulnerable to contagion will have large negative return when the global market is under shock, we first examine cumulative market returns (CR) of the 10 EMs around global index shocks. We define the Index is under shock when it has 5% bottom tail returns during the sample period. Since we have 1150 weekly observations for each market or index, there are 57 index shock weeks. For each EM, we calculate the one-week, three-week, and seven-week CRs around each index shock and then take average across all shocks. As shown in Panel A of Table 3, China has insignificant CR in all windows, while all other EMs have very large and significantly negative CR. For example, the seven-week CR of Indonesia and Turkey are -10.213% and -9.995%, respectively. Even the two markets have relatively low correlations with the global market, they still suffer from large negative returns during global shocks. Therefore, our results from CR suggest that although most EMs are vulnerable to contagion as shown in previous studies, China may be an exception.

4.2.2. *Abnormal Dynamic Conditional Correlations*

Our second method is to conduct an event study test on the DCC of EMs with the Index to examine whether EMs are more correlated with global market during global index shocks. Specifically, in the spirit of Chae (2005) and Schiller (2017), we measure contagion using *abnormal DCC* (ADCC) of EMs with the Index around global shocks. ADCC of market i at time t is defined as

$$\begin{aligned} &ADCC_{i,t} = DCC_{i,t} - \overline{DCC}_{i,t} \\ &where \;\; \overline{DCC}_{i,t} = \tfrac{1}{T-k+1} \textstyle\sum_{j=k}^{T} DCC_j. \end{aligned} \tag{1}$$

Therefore, ADCC of market i in week t is the difference between DCC in week t and the average DCC over an estimation window from 30 to 5 weeks prior to week t. Then for each index shock, we calculate average ADCC over the weeks during the event window. Last we take average across all of the 57 events for each window to measure financial contagion. The results are reported in Panel B of Table 3. Similar to CRs around global index shocks, all markets except China have large and significantly positive ADCC. For example, the ADCC of Russia in the event week is 0.052, which is equivalent to 10% increase of its average DCC. On the contrary, ADCC of China is not significant in the three-week and seven-week windows and even significantly negative in the event week. Therefore, unlike other EMs, China is not more correlated with the global market during global shocks. Our results from ADCC again suggest that China is not vulnerable to financial contagion of global market.

4.2.3. *Coexceedance*

As in Bae et al. (2003), correlations may not be appropriate for an evaluation of the differential impact of large returns. Therefore, in this subsection, we abandon the correlation framework and use *coexceedance* to measure connectedness when markets are volatile. In the spirit of Bae et al. (2003), we define bottom coexceedance as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. The bottom coexceedance for each pair of markets can have a maximum value of 1. If a pair of markets have a large coexceedance, it suggests that they are very likely to have market downturns at the same time so that they are vulnerable to financial contagion.

Panel C of Table 3 reports cross-market bottom coexceedances. The results show similar pattern with the cross-market correlations in Table 2. Each pair of markets have a bottom coexceedance and each market has a coexceedance of 1 with itself. DMs tend to have higher coexceedances than EMs. For example, the coexceedance of US and UK is 0.544, but that of China and Turkey is only 0.07. However, some EMs like South Africa, Brazil, and Mexico have very large coexceedances, with some of them are even greater than those of DMs. For instance, while Hong Kong and Canada only have a coexceedance of 0.368, the coexceedance of South Africa and Canada is 0.579. Therefore, although some EMs have lower correlations than DMs, they may be even more vulnerable to financial contagion. On the contrary, China seems to be least affected by contagion, as evident by the lowest coexceedances among all markets. The highest coexceedance of China is only 0.175, which is still lower than all other markets' coexceedances.

The cross-market bottom coexceedances for the sub-period from 2006 to 2017 are reported in Panel C of Table IA1. Consistent with recent studies, both DMs and EMs are more vulnerable to financial contagion in the last decade, as coexceedances of all markets are larger compared to the full sample period. While the coexceedances of China also increase, they are still the lowest. Therefore, all of our three measures of contagion suggest that China is not or the least vulnerable to global financial contagion and thus it can be a safe haven for international investors when the global market is under shock.

4.3. Diversification Benefits of Emerging Markets

In this subsection, we directly examine diversification benefits of EMs by testing whether adding any of the 10 EMs to the Index can increase Sharpe ratio (SR) of the Index. We first calculate SR for each market or index each year. Then we construct portfolios that contain the Index and each of the 10 EMs and calculate SR of the optimal portfolios. Since many EMs including China have short-selling constraints, we do not allow short-selling when constructing the portfolio. Last we take time-series average of the SR and the results are summarized in Table 4. Column 1 shows that the Index has higher SR than all EMs as the Index includes 23 DMs and is well-diversified. The second column shows that all EMs can provide some diversification, as evident by the higher SR of optimal portfolios than that of the Index. The third column reports the differences between SR of the optimal portfolios and that of the Index and their significance level from t-tests. While the increase in SR is significant for all EMs, China can increase SR the most, which is consistent with the low correlation of China and global market. The next three columns show results for the sub-period from 2006 to 2017. China has the largest increases in SR in the recent decade. Particularly, while most EMs can provide less diversification since the differences are smaller than those in the full sample period, China can increase the SR even more in the recent decade. Therefore, we find novel evidence that China's stock market provides more diversification benefits than other EMs to international investors.

5. Dissecting the Isolation of China's Stock Market

5.1. Foreign Ownership

In this section, we employ firm-level data to investigate explanations for the isolation of China's stock market. First, Bartram et al. (2015) show that common ownership is as important as traditional country and industry factors in explaining international stock returns. However, it is well known that China's stock market is dominated by domestic investors because of capital control. And Chinese investors are also restricted to invest in other markets. As a result, China's market has low common ownership and thus potentially low comovement with other markets. Moreover, "common ownership" is an important channel of financial contagion documented in existing studies (e.g., Elliott et al., 2014). When some investors fire sell assets because of exogenous shocks, other investors' portfolio value will also decrease if they have common holdings. China's market is less likely to be affected by fire sales during global shocks because of the low common ownership. Therefore, it can withstand the "common ownership" channel of contagion.

To investigate the effect of foreign ownership on stock's connectedness with the global market, we exploit the QFII holding data as QFII program has long been used by international investors as the main access to A-share market. We first perform an univariate analysis to test whether stocks with QFII holdings are more connected with the global market. We divide all A-share stocks into two groups every year based on their $QFII$, a dummy variable which is equal to 1 if stock i has QFII holdings in year t and 0 otherwise. Then we calculate the weekly market-weighted USD return of each group as the portfolio return. Last we compare connectedness of the two portfolios with the global market. The results are reported in Panel A of Table 5. Average DCC in the table is the time series average DCC of the portfolio with the Index and bottom coexceedance is the average bottom coexceedance of the portfolio with the other 18 sample markets. We also report diversification benefits of the two portfolios by comparing the largest SR achieved after adding each portfolio to the Index. As expected, stocks with QFII holdings has significantly higher correlation, average DCC, and bottom coexceedance with the global market than the other stocks, suggesting they are more connected with the global market and more vulnerable to financial contagion. Therefore, although QFII held stocks have higher return possibly because of the superior stock-picking skills of large foreign institutional investors, they can provide less diversification benefits than other stocks.

Next, in order to build the causal relation, we estimate the following regression model:

$$Connect_{it} = \beta_0 + \beta_1 \times QFII_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}, \tag{2}$$

where $Connect_{it}$ is the connectedness of stock i with the global market in year t, $QFII_{it}$ is defined as above, and ω and λ are industry and year fixed effect. We control for firm and stock characteristics in the regression. All variables are defined in Appendix A. To control for within-industry correlations among firms, standard errors are clustered by industry in all regressions throughout the paper. We use two variables to measure stock's connectedness with the global market. First, *Connect* is measured using the correlation of stock i with the Index in year t based on weekly USD return (*Correlation*). Second, *Connect* is measured using global beta of stock i in year t (*Global beta*), which is defined as the loading of weekly excess return of stock i on excess return of the Index. Specifically, $Global\ beta_i$ is estimated using the following regression model:

$$Return_{ik} - R_{f,k} = \alpha + Global\ beta_i \times (Return_{gm,k} - R_{f,k}) + \epsilon_{ik}, \tag{3}$$

where $Return_{ik}$ is USD return of stock i in week k, $R_{f,k}$ is USD risk free rate, and $Return_{gm,k}$ is return of the Index. We estimated the model for each stock each year. The results from regression (2) are reported in column (1) and (2) of Table 5. The sample includes all non-financial A-share firms from 2003 to 2017 since the QFII program is launched in late 2002. The dependent variables are *Correlation* and *Global beta* in column (1) and (2), respectively. Coefficients on $QFII$ are significantly positive at 5% level in both columns, suggesting that stocks held by QFII are more connected with the global market. Column (1) shows that QFII held stocks have 0.006 higher *Correlation* than the others. This difference is economically large as the average *Correlation* is only 0.046 as shown in Table 1.

To further address the causal effect, we use the following difference-in-difference (DID) regression model to explore whether stock's connectedness with the global market increases after they have QFII holdings:

$$Connect_{it} = \beta_0 + \beta_1 \times In\ QFII_i + \beta_2 \times In\ QFII_i \times Post + Controls_{it} + \omega + \lambda + \epsilon_{it}, \tag{4}$$

where $In\ QFII_i$ is a dummy variable which is equal to 1 if stock i ever has QFII holdings during the sample period and 0 otherwise, *Post* is a dummy variable which is equal to 1 after stock i first has QFII holdings and 0 otherwise, and the other variables are defined as above. Our main interest variable is the interaction term. The regression results are reported in column (3) and (4) of Table 5. The sample includes all non-financial A-share firms from 1995 to 2017. The dependent variables are *Correlation* and *Global beta* in column (3) and (4), respectively. Consistent with previous results, the coefficients on $In\ QFII_i \times Post$ are significantly positive at 1% level in both columns. Stocks have 0.008 higher *Correlation* with the global market and 0.037 higher *Global beta* after they have QFII holdings. Therefore, we conclude from Table 5 that stocks with foreign ownership are more connected with the global market. However, since only 13.1% of A-share stocks have QFII holding as shown in Table 1 and the holdings are normally small because of capital control, the whole A-share market has very low common ownership with the other markets, which can partly explain its low connectedness with the global market. It has important implication for international investors that investing on A-share stocks with less foreign ownership may provide more diversification benefits.

5.2. Disconnection with Real Economy

As the world's largest exporter and second largest importer, China's economy is sensitive to global market. For example, China's economic growth decreased dramatically during the global financial crisis. Moreover, studies find international trade, or "globalization hypothesis" as summarized in Bekaert et al. (2014), is also a channel of financial contagion. The recent work of Lin and Ye (2017) show that despite the tight capital control, Chinese manufacturing firms are still affected by global shocks through the trade credit channel of foreign direct investments. However, as shown in Allen et al. (2018), China's stock market is disconnected with the real economy because of problematic IPO process, inefficient investment, and poor corporate governance. As a result, even China's economy is highly correlated with the global market, the stock market may fail to incorporate this information.

In this subsection, we investigate whether disconnection between stock market and real economy affects A-share stock's connectedness with the global market. In the spirit of Allen et al. (2018), we use correlation of stock return with GDP growth rate to measure stock's connection with real economy. Specifically, our first measure, *Economy connection*1, is constructed as follows: we first calculate the correlation of quarterly return of stock i with GDP growth rate in year t; then we rank all A-share firms based on the correlations in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). The second measure, *Economy connection*2, is constructed the same as *Economy connection*1 except that we use the average eight-quarter rolling correlation of stock return with GDP growth rate. We first perform an univariate analysis by dividing all stocks into four quantiles every year based on their *Economy connection*1 and comparing connectedness of the top and bottom quantile portfolios with the global market. As shown in Panel A of Table 6, although the differences are not significant, stocks disconnected with the real economy (bottom quantile) generally have lower correlation, average DCC, and bottom coexceedance with the global market.

Next, we estimate regression model (2) and replace $QFII$ with *Economy connection*. The regression results are reported in Panel B of Table 6. The dependent variables are $Correlation$ in column (1) and (3) and *Global beta* in column (2) and (4). The sample includes all non-financial A-share firms from 1995 to 2017. As shown in column (1) and (2), coefficients on *Economy connection*1 are significantly positive at 1% level. Column (1) suggests that $Correlation$ of stocks that are most connected with the real economy is 0.011 higher than that of the least connected, which is equivalent to 23.91% of the average $Correlation$. Column (3) and (4) present results for *Economy connection*2. Although the coefficient in column (3) is not significant, it is still large and significant in column (4). Therefore, consistent with our expectation, stocks that are more connected with the real economy are also more correlated with the global market. Since the correlation of A-share market and the real economy is very low as shown in Allen et al. (2018), China's market potentially has low connectedness with the global market. Note that we also use the raw correlation of stock return with GDP growth rate without ranking to measure firm's connection with the real economy. The results are reported in Panel A of Table IA2 and consistent with the main results.

5.3. *Government Intervention*

As shown in previous studies, government policy in China has a huge impact on market performance. With the aim of stabilizing financial market, Chinese government tends to intervene whenever the market is extremely volatile. For example, during the stock market crash from June 2015 to January 2016, the government took various action to stimulate the market, including cutting reserve requirement ratio and interest rate, suspending IPO, providing unlimited liquidity to security companies, and forbidding state-controlled financial companies to sell shares. Moreover, as part of the reform and open of the financial market, Chinese government frequently perform some regulatory experiments (Carpenter and Whitelaw, 2017). Market often reacts violently to the experiments. For instance, the government tried to revise the restrictions on margin financing during 2014 to 2015. As a result, the amount of margin trade increased dramatically and it triggered the rapid increase of market index. While government intervention may bring more country-specific risk, it makes China less correlated with global market. Furthermore, one of the channels of financial contagion documented in the literature is "wake-up call", which suggests that crisis initially restricted to one market provides new information that may prompt investors to reassess the vulnerability of other markets (e.g., Goldstein, 1998). Since Chinese government is powerful and has more willingness and flexibility to deal with shocks, investors may not reassess upward the vulnerability of China when crisis happens in other markets.

In this subsection, we examine whether government intervention affects A-share stock's connectedness with the global market. Specifically, we test whether stocks that are less sensitive to government policy are more connected with the global market. We use two different variables to measure stock's policy sensitivity. In the spirit of Baker et al. (2016), our first measure, *Policy sensitivity*1, is based on the correlation of stock return with China's

Economic Policy Uncertainty Index (EPUI). We first calculate the correlation of stock i's monthly return with EPUI in year t; then we rank all A-share stocks based on the absolute values of the correlations in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). As the main regulatory body of China's stock market, CSRC has a huge impact on market performance. For example, Chen et al. (2005) find that enforcement actions of CSRC have a negative impact on stock prices with most firms suffering wealth losses of around 1-2% in the 5 days window surrounding the event. Therefore, our second measure, *Policy sensitivity*2, is based on stock's abnormal return around announcements of regulatory documents issued by CSRC. In the spirit of Liu et al. (2017), we first calculate the three-day CAR of stock i around announcements of new regulatory documents issued by CSRC based on the following market model:

$$Return_{ik} - R_{f,k} = \alpha + \beta_i \times (R_{m,k} - R_{f,k}) + \epsilon_{ik}, \tag{5}$$

where $Return_{ik}$ is return of stock i in week k, $R_{f,k}$ is China's risk-free rate, and $R_{m,k}$ is China's market return. We estimate the model for each stock each year. Second, we rank all A-share stocks based on the sum of absolute value of these CAR in year t. Last, we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1).

We first perform an univariate analysis by dividing all A-share stocks into four quantiles every year based on their *Policy sensitivity*1. As shown in Panel A of Table 7, the top quantile portfolio has lower correlation, significantly lower average DCC and bottom coexceedance with the global market than the bottom quantile portfolio, suggesting that policy-sensitive stocks are less connected with the global market and less vulnerable to contagion. As a result, they can provide more diversification benefits. Moreover, the top quantile portfolio also provides higher return and SR to international investors.

We then estimate regression model (2) and replace $QFII$ with *Policy sensitivity*. Panel B of Table 7 reports the results. The sample in column (1) and (2) includes all non-financial

A-share firms from 1995 to 2017. Column (1) suggests that *Correlation* of the most policy-sensitive firms is 0.013 lower than that of the least sensitive firms. The difference is large and equivalent to 28.26% of the average *Correlation*. The coefficient on *Policy sensitivity*1 is -0.057 in column (2) and it is also economically large as the average *Global beta* is only 0.135. The sample in column (3) and (4) includes all non-financial A-share firms from 2001 to 2017 since the first CSRC regulatory document is issued in 2001. Consistent with previous results, coefficients on *Policy sensitivity*2 are significantly negative and are even larger in magnitude. Therefore, Table 7 suggests that stocks less sensitive to policy are more correlated with the global market, because their performance are less affected by government intervention. Since the A-share market is heavily affected by policy, government intervention can partly explain its low connectedness with the global market. It also has important implication for international investors that policy-sensitive A-share stocks may provide more diversification benefits.

Note that we also use the raw correlation of stock return with EPUI and absolute CAR without ranking to measure firm's policy sensitivity. The results are reported in Panel B of Table IA2 and consistent with the main results. Last, we run a unified regression that includes all three factors, $QFII$, *Economy connection*, and *Policy sensitivity* as a robustness test. The results are reported in Table IA3. Both the magnitude and significance level of the coefficients are consistent with previous results. More importantly, the magnitude of coefficients on *Policy sensitivity* are larger than those on $QFII$ and *Economy connection* in all columns except column, suggesting that government intervention may be the dominant reason for the isolation of China's market.

Although policy-sensitive stocks are less correlated with the global market, one concern is that they may have more policy risk, which can decrease realized return. To address this concern, we examine the relation of policy sensitivity and stock performance using the following regression model:

$$Performance_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}, \tag{6}$$

where $Performance_{it}$ is a variable used to measure the performance of stock i in year t. We use ROE, Tobin's q, stock return, and SR to measure stock performance. The regression results are reported in Table 8. Overall, the coefficients on *Policy sensitivity* are significantly positive. Particularly, SR of A-share stocks increases with policy sensitivity, suggesting that while policy-sensitive stocks may have higher risk, they are compensated by even higher return. One potential reason is that some policy-sensitive firms may also have more connections with the government, which is a valuable resource as shown in previous studies (e.g., Claessens, Feijen, and Laeven, 2008; Fisman, 2001). To conclude, policy-sensitive stocks not only provide more diversification benefits to international investors, but also perform better than other stocks.

5.4. Connectedness of Shanghai/Shenzhen-Hong Kong Connected Stocks

As China gradually liberalizes its financial market, one concern is that the low correlation may not persist in the future when A-share market has more international investors. However, beside market openness, disconnection with the real economy and government intervention may be more important reasons for the low connectedness. To further address this issue, we exploit the introduction of Shanghai-Hong Kong Stock Connect Program (SH-HK) and Shenzhen-Hong Kong Stock Connect Program (SZ-HK). Since the connected stocks are more open to international investors, they should have more international investors and higher correlation with the global market. Figure 4 compares connected A-share stocks' DCC with the Index and other stocks' DCC throughout the sample period. Figure (a) and (b) show that connected stocks and the other stocks in SSE have similar trend from 2014 to 2017. Both of their DCC increase from 2014 to 2015 and decrease from 2016 to 2017. Figure (c) and (d) show that connected stocks and the other stocks in SZSE also have the same trend during 2016 to 2017. Therefore, the DCC analysis suggests that the connected stocks are not more correlated with the global market.

Next, we estimate the following DID regression to examine the change of correlation with global market of connected stocks after the introduction of SH-HK and SZ-HK:

$$Connect_{it} = \beta_0 + \beta_1 \times HK\ connected_i + \beta_2 \times HK\ connected_i \times Post + Controls_{it} + \omega + \lambda + \epsilon_{it}, \tag{7}$$

where $HK\ connected_i$ is a dummy variable which is equal to 1 if stock i is in the SH-HK or SZ-HK and 0 otherwise, $Post$ is a dummy variable which is equal to 1 after the start of each program and 0 otherwise, and the other variables are defined as above. The regression results are reported in Table 9. The dependent variables are *Correlation* in column (1), (3), (5), (7), and (9) and *Global beta* in column (2), (4), (6), (8), and (10). In column (1) and (2), the sample includes all A-share stocks in SSE and SZSE from one year before to one year after the start of each program. The coefficients on $HKconnected_i \times Post$ are not significant in both columns, suggesting that connected stocks in SH-HK and SZ-HK are not more correlated with the global market after the introduction of the programs. Therefore, market openness itself may not explain the isolation of China's market.

Next, we perform some sub-sample analysis. We first divide the stocks into high and low real economy connection sub-samples and the results are reported in column (3) to (6). We find that connected stocks in the high real economy connection sub-sample tend to increase in correlation with the global market, but stocks in the low sub-sample tend to decrease in correlation. Then we divide the sample stocks into high and low policy sensitivity sub-samples and the regression results are reported in column (7) to (10). It shows that connected stocks in the low policy sensitivity sub-sample increase in correlation with the global market, while those in high sub-sample are even less correlated with the global market. In general, we find that the change of SH/SZ-HK stocks' connectedness with global market depends on their connection with the real economy and policy sensitivity, suggesting that disconnection with real economy and government intervention may contribute more to the isolation of China's market.

6. Conclusions

Recent studies find that stock markets are increasingly correlated and more vulnerable to financial contagion, which decrease international diversification benefits. However, China may be an exception considering its special features. In this study, we investigate the low connectedness of China with global market and the underlying explanations. We have four important findings. First, using a sample of 9 DMs, 10 EMs and the global market, we find that China has the lowest correlation with other markets. Moreover, the DCC analysis shows that all markets are increasingly correlated during 1995 to 2017 except China. Therefore, China's stocks market can provide more diversification benefits for international investors. Second, using different measures of financial contagion, we show that while all other markets are vulnerable to contagion, China can withstand global shocks. Therefore, China can be a safe haven for international investors during global shocks. Third, using firm-level data, we find that A-share stocks are more connected with global market if they are held by Qualified Foreign Institutional Investors (QFII), more connected with real economy, and less policy-sensitive. Thus, the special features of China's stock market can potentially explain the isolation of China's market: small foreign ownership, disconnection with the real economy, and frequent government intervention. Fourth, further analysis shows that disconnection with real economy and government intervention may be more important than market access in explaining the isolation of China's stock market. Thus, the low connectedness can persist even China is gradually opening its stock market.

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Appendix A. Variable Definitions

Table A1: Variable Definitions

Variable	Definition
ADCC	Abnormal dynamic conditional correlation (DCC), which is defined as the difference of DCC between of a sample market with the MSCI World Index in the global index shock week and the average DCC over an estimation window from 30 to 5 weeks prior to the shock week.
Bottom coexceedance	The ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes.
Correlation	The correlation of weekly USD return of the stock with MSCI World Index.
Global beta	The loading of weekly excess return of the stock on excess return of MSCI World Index (the Index). It is estimated using the regression model: $Return_{ik} - R_{f,k} = \alpha + Global\ beta_i \times (Return_{gm,k} - R_{f,k}) + \epsilon_{ik}$, where $Return_{ik}$ is USD return of stock i in week k, $R_{f,k}$ is USD risk free rate, and $Return_{gm,k}$ is return of the Index.
QFII	A dummy variable which is equal to 1 if the stock has Qualified Foreign Institutional Investor (QFII) holdings and 0 otherwise.
In QFII	A dummy variable which is equal to 1 if the stock ever has Qualified Foreign Institutional Investor (QFII) holdings during the sample period and 0 otherwise.
Economy connection1	The ranking of correlation of the stock's quarterly return with GDP growth rate. We first calculate the correlation of the stock's quarterly return with GDP growth rate; then we rank all A-share firms based on the the correlations in the year; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1).
Economy connection2	The ranking of average eight-quarter rolling correlation of the stock's quarterly return with GDP growth rate. We first calculate the eight-quarter rolling correlation of the stock's quarterly return with GDP growth rate; then we rank all A-share firms based on the average correlations in the year; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1).

Table A1 Continued

Variable	Definition
Policy sensitivity1	The ranking of the absolute value of the correlation of the stock's monthly return with China's Economic Policy Uncertainty Index (EPUI). We first calculate the correlation of the stock's monthly return with EPUI; then we rank all A-share firms based on the absolute value of the correlations in the year; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1).
Policy sensitivity2	The ranking of the absolute cumulative abnormal returns (CAR) over the three-day window around announcements of the new regulatory documents issued by China Securities Regulatory Commission (CSRC). We first calculate the three-day CAR of the stock around announcements of new regulatory documents issued by CSRC using market model; then we rank all A-share firms based on the sum of absolute value of these CAR in the year; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1).
HK connected	A dummy variable which is equal to 1 if the stock is in the Shanghai-Hong Kong or Shenzhen-Hong Kong Stock Connect Program and 0 otherwise.
Firm size	The natural logarithm of total assets.
Volatility	The standard deviation of weekly return of the stock.
ROE	Return on equity is defined as the ratio of net profit to book value of equity.
Leverage	The ratio of total liabilities to total assets.
B/M	The ratio of book value of equity to market value of equity.
Tangibility	The ratio of tangible assets to total assets.
Firm age	The natural logarithm of firm age.
AH cross-listed	A dummy variable which is equal to 1 if the stock is cross-listed in A- and H-share market and 0 otherwise.
SOE	A dummy variable which is equal to 1 if the firm is a state owned enterprise and 0 otherwise.
Tobin's q	The ratio of market value of equity to book value of equity plus book value of debt.

Appendix B. Model Specification and Estimates

We first estimate the following AR(2) model for each market i at time t:

$$R_{i,t} = \mu + \phi_{1i} R_{i,t-1} + \phi_{2i} R_{i,t-2} + \epsilon_{i,t}, \tag{8}$$

where $\epsilon_{i,t}$ is assumed to be uncorrelated with $R_{i,s}$ for $s < t$. Then we fit the GARCH(1,1) model to the AR filtered residual $\epsilon_{i,t}$:

$$\begin{aligned} \epsilon_{i,t} &= \sigma_{i,t} z_{i,t} \\ \sigma^2_{i,t} &= \omega_i + \alpha_i \epsilon^2_{i,t-1} + \beta_i \sigma^2_{i,t-1} \end{aligned} \tag{9}$$

where $\alpha_i > 0$, $\beta_i > 0$ and $\alpha_i + \beta_i < 1$. Because of the inability of normal return to match skewness and kurtosis in residuals, the i.i.d. return residuals $z_{i,t}$ are assumed to follow t-distribution. Because the covariance is given by the product of correlation and standard deviations, we can write

$$\Sigma_t = D_t \Gamma_t D_t, \tag{10}$$

where D_t has the standard deviations $\sigma_{i,t}$ on the diagonal and zeros elsewhere, and Γ_t has ones on the diagonal and conditional correlations off the diagonal. The correlation dynamics are driven by the cross-product of the return shocks $z_{i,t}$ in equation (9):

$$\tilde{\Gamma}_t = (1 - \lambda_1 - \lambda_2)\tilde{\Gamma} + \lambda_1 (z_{t-1} {z'}_{t-1}) + \lambda_2 \tilde{\Gamma}_{t-1}, \tag{11}$$

where λ_1 and λ_2 are set to be non-negative scalar parameters satisfying $\lambda_1 + \lambda_2 < 1$. Lastly, we normalize the conditional correlation between market i and j by

$$\Gamma_{ij,t} = \tilde{\Gamma}_{ij,t} / \sqrt{\tilde{\Gamma}_{ii,t} \tilde{\Gamma}_{jj,t}}, \tag{12}$$

which ensures that all correlations are between -1 and 1. We use $1/T\sum_{t=1}^{T} z_t z'_t$ to estimate $\tilde{\Gamma}$ so that only two correlation parameters, λ_1 and λ_2 need to be estimated simultaneously using numerical optimization. Following Christoffersen et al. (2014), we reply on composite likelihood estimation using

$$CL(\lambda_1, \lambda_2) = \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j>i} \ln f(\lambda_1, \lambda_2; z_{it}, z_{jt}) \tag{13}$$

for each pair of sample markets i and j. $f(\lambda_1, \lambda_2; z_{it}, z_{jt})$ denotes the bivariate normal distribution of return residuals of i and j and covariance targeting is imposed.

Table B.1 reports results from the estimation of the AR(2)-GARCH(1,1) models on sample markets. The results are fairly standard. The volatility updating parameter, α, is around 0.1. And the autoregressive variance parameter, β, is mostly between 0.8 and 0.9. Therefore, consistent with previous literature, we find a high degree of volatility persistence. The p-values of Ljung-Box (LB) test on model residuals show that AR(2) models are able to pick up the potential return predictability of sample markets. Moreover, p-values of LB test on absolute residuals suggest that GARCH models are able to pick up the potential predictability in absolute returns. Therefore, we conclude from Table B.1 that the AR(2)-GARCH(1,1) models are successfully in delivering the white-noise residuals required to obtain unbiased estimates of the dynamic correlations. Table B.2 reports estimation results of the DCC model. Consistent with prior literature (e.g., Christoffersen et al., 2014), the correlation persistence defined as $(\lambda_1 + \lambda_2)$ is very close to 1, implying very slow mean-reversion in correlations. We also report the special case of no dynamics in the last row.

Table B1: AR(2)-GARCH(1,1) Model Parameter Estimates

This table reports parameter estimates and residual diagnostics of the AR(2)-GARCH(1,1) models fitted to weekly returns of the 19 sample markets. The sample period is from Janaury 1995 to December 2017. The coefficients from the AR models are not shown. Data source: CSMAR and DATASTREAM.

Market	α	β	LB(20) P-Value on Residuals	LB(20) P-Value on Absolute Residuals	Residual Mean	Residual Skewness	Residual Excess Kurtosis
China	0.152	0.819	0.657	0.906	0.001	0.954	16.653
US	0.122	0.867	0.421	0.282	-0.001	-0.710	5.818
Japan	0.056	0.938	0.877	0.597	-0.001	0.124	1.751
Hong Kong	0.077	0.915	0.203	0.444	-0.001	-0.235	3.149
UK	0.104	0.864	0.335	0.170	-0.002	-0.938	10.031
Germany	0.092	0.899	0.841	0.477	-0.002	-0.566	4.626
France	0.071	0.916	0.437	0.332	-0.001	-0.637	5.145
Canada	0.117	0.870	0.727	0.073	-0.001	-0.680	6.730
Italy	0.081	0.900	0.417	0.946	-0.001	-0.433	4.797
Australia	0.104	0.861	0.497	0.238	-0.001	-0.960	9.305
South Africa	0.115	0.866	0.596	0.195	-0.001	0.172	5.519
South Korea	0.124	0.860	0.551	0.473	-0.001	-0.211	8.621
India	0.081	0.897	0.975	0.468	-0.001	-0.026	2.500
Indonesia	0.152	0.850	0.225	0.667	-0.002	0.126	12.707
Brazil	0.102	0.864	0.922	0.620	-0.002	-0.107	3.610
Mexico	0.104	0.868	0.771	0.942	-0.001	-0.050	4.799
Russia	0.132	0.856	0.217	0.753	0.000	0.902	10.091
Turkey	0.082	0.892	0.854	0.111	-0.001	0.193	8.499
Argentina	0.103	0.839	0.991	0.203	-0.001	-0.032	4.297
World	0.090	0.904	0.503	0.211	-0.001	-0.906	8.164

Table B2: Dynamic Conditional Correlation Model Parameter Estimates

This table reports parameter estimates of the dynamic conditional correlation models fitted to weekly returns of the 19 sample markets. The sample period is from January 1995 to December 2017. We also report the special case of no dynamics. Data source: CSMAR and DATASTREAM.

Market	λ_1	λ_2	Log Likelihood
China	0.022	0.812	4444.311
US	0.033	0.943	5302.217
Japan	0.026	0.945	4922.675
Hong Kong	0.040	0.908	4926.350
UK	0.038	0.903	5242.330
Germany	0.046	0.883	5014.976
France	0.042	0.896	5065.420
Canada	0.039	0.885	5066.029
Italy	0.036	0.940	4896.195
Australia	0.035	0.932	5007.404
South Africa	0.033	0.948	4712.220
South Korea	0.037	0.943	4529.017
India	0.029	0.943	4651.815
Indonesia	0.024	0.959	4354.062
Brazil	0.030	0.956	4406.130
Mexico	0.035	0.924	4664.868
Russia	0.040	0.932	4162.212
Turkey	0.038	0.937	4064.726
Argentina	0.035	0.892	4265.520
Average	0.035	0.920	4720.972
No Dynamics	0.000	0.000	4361.075

Table 1: Summary Statistics

This table reports summary statistics of annualized weekly USD returns of the 19 sample markets and MSCI World Index (the Index) over the period from January 1995 to December 2017 in Panel A, and summary statistics of firm-level variables used in the study for all non-financial listed A-share firms from 1995 to 2017 in Panel B. All returns and volatilities in Panel A are in %. All variables in Panel B are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Data source: CSMAR and DATASTREAM.

Panel A: market return in USD

Market	N	Mean	S.D.	p25	p50	p75
China	1150	15.132	28.768	-91.237	14.940	119.408
US	1150	9.462	16.908	-54.184	13.836	74.816
Japan	1150	3.335	19.917	-85.794	-0.680	81.823
Hong Kong	1150	6.909	22.637	-85.413	12.974	97.335
UK	1150	4.220	19.094	-63.610	12.139	78.628
Germany	1150	7.966	23.737	-80.398	20.813	98.423
France	1150	7.292	22.099	-76.535	17.557	96.271
Canada	1150	9.752	21.689	-62.058	19.290	91.410
Italy	1150	3.860	24.969	-93.495	9.849	106.726
Australia	1150	7.128	22.277	-73.988	19.090	97.558
South Africa	1150	7.160	28.229	-99.345	13.415	116.836
South Korea	1150	11.947	35.571	-117.330	15.500	135.104
India	1150	8.762	26.504	-106.997	14.340	123.801
Indonesia	1150	8.364	42.442	-118.339	10.125	128.946
Brazil	1150	11.499	37.342	-125.765	21.518	157.558
Mexico	1150	11.646	29.993	-101.271	17.695	130.125
Russia	1150	20.768	49.431	-136.294	19.635	179.611
Turkey	1150	17.994	47.386	-159.495	22.684	190.797
Argentina	1150	15.367	37.890	-132.523	14.460	164.225
The Index	1150	6.785	16.106	-54.038	14.545	66.636

Panel B: firm-level variables

Variable	N	Mean	S.D.	p25	p50	p75
Correlation	37,227	0.046	0.181	-0.076	0.041	0.161
Global beta	37,227	0.135	0.861	-0.234	0.109	0.530
QFII	30,797	0.131	0.337	0	0	0
In QFII	37,967	0.586	0.492	0	1	1
Economy connection1	37,908	0.500	0.288	0.251	0.500	0.749
Economy connection2	34,387	0.500	0.288	0.251	0.499	0.749
Policy sensitivity1	36,817	0.500	0.289	0.250	0.501	0.750
Policy sensitivity2	32,772	0.508	0.158	0.402	0.504	0.609
Firm size	37,316	21.598	1.270	20.709	21.444	22.308
Volatility	37,227	0.068	0.032	0.047	0.060	0.080
Return	34,305	0.241	0.736	-0.240	0.015	0.497
ROE	34,499	0.060	0.169	0.026	0.071	0.122
Leverage	37,316	0.455	0.221	0.289	0.448	0.607
B/M	36,437	0.505	0.245	0.309	0.475	0.680
Tangibility	37,316	0.944	0.076	0.933	0.968	0.988
Firm age	37,314	2.449	0.598	2.197	2.565	2.890
AH cross-listed	37,318	0.025	0.157	0	0	0
SOE	37,318	0.651	0.477	0	1	1

Table 2: Correlations of Sample Markets

This table reports correlations of the 19 sample markets for the period from January 1995 to December 2017 based on weekly USD returns. Panel A reports cross-market unconditional correlations. Panel B reports average dynamic conditional correlations (DCC). We report three average DCC for each market: average DCC with all the other 18 markets; average DCC with 9 developed markets (DMs) (or the other 8 DMs for a DM), average DCC with 10 emerging markets (EMs) (or the other 9 EMs for a EM). Data source: CSMAR and DATASTREAM.

Panel A: cross-market unconditional correlation

	CNH	USA	JPN	HKG	GBR	DEU	FRA	CAN	ITA	AUS	ZAF	KOR	IND	IDN	BRA	MEX	RUS	TUR	ARG
CNH	1																		
USA	0.038	1																	
JPN	0.115	0.362	1																
HKG	0.114	0.474	0.439	1															
GBR	0.073	0.743	0.426	0.539	1														
DEU	0.104	0.736	0.426	0.514	0.817	1													
FRA	0.083	0.737	0.449	0.512	0.846	0.900	1												
CAN	0.076	0.752	0.398	0.498	0.734	0.693	0.730	1											
ITA	0.097	0.641	0.370	0.417	0.742	0.795	0.842	0.628	1										
AUS	0.117	0.610	0.493	0.585	0.736	0.655	0.679	0.708	0.628	1									
ZAF	0.103	0.541	0.373	0.485	0.659	0.638	0.634	0.660	0.524	0.656	1								
KOR	0.106	0.441	0.438	0.507	0.477	0.470	0.449	0.471	0.401	0.536	0.486	1							
IND	0.117	0.395	0.294	0.446	0.451	0.474	0.471	0.450	0.445	0.488	0.485	0.449	1						
IDN	0.078	0.254	0.293	0.436	0.301	0.299	0.302	0.326	0.250	0.376	0.355	0.406	0.309	1					
BRA	0.086	0.556	0.325	0.434	0.601	0.576	0.584	0.613	0.505	0.587	0.602	0.446	0.408	0.327	1				
MEX	0.052	0.658	0.354	0.445	0.619	0.606	0.607	0.612	0.544	0.575	0.601	0.447	0.405	0.308	0.679	1			
RUS	0.066	0.414	0.287	0.380	0.484	0.474	0.454	0.490	0.408	0.425	0.516	0.409	0.321	0.334	0.477	0.455	1		
TUR	0.075	0.343	0.253	0.303	0.407	0.429	0.418	0.368	0.382	0.400	0.468	0.345	0.308	0.183	0.440	0.422	0.379	1	
ARG	0.089	0.437	0.265	0.353	0.478	0.460	0.487	0.456	0.437	0.438	0.420	0.335	0.299	0.266	0.535	0.537	0.355	0.285	1

Table 2 Continued

Panel B: average dynamic conditional correlation (DCC)			
Market	All Markets	DMs	EMs
China	0.097	0.101	0.094
US	0.502	0.621	0.407
Japan	0.378	0.433	0.329
Hong Kong	0.453	0.501	0.410
UK	0.552	0.680	0.449
Germany	0.575	0.675	0.486
France	0.557	0.694	0.447
Canada	0.530	0.623	0.456
Italy	0.524	0.613	0.446
Australia	0.519	0.598	0.456
South Africa	0.502	0.545	0.466
South Korea	0.442	0.480	0.411
India	0.391	0.422	0.366
Indonesia	0.314	0.316	0.313
Brazil	0.515	0.518	0.513
Mexico	0.502	0.555	0.459
Russia	0.408	0.434	0.387
Turkey	0.356	0.368	0.347
Argentina	0.390	0.433	0.360

Table 3: Financial Contagion of Sample Markets

This table reports financial contagion of the 19 sample markets using different measures for the period from January 1995 to December 2017. Panel A reports cumulative market returns (CR) of the 10 emerging markets (EMs) around index shocks of MSCI World Index (the Index) and their significance levels from t-tests. We define the Index is under shock when it has 5% bottom tail returns during the sample period. And we calculate the average CR across all global index shocks for each EM. Panel B reports average abnormal dynamic conditional correlation (ADCC) of the 10 EMs with the Index around 5% shocks of the Index for different windows and their significance levels from t-tests. The average ADCC is calculated as the mean of ADCC over the event window across all global index shocks, where ADCC of week t is the difference between the DCC in week t and the average DCC over an estimation window from 30 to 5 weeks prior to week t. Panel C reports bottom coexceedances of each pair of the 19 sample markets. We define bottom coexceedance as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Panel A: cumulative market return (CR)			
Market	0	[-1,1]	[-3,3]
China	-0.885	-0.547	0.066
South Africa	-6.274***	-4.929***	-5.623***
South Korea	-5.460***	-4.854***	-6.710***
India	-4.562***	-6.255***	-9.172***
Indonesia	-5.875***	-3.960**	-10.213***
Brazil	-7.805***	-6.900***	-7.445***
Mexico	-7.116***	-5.362***	-5.721***
Russia	-7.349***	-6.311***	-5.979**
Turkey	-6.624***	-6.233***	-9.995***
Argentina	-6.937***	-5.556***	-7.540***

Panel B: average abnormal dynamic conditional correlation (ADCC)			
Market	0	[-1,1]	[-3,3]
China	-0.016*	0.006	-0.003
South Africa	0.004	0.015*	0.017*
South Korea	0.034**	0.044***	0.042***
India	0.033**	0.042***	0.040***
Indonesia	0.023**	0.029***	0.028***
Brazil	0.021***	0.027***	0.027***
Mexico	0.012*	0.018***	0.019***
Russia	0.052***	0.064***	0.061***
Turkey	0.033*	0.040**	0.037**
Argentina	0.033**	0.042***	0.042***

Table 3 Continued

Panel C: cross-market bottom coexceedances

	CNH	USA	JPN	HKG	GBR	DEU	FRA	CAN	ITA	AUS	ZAF	KOR	IND	IDN	BRA	MEX	RUS	TUR	ARG
CNH	1																		
USA	0.105	1																	
JPN	0.105	0.193	1																
HKG	0.105	0.316	0.316	1															
GBR	0.140	0.544	0.281	0.316	1														
DEU	0.140	0.526	0.298	0.316	0.632	1													
FRA	0.123	0.491	0.298	0.316	0.614	0.667	1												
CAN	0.175	0.579	0.281	0.368	0.596	0.491	0.526	1											
ITA	0.088	0.368	0.281	0.263	0.439	0.544	0.649	0.404	1										
AUS	0.105	0.421	0.386	0.386	0.544	0.491	0.526	0.561	0.421	1									
ZAF	0.140	0.421	0.386	0.368	0.526	0.456	0.456	0.579	0.404	0.526	1								
KOR	0.140	0.193	0.263	0.404	0.281	0.281	0.281	0.351	0.246	0.298	0.368	1							
IND	0.105	0.316	0.246	0.386	0.333	0.351	0.351	0.404	0.246	0.421	0.368	0.316	1						
IDN	0.123	0.246	0.193	0.404	0.228	0.228	0.228	0.333	0.193	0.298	0.316	0.404	0.333	1					
BRA	0.070	0.333	0.246	0.316	0.404	0.404	0.351	0.439	0.316	0.404	0.509	0.368	0.281	0.316	1				
MEX	0.140	0.421	0.263	0.368	0.491	0.474	0.439	0.491	0.421	0.404	0.474	0.281	0.298	0.246	0.509	1			
RUS	0.175	0.263	0.211	0.246	0.298	0.316	0.333	0.421	0.281	0.281	0.439	0.368	0.333	0.386	0.351	0.333	1		
TUR	0.070	0.246	0.246	0.193	0.298	0.333	0.298	0.316	0.228	0.333	0.439	0.263	0.298	0.228	0.333	0.333	0.298	1	
ARG	0.140	0.211	0.193	0.228	0.281	0.281	0.281	0.316	0.263	0.263	0.316	0.263	0.211	0.246	0.404	0.351	0.298	0.246	1

Table 4: Diversification Benefits: Sharpe Ratio

This table reports average annual Sharpe Ratios (SR) of the 10 emerging markets (EMs) and MSCI World Index (the Index) based on weekly return over January 1995 to December 2017 and January 2005 to December 2017, and the average annual SR of the optimal portfolio that contains the Index and each of the 10 EMs. It also reports the difference between SR of each optimal portfolio and SR of the Index and their significance levels from t-tests. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

	1995-2017			2006-2017		
Market	Market SR	Portfolio SR	Difference	Market SR	Portfolio SR	Difference
China	0.304	0.468	0.111***	0.339	0.489	0.114***
South Africa	0.311	0.417	0.059***	0.302	0.411	0.036***
South Korea	0.305	0.402	0.045***	0.337	0.412	0.037***
India	0.340	0.458	0.100***	0.354	0.450	0.076***
Indonesia	0.286	0.432	0.074***	0.321	0.455	0.080***
Brazil	0.285	0.406	0.049***	0.273	0.399	0.024**
Mexico	0.350	0.427	0.069***	0.334	0.423	0.049***
Russia	0.302	0.418	0.061***	0.312	0.417	0.042***
Turkey	0.267	0.411	0.054***	0.303	0.429	0.055***
Argentina	0.257	0.401	0.044***	0.271	0.414	0.039***
The Index	0.357			0.375		

Table 5: Foreign Ownership and Isolation of A-share Market

This table reports the effect of foreign ownership on A-share stock's connectedness with the global market. Panel A reports the univariate test results. We divide all A-share stocks into two groups every year based on their $QFII$, a dummy variable which is equal to 1 if stock i has qualified foreign institutional investor (QFII) holdings in year t and 0 otherwise. Then we calculate the weekly market-weighted USD return of each group as the portfolio return (%). We compare the two portfolios in Panel A. Correlation is the unconditional correlation of the portfolio with the MSCI World Index (the Index) based on weekly return. Average dynamic conditional correlation (DCC) is the average DCC of the portfolio with the Index based on weekly return. Bottom coexceedances is the average bottom coexceedance of the portfolio with the other 18 sample markets. Bottom coexceedance is defined as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. Diversification benefits is the maximum Sharpe ratio (SR) achieved when adding each portfolio to the Index. We also report significance levels of the differences between the two portfolios from t-tests. Panel B reports regression results. The first two columns report results using the following regression model: $Connect_{it} = \beta_0 + \beta_1 \times QFII_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connect_{it}$ is the connectedness of stock i with the global market in year t, $QFII_i$ is defined as above, and ω and λ are industry and year fixed effect. The sample includes all non-financial A-share firms from 2003 to 2017. The last two columns report results using the following difference-in-difference regression model: $Connect_{it} = \beta_0 + \beta_1 \times In\ QFII + \beta_2 \times In\ QFII \times Post + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $In\ QFII$ is a dummy variable which is equal to 1 if stock i ever has QFII holdings during the sample period and 0 otherwise, and $Post$ is a dummy variable which is equal to 1 after stock i first has QFII holdings and 0 otherwise. The sample includes all non-financial A-share firms from 1995 to 2017. In column (1) and (3), *Connect* is measured using the correlation of stock i with the Index in year t based on weekly USD return (*Correlation*). In column (2) and (4), *Connect* is measured using global beta of stock i in year t (*Global beta*), which is defined as the loading of weekly excess return of stock i on excess return of the Index: $Return_{ik} - R_{f,k} = \alpha + Global\ beta_i \times (Return_{gm,k} - R_{f,k}) + \epsilon_{ik}$, where $Return_{ik}$ is USD return of stock i in week k, $R_{f,k}$ is USD risk free rate, and $Return_{gm,k}$ is return of the Index. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are clustered by industry and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Panel A: univariate analysis

	Portfolio Return	Portfolio SR	Correlation
QFII	0.507	0.343	0.076
No QFII	0.442	0.353	0.061
Difference	0.065*	-0.011	0.016*

	Average DCC	Bottom Coexceedance	Diversification Benefits
QFII	0.100	0.085	0.517
No QFII	0.065	0.059	0.525
Difference	0.034***	0.025***	-0.009

Table 5 Continued

Panel B: regression results	(1)	(2)	(3)	(4)
QFII	0.006**	0.023**		
	(0.002)	(0.008)		
In QFII			0.000	0.002
			(0.002)	(0.009)
In QFII × *Post*			0.008***	0.037***
			(0.002)	(0.008)
Firm size	0.006***	0.017**	0.005***	0.009
	(0.001)	(0.006)	(0.001)	(0.006)
Volatility	-0.252***	1.264***	-0.196**	0.943**
	(0.078)	(0.434)	(0.074)	(0.431)
ROE	-0.003	0.023	-0.007	0.010
	(0.006)	(0.029)	(0.006)	(0.026)
Leverage	-0.006	-0.037	-0.002	-0.012
	(0.007)	(0.025)	(0.005)	(0.020)
B/M	0.008	0.037	0.009	0.028
	(0.008)	(0.040)	(0.008)	(0.041)
Tangibility	0.026***	0.035	0.030***	0.048
	(0.007)	(0.032)	(0.007)	(0.031)
Firm age	-0.002	-0.010	-0.001	-0.011
	(0.002)	(0.013)	(0.002)	(0.010)
AH cross-listed	0.019***	0.015	0.017***	0.013
	(0.005)	(0.013)	(0.005)	(0.011)
SOE	0.001	0.003	0.001	0.000
	(0.001)	(0.004)	(0.001)	(0.004)
Constant	-0.177***	-0.496***	-0.281***	-1.555***
	(0.020)	(0.105)	(0.016)	(0.088)
N	27,922	27,922	33,621	33,621
Adj. R^2	0.461	0.382	0.454	0.412

Table 6: Disconnection with the Real Economy and Isolation of A-share Market

This table reports the effect of disconnection with the real economy on A-share stock's connectedness with the global market. Panel A reports the univariate test results. We divide all A-share stocks into four quantiles every year based on their *Economy connection*1, which is constructed as follows: we first calculate the correlation of stock i's quarterly return with GDP growth rate in year t; then we rank all A-share firms based on the correlations in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). Then we calculate the weekly market-weighted USD return of each quantile as the portfolio return (%). We compare the top and bottom quantile portfolios in Panel A. Correlation in the table is the unconditional correlation of the portfolio with the MSCI World Index (the Index) based on weekly return. Average dynamic conditional correlation (DCC) is the average DCC of the portfolio with the Index based on weekly return. Bottom coexceedances is the average bottom coexceedance of the portfolio with the other 18 sample markets. Bottom coexceedance is defined as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. Diversification benefits is the maximum Sharpe ratio (SR) of achieved when adding each quantile portfolio to the Index. We also report significance levels of the differences between the two portfolios from t-tests. Panel B reports regression results using the following model: $Connect_{it} = \beta_0 + \beta_1 \times Economy\ connection_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connect_{it}$ is the connectedness of stock i with the global market in year t, $Economy\ connection_{it}$ is a variable constructed to measure connection of stock i with the real economy in year t, and ω and λ are industry and year fixed effect. In column (1) and (2), *Economy connection*1 is constructed as above. In column (3) and (4), *Economy connection*2 is constructed the same as *Economy connection*1 except that we use the average eight-quarter rolling correlation of stock return with GDP growth rate. In column (1) and (3), *Connect* is measured using the correlation of stock i with the Index in year t based on weekly USD return (*Correlation*). In column (2) and (4), *Connect* is measured using global beta of stock i in year t (*Global beta*), which is defined as the loading of weekly excess return of stock i on excess return of the Index: $Return_{ik} - R_{f,k} = \alpha + Global\ beta_i \times (Return_{gm,k} - R_{f,k}) + \epsilon_{ik}$, where $Return_{ik}$ is USD return of stock i in week k, $R_{f,k}$ is USD risk free rate, and $Return_{gm,k}$ is return of the Index. The sample includes all non-financial A-share firms from 1995 to 2017. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are clustered by industry and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Panel A: univariate analysis

	Portfolio Return	Portfolio SR	Correlation
Top quantile	0.392	0.327	0.042
Bottom quantile	0.475	0.306	0.033
Difference	-0.082	0.021	0.009

	Average DCC	Bottom Coexceedance	Diversification Benefits
Top quantile	0.051	0.093	0.490
Bottom quantile	0.048	0.088	0.482
Difference	0.003	0.005	0.008

Table 6 Continued

Panel B: regression results	(1)	(2)	(3)	(4)
*Economy connection*1	0.012***	0.042***		
	(0.003)	(0.010)		
*Economy connection*2			-0.001	0.028***
			(0.002)	(0.009)
Firm size	0.006***	0.015**	0.006***	0.014*
	(0.001)	(0.006)	(0.001)	(0.007)
Volatility	-0.211**	0.880*	-0.258***	0.707
	(0.077)	(0.442)	(0.080)	(0.521)
ROE	-0.007	0.011	-0.008	0.004
	(0.006)	(0.026)	(0.006)	(0.026)
Leverage	-0.002	-0.016	-0.004	-0.021
	(0.005)	(0.021)	(0.005)	(0.019)
B/M	0.006	0.016	0.007	0.021
	(0.008)	(0.041)	(0.008)	(0.044)
Tangibility	0.031***	0.053	0.031***	0.051
	(0.007)	(0.031)	(0.006)	(0.030)
Firm age	-0.000	-0.008	0.001	-0.004
	(0.002)	(0.010)	(0.002)	(0.010)
AH cross-listed	0.016***	0.012	0.016***	0.010
	(0.005)	(0.011)	(0.005)	(0.011)
SOE	0.002	0.005	0.002	0.005
	(0.001)	(0.004)	(0.001)	(0.005)
Constant	-0.311***	-1.680***	-0.298***	-1.647***
	(0.015)	(0.080)	(0.014)	(0.083)
N	33,621	33,621	33,205	33,205
Adj. R^2	0.454	0.412	0.456	0.417

Table 7: Government Intervention and Isolation of A-share Market

This table reports the effect of government intervention on A-share stock's connectedness with the global market. Panel A reports the univariate test results. We divide all A-share stocks into four quantiles every year based on their *Policy sensitivity*1, which is constructed as follows: we first calculate the correlation of stock i's monthly return with the Economic Policy Uncertainty Index in year t; then we rank all A-share firms based on the absolute values of the correlations in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). Then we calculate the weekly market-weighted USD return of each quantile as the portfolio return (%). We compare the top and bottom quantile portfolios in Panel A. Correlation is the unconditional correlation of the portfolio with the MSCI World Index (the Index) based on weekly return. Average dynamic conditional correlation (DCC) is the average DCC of the portfolio with the Index based on weekly return. Bottom coexceedances is the average bottom coexceedance of the portfolio with the other 18 sample markets. Bottom coexceedance is defined as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. Diversification benefits is the maximum Sharpe ratio (SR) achieved when adding each quantile portfolio to the Index each year. We also report significance levels of the differences between the two portfolios from t-tests. Panel B reports regression results using the following model: $Connect_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connect_{it}$ is the connectedness of stock i with the global market in year t, $Policy\ sensitivity_{it}$ is a variable constructed to measure sensitivity of stock i to government intervention in year t, and ω and λ are industry and year fixed effect. In column (1) and (2), *Policy sensitivity*1 is constructed as above. The sample includes all non-financial A-share firms from 1995 to 2017. In column (3) and (4), *Policy sensitivity*2 is constructed as follows: we first calculate the three-day cumulative abnormal return (CAR) of stock i around announcements of new regulatory documents issued by China Securities Regulatory Commission based on market model in year t; then we rank all A-share firms based on the sum of absolute value of these CARs in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). The sample includes all non-financial A-share firms from 2001 to 2017. In column (1) and (3), *Connect* is measured using the correlation of stock i with the Index in year t based on weekly USD return (*Correlation*). In column (2) and (4), *Connect* is measured using global beta of stock i in year t (*Global beta*), which is defined as the loading of weekly excess return of stock i on excess return of the Index: $Return_{ik} - R_{f,k} = \alpha + Global\ beta_i \times (Return_{gm,k} - R_{f,k}) + \epsilon_{ik}$, where $Return_{ik}$ is USD return of stock i in week k, $R_{f,k}$ is USD risk free rate, and $Return_{gm,k}$ is return of the Index. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are clustered by industry and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Panel A: univariate analysis			
	Portfolio Return	Portfolio SR	Correlation
Top quantile	0.486	0.333	0.023
Bottom quantile	0.391	0.319	0.047
Difference	0.095	0.014	-0.024
	Average DCC	Bottom Coexceedance	Diversification Benefits
Top quantile	0.035	0.080	0.495
Bottom quantile	0.056	0.103	0.489
Difference	-0.021***	-0.023***	0.005

Table 7 Continued

Panel B: regression results	(1)	(2)	(3)	(4)
*Policy sensitivity*1	-0.013***	-0.057***		
	(0.003)	(0.012)		
*Policy sensitivity*2			-0.018**	-0.087***
			(0.008)	(0.027)
Firm size	0.006***	0.014**	0.007***	0.018***
	(0.001)	(0.006)	(0.001)	(0.006)
Volatility	-0.193**	0.986**	-0.168*	1.656***
	(0.076)	(0.411)	(0.081)	(0.398)
ROE	-0.006	0.015	-0.004	0.020
	(0.006)	(0.024)	(0.006)	(0.029)
Leverage	-0.002	-0.014	-0.006	-0.032
	(0.005)	(0.021)	(0.007)	(0.026)
B/M	0.008	0.023	0.006	0.026
	(0.008)	(0.040)	(0.008)	(0.038)
Tangibility	0.032***	0.054	0.025***	0.035
	(0.007)	(0.032)	(0.007)	(0.033)
Firm age	0.000	-0.007	-0.001	-0.007
	(0.002)	(0.010)	(0.002)	(0.011)
AH cross-listed	0.016***	0.011	0.019***	0.017
	(0.005)	(0.011)	(0.005)	(0.014)
SOE	0.002	0.006	0.001	0.005
	(0.001)	(0.004)	(0.001)	(0.004)
Constant	-0.301***	-1.643***	-0.083***	-0.328***
	(0.013)	(0.082)	(0.019)	(0.107)
N	33,615	33,615	30,051	30,051
Adj. R^2	0.454	0.413	0.450	0.383

Table 8: Policy Sensitivity and A-share Stock Performance

This table reports the relation of policy sensitivity and A-share stock's performance using the following regression: $Performance_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Performance_{it}$ is a variable used to measure performance of stock i in year t, $Policy\ sensitivity_{it}$ is a variable constructed to measure sensitivity of stock i to government intervention in year t, and ω and λ are industry and year fixed effect. We use ROE in column (1) and (2), Tobin's q in column (3) and (4), stock return in column (5) and (6), and Sharpe ratio (SR) in column (7) and (8) to measure $Performance$. In column (1), (3), (5), and (7), *Policy sensitivity*1 is constructed as follows: we first calculate the correlation of stock i's monthly return with the Economic Policy Uncertainty Index in year t; then we rank all A-share firms based on the absolute values of the correlations in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). The sample includes all non-financial A-share firms from 1995 to 2017. In column (2), (4), (6), and (8), *Policy sensitivity*2 is constructed as follows: we first calculate the three-day cumulative abnormal return (CAR) of stock i around announcements of new regulatory documents issued by China Securities Regulatory Commission based on market model in year t; then we rank all A-share firms based on the sum of absolute value of these CARs in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). The sample includes all non-financial A-share firms from 2001 to 2017. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are clustered by industry and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Table 8 Continued

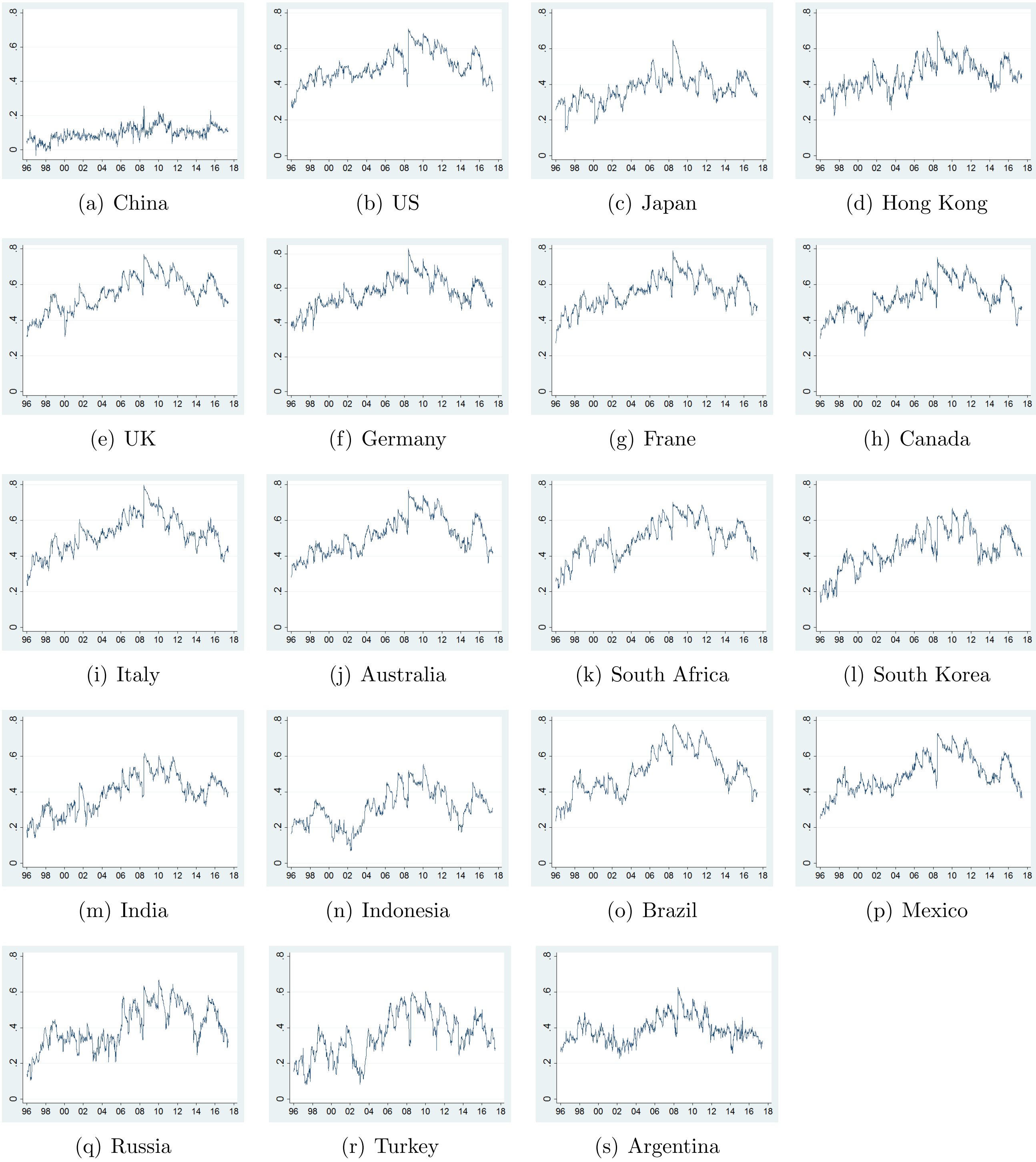
	ROE		Tobin's q		Return		SR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy sensitivity1	0.017***		-0.072		0.052***		0.014***	
	(0.004)		(0.043)		(0.018)		(0.004)	
Policy sensitivity2		-0.001		0.664***		0.097***		0.041***
		(0.007)		(0.072)		(0.025)		(0.006)
Firm size	0.057***	0.056***	-0.821***	-0.810***	0.107***	0.108***	0.026***	0.027***
	(0.004)	(0.004)	(0.033)	(0.035)	(0.006)	(0.007)	(0.001)	(0.001)
Volatility	-0.310***	-0.261**	12.612***	10.255***	8.902***	8.448***	1.224***	1.086***
	(0.104)	(0.096)	(0.915)	(0.858)	(0.358)	(0.383)	(0.063)	(0.077)
ROE			1.473***	1.448***	0.340***	0.307***	0.085***	0.081***
			(0.128)	(0.131)	(0.014)	(0.014)	(0.004)	(0.005)
Leverage	-0.172***	-0.169***	0.117	0.155*	0.030*	0.015	0.008	0.002
	(0.016)	(0.016)	(0.068)	(0.082)	(0.016)	(0.015)	(0.006)	(0.006)
B/M	-0.208***	-0.202***			-0.746***	-0.708***	-0.201***	-0.196***
	(0.018)	(0.020)			(0.044)	(0.044)	(0.008)	(0.007)
Tangibility	0.065*	0.066*	-0.236	-0.120	0.022	0.031	0.031**	0.033**
	(0.034)	(0.033)	(0.352)	(0.340)	(0.043)	(0.044)	(0.015)	(0.015)
Firm age	-0.003	-0.002	0.054	0.093	0.019***	0.010*	0.005***	0.004***
	(0.002)	(0.003)	(0.074)	(0.078)	(0.004)	(0.006)	(0.001)	(0.001)
AH cross-listed	-0.069***	-0.062***	1.022***	1.054***	-0.092***	-0.086***	-0.022***	-0.022***
	(0.005)	(0.006)	(0.120)	(0.110)	(0.011)	(0.009)	(0.002)	(0.002)
SOE	-0.017***	-0.018***	-0.082	-0.091	-0.002	-0.005	0.003	0.002
	(0.005)	(0.005)	(0.059)	(0.056)	(0.010)	(0.009)	(0.003)	(0.003)
Constant	-0.901***	-1.056***	17.162***	18.967***	-2.670***	-2.710***	-0.568***	-0.724***
	(0.077)	(0.089)	(0.742)	(0.811)	(0.100)	(0.149)	(0.023)	(0.031)
N	33,615	30,051	33,615	30,051	33,068	29,511	33,615	30,051
Adj. R^2	0.139	0.139	0.447	0.446	0.688	0.703	0.660	0.668

Table 9: Shanghai/Shenzhen-Hong Kong Connected Stocks

This table reports change of connectedness with the global market of A-share stocks in the Shanghai-Hong Kong Connect Program (SH-HK) and Shenzhen-Hong Hong Stock Connect Program (SZ-HK) using the following difference-in-difference regression model: $Connect_{it} = \beta_0 + \beta_1 \times HK\ connected_i + \beta_2 \times HK\ connected_i \times Post + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connect_{it}$ is the connectedness of stock i with the global market in year t, $HK\ connected_i$ is a dummy variable which is equal to 1 if stock i is in the Programs and 0 otherwise, $Post$ is a dummy variable which is equal to 1 after the start of each Program and 0 otherwise, and ω and λ are industry and year fixed effect. In column (1) and (2), the sample includes all non-financial A-share firms from one year before to one year after the start of each program. In column (3) and (4), the sample includes firms in the top half of *Economy connection*1, which is constructed as follows: we first calculate the correlation of stock i's quarterly return with GDP growth rate in year t; then we rank all A-share firms based on the correlations in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). In column (5) and (6), the sample includes firms in the bottom half of *Economy connection*1. In column (7) and (8), the sample includes firms in the top half of *Policy sensitivity*1, which is constructed as follows: we first calculate the correlation of stock i's monthly return with the Economic Policy Uncertainty Index in year t; then we rank all A-share firms based on the absolute values of the correlations in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). In column (9) and (10), the sample includes firms in the bottom half of *Policy sensitivity*1. In column (1), (3), (5), (7), and (9), *Connect* is measured using the correlation of stock i with MSCI World Index (the Index) in year t based on weekly USD return (*Correlation*). In column (2), (4), (6), (8), and (10), *Connect* is measured using global beta of stock i in year t (*Global beta*), which is defined as the loading of weekly excess return of stock i on excess return of the Index: $Return_{ik} - R_{f,k} = \alpha + Global\ beta_i \times (Return_{gm,k} - R_{f,k}) + \epsilon_{ik}$, where $Return_{ik}$ is USD return of stock i in week k, $R_{f,k}$ is USD risk free rate, and $Return_{gm,k}$ is return of the Index. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are clustered by industry and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Table 9 Continued

	Full Sample		High GDP Connection		Low GDP Connection		High Policy Sensitivity		Low Policy Sensitivity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HK connected	-0.005	-0.043	-0.014**	-0.062***	0.002	-0.021	0.014**	0.077**	-0.023***	-0.133***
	(0.005)	(0.031)	(0.007)	(0.021)	(0.007)	(0.050)	(0.006)	(0.032)	(0.007)	(0.041)
HK connected $\times$ *Post*	-0.009	0.047	0.006	0.181**	-0.021**	-0.045	-0.030***	-0.020	0.015	0.163**
	(0.006)	(0.052)	(0.009)	(0.068)	(0.007)	(0.053)	(0.006)	(0.063)	(0.010)	(0.058)
Firm size	0.003	0.002	-0.002	-0.025	0.013***	0.052**	0.001	-0.010	0.003	0.001
	(0.002)	(0.021)	(0.003)	(0.024)	(0.003)	(0.021)	(0.003)	(0.022)	(0.004)	(0.020)
Volatility	-0.366***	1.053	0.129*	5.559**	-0.841***	-3.272**	-0.539***	1.893	-0.104	1.607**
	(0.080)	(0.777)	(0.064)	(2.352)	(0.147)	(1.125)	(0.089)	(1.723)	(0.115)	(0.637)
ROE	-0.017	-0.040	0.010	0.034	-0.050	-0.320	-0.041**	-0.340***	0.002	0.096
	(0.019)	(0.143)	(0.014)	(0.094)	(0.045)	(0.271)	(0.015)	(0.107)	(0.035)	(0.248)
Leverage	0.012	0.118	0.030	0.323**	-0.005	-0.053	0.051***	0.302***	-0.022	-0.010
	(0.014)	(0.097)	(0.028)	(0.148)	(0.013)	(0.090)	(0.012)	(0.084)	(0.026)	(0.159)
B/M	0.031***	0.172**	0.060***	0.207	-0.015	0.054	0.024**	0.081	0.047***	0.309***
	(0.009)	(0.079)	(0.014)	(0.119)	(0.015)	(0.099)	(0.009)	(0.079)	(0.014)	(0.093)
Tangibility	0.077***	0.184	0.054**	0.082	0.095**	0.291	0.074	0.169	0.071**	0.156
	(0.025)	(0.127)	(0.024)	(0.146)	(0.043)	(0.260)	(0.053)	(0.267)	(0.033)	(0.167)
Firm age	0.010	0.061	0.008	0.019	0.009	0.086	0.008	0.075	0.011	0.048
	(0.008)	(0.057)	(0.006)	(0.048)	(0.014)	(0.077)	(0.009)	(0.079)	(0.007)	(0.049)
AH cross-listed	0.004	0.010	-0.002	0.011	0.009	0.018	-0.003	-0.010	0.014***	0.060***
	(0.005)	(0.030)	(0.006)	(0.024)	(0.006)	(0.041)	(0.008)	(0.057)	(0.004)	(0.021)
SOE	-0.012	-0.110	-0.013	-0.121	-0.008	-0.056	-0.017	-0.166	-0.008	-0.056
	(0.015)	(0.064)	(0.020)	(0.094)	(0.021)	(0.071)	(0.025)	(0.103)	(0.011)	(0.049)
Constant	-0.210***	-0.763	-0.123*	-0.300	-0.421***	-1.732***	-0.164**	-0.609	-0.216**	-0.782
	(0.056)	(0.474)	(0.067)	(0.578)	(0.071)	(0.435)	(0.070)	(0.487)	(0.100)	(0.541)
N	4,473	4,473	2,298	2,298	2,175	2,175	2,141	2,141	2,332	2,332
Adj. R^2	0.541	0.396	0.562	0.369	0.533	0.432	0.480	0.288	0.607	0.519



(a) China (b) US (c) Japan (d) Hong Kong

(e) UK (f) Germany (g) Frane (h) Canada

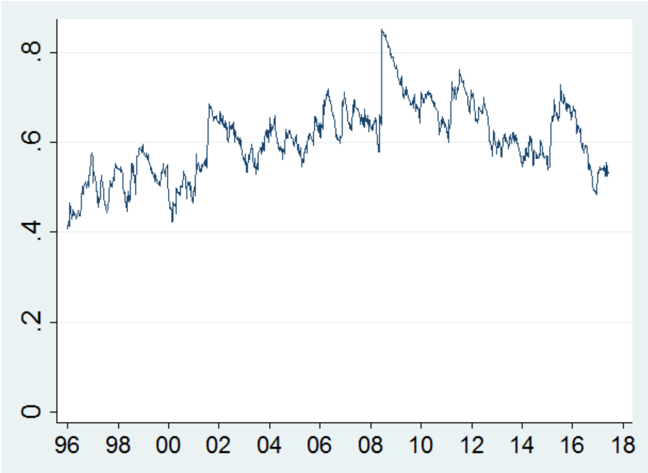
(i) Italy (j) Australia (k) South Africa (l) South Korea

(m) India (n) Indonesia (o) Brazil (p) Mexico

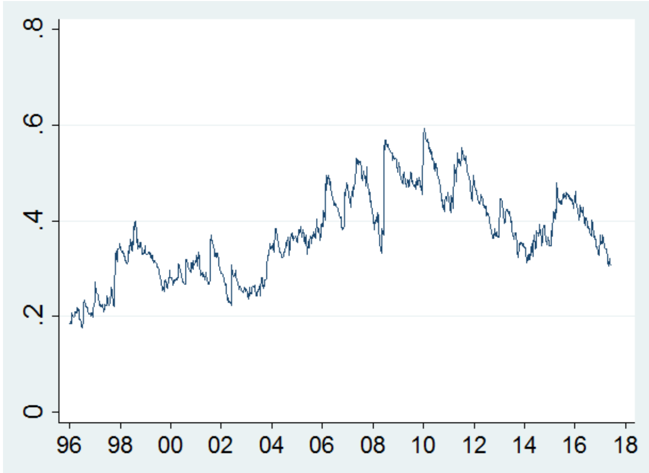
(q) Russia (r) Turkey (s) Argentina

Fig. 1. Average Dynamic Conditional Correlations of Sample Markets

This figure plots average dynamic conditional correlations of each sample market with the other 18 markets based on weekly returns from January 1996 to December 2017. Data source: CSMAR and DATASTREAM.



(a) DM-DM

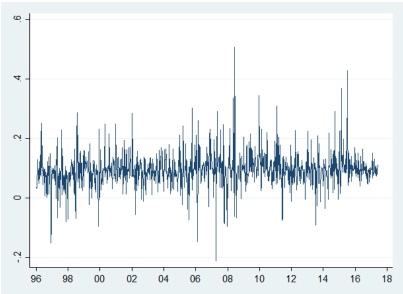


(b) EM-EM

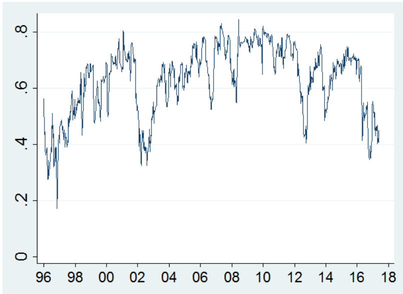
(c) DM-EM

Fig. 2. Average Dynamic Conditional Correlations of Developed Markets and Emerging Markets

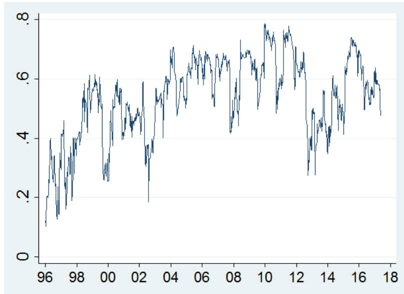
This figure plots average dynamic conditional correlations (DCC) of developed markets (DMs) and emerging markets (EMs) based on weekly returns from January 1996 to December 2017. For the average DCC of DMs with other DMs (DM-DM), we report the average of the DCC of all pairs of DMs; for the average DCC of EMs with other EMs (EM-EM), we report the average of the DCC of all pairs of EMs; for the average DCC of DMs with EMs (DM-EM), we report the average of the DCC of all pairs of DMs and EMs. Data source: CSMAR and DATASTREAM.



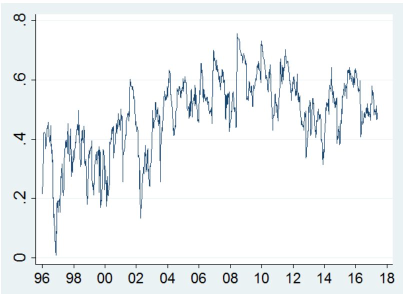
(a) China



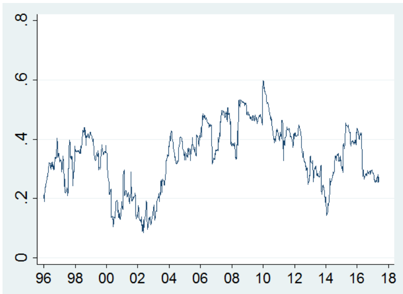
(b) South Africa



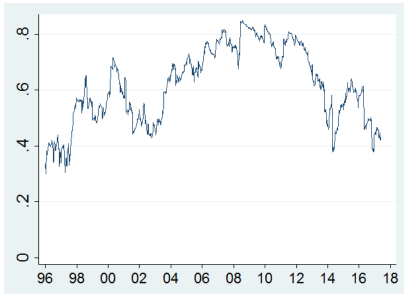
(c) South Korea



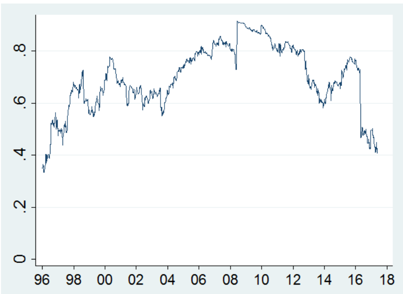
(d) India



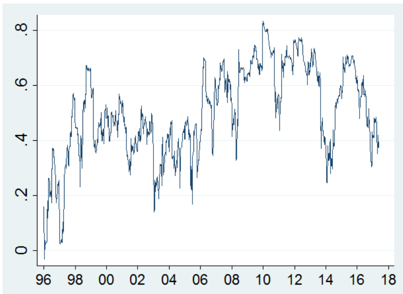
(e) Indonesia



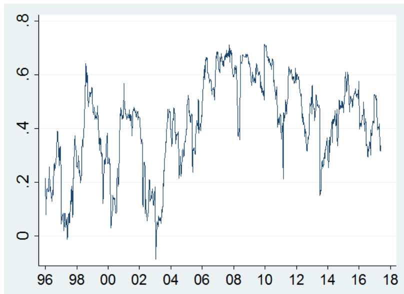
(f) Brazil



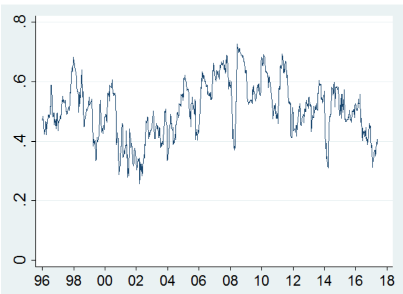
(g) Mexico



(h) Russia



(i) Turkey

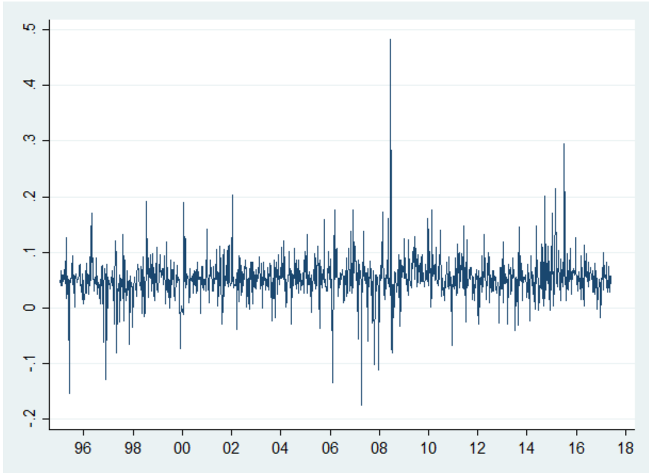


(j) Argentina

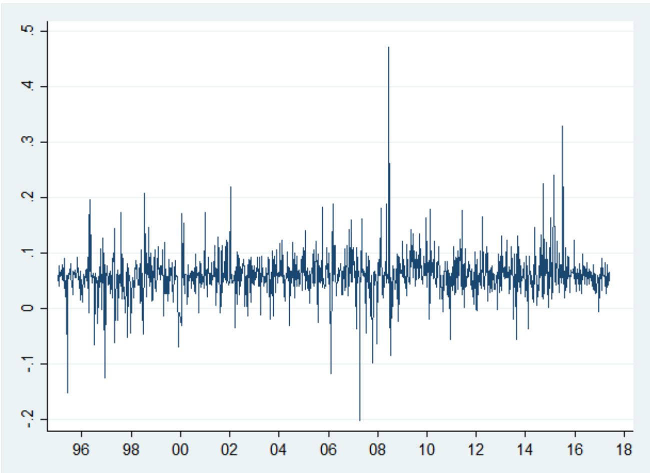
Fig. 3. Dynamic Conditional Correlations of Emerging Markets with Global Market

This figure plots dynamic conditional correlations of the 10 emerging markets with MSCI World Index based on weekly returns from January 1996 to December 2017. Data source: CSMAR and DATASTREAM.

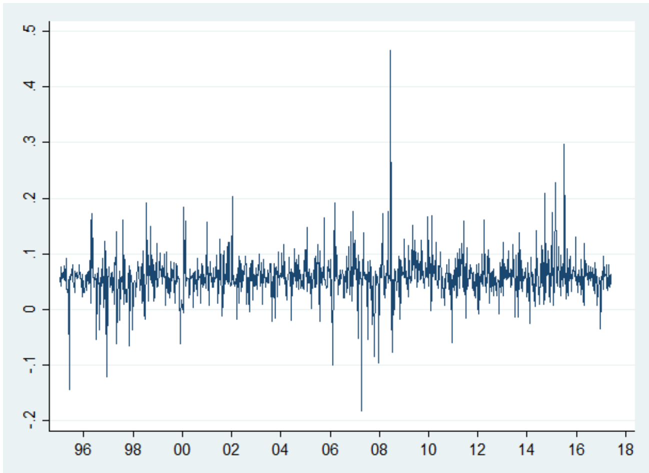
(a) Connected Stocks in SSE



(b) Other Stocks in SSE



(c) Connected Stocks in SZSE



(d) Other Stocks in SZSE

Fig. 4. Dynamic Conditional Correlations of Connected Stocks with Global Market

This figure compares dynamic conditional correlations (DCC) of A-share stocks in the Shanghai-Hong Kong Stock Connect Program and Shenzhen-Hong Kong Stock Connect Program with MSCI World Index (the Index) and DCC of A-share stocks not in the programs based on weekly return. Data source: CSMAR and DATASTREAM.

Internet Appendix

The Diversification Benefits and Policy Risks of Accessing China's Stock Market

October 31, 2018

Table IA1: Correlations and Financial Contagion of Sample Markets from 2006 to 2017

This table reports correlations and bottom coexceedances of the 19 sample markets for the period from January 2006 to December 2017 based on weekly USD returns. Panel A reports cross-market unconditional correlations. Panel B reports average dynamic conditional correlations (DCC). We report three average DCC for each market: average DCC with all the other 18 markets; average DCC with 9 developed markets (DMs) (or the other 8 DMs for a DM), average DCC with 10 emerging markets (EMs) (or the other 9 EMs for a EM). Panel C reports bottom coexceedances of each pair of the 19 sample markets. We define bottom coexceedance as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. Data source: CSMAR and DATASTREAM.

Panel A: cross-market unconditional correlation

	CNH	USA	JPN	HKG	GBR	DEU	FRA	CAN	ITA	AUS	ZAF	KOR	IND	IDN	BRA	MEX	RUS	TUR	ARG
CNH	1																		
USA	0.120	1																	
JPN	0.206	0.522	1																
HKG	0.267	0.577	0.593	1															
GBR	0.138	0.832	0.564	0.649	1														
DEU	0.149	0.810	0.553	0.604	0.883	1													
FRA	0.148	0.807	0.574	0.624	0.897	0.951	1												
CAN	0.131	0.799	0.513	0.647	0.858	0.784	0.810	1											
ITA	0.145	0.725	0.534	0.560	0.812	0.872	0.919	0.731	1										
AUS	0.218	0.732	0.624	0.724	0.824	0.754	0.780	0.818	0.709	1									
ZAF	0.158	0.637	0.459	0.600	0.759	0.713	0.705	0.737	0.587	0.722	1								
KOR	0.224	0.615	0.548	0.683	0.674	0.673	0.644	0.643	0.577	0.713	0.684	1							
IND	0.177	0.552	0.452	0.661	0.603	0.619	0.606	0.588	0.571	0.614	0.598	0.645	1						
IDN	0.180	0.421	0.417	0.559	0.496	0.473	0.478	0.538	0.418	0.577	0.485	0.521	0.552	1					
BRA	0.160	0.673	0.452	0.610	0.770	0.720	0.726	0.789	0.629	0.729	0.753	0.667	0.585	0.518	1				
MEX	0.130	0.786	0.476	0.589	0.783	0.768	0.754	0.762	0.664	0.721	0.750	0.667	0.583	0.509	0.782	1			
RUS	0.111	0.594	0.387	0.543	0.686	0.664	0.627	0.693	0.553	0.638	0.706	0.645	0.563	0.440	0.704	0.675	1		
TUR	0.141	0.569	0.423	0.535	0.618	0.622	0.610	0.576	0.546	0.586	0.682	0.581	0.528	0.471	0.654	0.651	0.600	1	
ARG	0.157	0.534	0.393	0.455	0.583	0.588	0.584	0.579	0.534	0.542	0.488	0.474	0.413	0.427	0.559	0.549	0.488	0.438	1

Table IA1 Continued

Panel B: average dynamic conditional correlation (DCC)			
Market	All Markets	DMs	EMs
China	0.119	0.121	0.118
US	0.551	0.660	0.463
Japan	0.421	0.480	0.369
Hong Kong	0.504	0.535	0.477
UK	0.615	0.728	0.524
Germany	0.625	0.713	0.546
France	0.607	0.733	0.507
Canada	0.583	0.662	0.520
Italy	0.578	0.663	0.503
Australia	0.584	0.656	0.526
South Africa	0.565	0.596	0.540
South Korea	0.508	0.541	0.481
India	0.461	0.492	0.437
Indonesia	0.376	0.368	0.384
Brazil	0.594	0.595	0.594
Mexico	0.566	0.612	0.529
Russia	0.485	0.519	0.458
Turkey	0.437	0.452	0.425
Argentina	0.421	0.462	0.392

Table IA1 Continued

Panel C: cross-market bottom coexceedance

	CNH	USA	JPN	HKG	GBR	DEU	FRA	CAN	ITA	AUS	ZAF	KOR	IND	IDN	BRA	MEX	RUS	TUR	ARG
CNH	1																		
USA	0.167	1																	
JPN	0.200	0.267	1																
HKG	0.167	0.467	0.400	1															
GBR	0.133	0.633	0.433	0.567	1														
DEU	0.200	0.567	0.433	0.433	0.633	1													
FRA	0.133	0.567	0.400	0.467	0.700	0.767	1												
CAN	0.200	0.667	0.333	0.567	0.733	0.633	0.633	1											
ITA	0.100	0.500	0.333	0.400	0.600	0.633	0.767	0.500	1										
AUS	0.167	0.600	0.467	0.600	0.767	0.600	0.633	0.733	0.567	1									
ZAF	0.200	0.500	0.400	0.500	0.600	0.533	0.533	0.600	0.433	0.633	1								
KOR	0.267	0.367	0.333	0.533	0.533	0.467	0.433	0.500	0.400	0.600	0.500	1							
IND	0.100	0.400	0.300	0.467	0.500	0.433	0.467	0.533	0.333	0.567	0.500	0.500	1						
IDN	0.167	0.333	0.200	0.367	0.400	0.333	0.300	0.433	0.233	0.433	0.367	0.500	0.467	1					
BRA	0.133	0.467	0.267	0.500	0.700	0.533	0.500	0.633	0.433	0.633	0.600	0.533	0.433	0.400	1				
MEX	0.167	0.633	0.333	0.467	0.700	0.633	0.567	0.733	0.500	0.633	0.600	0.467	0.433	0.367	0.667	1			
RUS	0.200	0.433	0.300	0.433	0.567	0.533	0.500	0.633	0.433	0.533	0.533	0.600	0.533	0.400	0.500	0.567	1		
TUR	0.067	0.367	0.267	0.367	0.400	0.333	0.400	0.367	0.333	0.433	0.467	0.433	0.467	0.367	0.467	0.400	0.433	1	
ARG	0.133	0.300	0.267	0.300	0.400	0.400	0.333	0.400	0.333	0.367	0.267	0.433	0.267	0.333	0.400	0.367	0.400	0.267	1

Table IA2: Regression Results of Robustness Tests

This table reports regression results of the robustness tests for Table 6 and 7. Panel A reports the effect of disconnection with the real economy on A-share stock's connectedness with the global market using the following regression model: $Connect_{it} = \beta_0 + \beta_1 \times Economy\ connection_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connect_{it}$ is the connectedness of stock i with the global market in year t, $Economy\ connection_{it}$ is a variable constructed to measure connection of stock i with the real economy in year t, and ω and λ are industry and year fixed effect. In column (1) and (2), *Economy connection*1 is the correlation of stock i's quarterly return with GDP growth rate in year t. In column (3) and (4), *Economy connection*2 the average eight-quarter rolling correlation of stock i's quarterly return with GDP growth rate in year t. The sample includes all non-financial A-share firms from 1995 to 2017. Panel B reports the effect of government intervention on A-share stocks' connectedness with the global market using the following regression model: $Connect_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Policy\ sensitivity_{it}$ is a variable constructed to measure sensitivity of stock i to government intervention in year t. In column (1) and (2), *Policy sensitivity*1 is the absolute value of the correlation of stock i's monthly return with China's Economic Policy Uncertainty Index in year t. The sample includes all non-financial A-share firms from 1995 to 2017. In column (3) and (4), *Policy sensitivity*2 is the absolute value of three-day cumulative abnormal return of stock i around announcements of new regulatory documents issued by China Securities Regulatory Commission based on market model in year t. The sample includes all non-financial A-share firms from 2001 to 2017. In column (1) and (3) of Panel A and B, *Connect* is measured using the correlation of stock i with MSCI World Index (the Index) in year t based on weekly USD return (*Correlation*). In column (2) and (4) of Panel A and B, *Connect* is measured using global beta of stock i in year t (*Global beta*), which is defined as the loading of weekly excess return of stock i on excess return of the Index: $Return_{ik} - R_{f,k} = \alpha + Global\ beta1_i \times (Return_{gm,k} - R_{f,k}) + \epsilon_{ik}$, where $Return_{ik}$ is USD return of stock i in week k, $R_{f,k}$ is USD risk free rate, and $Return_{gm,k}$ is return of the Index. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are clustered by industry and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Table IA2 Continued

Panel A: connection with the real economy	(1)	(2)	(3)	(4)
*Economy connection*1	0.009***	0.024***		
	(0.002)	(0.006)		
*Economy connection*2			-0.002	0.047***
			(0.003)	(0.015)
Firm size	0.006***	0.013**	0.006***	0.013*
	(0.001)	(0.006)	(0.001)	(0.007)
Volatility	-0.217***	0.941**	-0.259***	0.720
	(0.068)	(0.336)	(0.080)	(0.517)
ROE	-0.005	0.018	-0.008	0.004
	(0.005)	(0.022)	(0.006)	(0.026)
Leverage	-0.004	-0.027	-0.004	-0.020
	(0.005)	(0.021)	(0.005)	(0.019)
B/M	0.007	0.025	0.007	0.021
	(0.008)	(0.036)	(0.008)	(0.044)
Tangibility	0.034***	0.076**	0.031***	0.051
	(0.008)	(0.035)	(0.006)	(0.030)
Firm age	0.000	-0.006	0.000	-0.004
	(0.002)	(0.011)	(0.002)	(0.010)
AH cross-listed	0.017***	0.017	0.016***	0.011
	(0.005)	(0.011)	(0.005)	(0.011)
SOE	0.002	0.005	0.002	0.005
	(0.001)	(0.005)	(0.001)	(0.004)
Constant	-0.303***	-1.657***	-0.298***	-1.632***
	(0.013)	(0.075)	(0.014)	(0.083)
N	33,461	33,461	33,205	33,205
Adj. R^2	0.458	0.422	0.456	0.417

Table IA2 Continued

Panel B: government intervention	(1)	(2)	(3)	(4)
*Policy sensitivity*1	-0.020***	-0.087***		
	(0.005)	(0.022)		
*Policy sensitivity*2			-0.174**	-0.829***
			(0.079)	(0.278)
Firm size	0.006***	0.014**	0.007***	0.018***
	(0.001)	(0.006)	(0.001)	(0.006)
Volatility	-0.190**	0.996**	-0.159*	1.697***
	(0.076)	(0.408)	(0.087)	(0.395)
ROE	-0.006	0.016	-0.004	0.019
	(0.006)	(0.024)	(0.006)	(0.029)
Leverage	-0.002	-0.014	-0.007	-0.034
	(0.005)	(0.021)	(0.007)	(0.026)
B/M	0.008	0.023	0.006	0.027
	(0.008)	(0.040)	(0.008)	(0.038)
Tangibility	0.032***	0.054	0.025***	0.035
	(0.007)	(0.032)	(0.007)	(0.033)
Firm age	0.000	-0.007	-0.001	-0.007
	(0.002)	(0.010)	(0.002)	(0.011)
AH cross-listed	0.016***	0.011	0.019***	0.017
	(0.005)	(0.011)	(0.005)	(0.014)
SOE	0.002	0.006	0.001	0.005
	(0.001)	(0.004)	(0.001)	(0.004)
Constant	-0.303***	-1.654***	-0.088***	-0.354***
	(0.013)	(0.082)	(0.019)	(0.106)
N	33,615	33,615	30,051	30,051
Adj. R^2	0.454	0.413	0.450	0.383

Table IA3: Determinants of Low Connectedness of A-share stocks with Global Market

This table reports the effect of foreign ownership, disconnection with the real economy, and government intervention on A-share stock's connectedness with the global market using the following regression model: $Connect_{it} = \beta_0 + \beta_1 \times QFII + \beta_2 \times Economy\ connection_{it} + \beta_3 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connect_{it}$ is the connectedness of stock i with the global market in year t, $QFII_i$ is a dummy variable which is equal to 1 if stock i has qualified foreign institutional investor (QFII) holdings in year t and 0 otherwise, $Economy\ connection_{it}$ is a variable constructed to measure connection of stock i with the real economy in year t, $Policy\ sensitivity_{it}$ is a variable constructed to measure sensitivity of stock i to government intervention in year t, and ω and λ are industry and year fixed effect. In column (1), (2), (3), and (4), *Economy connection*1 is constructed as follows: we first calculate the correlation of stock i's quarterly return with GDP growth rate in year t; then we rank all A-share firms based on the correlations; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). In column (5), (6), (7), and (8), *Economy connection*2 is constructed the same as *Economy connection*1 except that we use the average eight-quarter rolling correlation of stock return with GDP growth rate. In column (1), (2), (5), and (6), *Policy sensitivity*1 is constructed as follows: we first calculate the correlation of stock i's monthly return with China's Economic Policy Uncertainty Index in year t; then we rank all A-share firms based on the absolute values of the correlations in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). In column (3), (4), (7), and (8), *Policy sensitivity*2 is constructed as follows: we first calculate the three-day cumulative abnormal return (CAR) of stock i around announcements of new regulatory documents issued by China Securities Regulatory Commission based on market model in year t; then we rank all A-share firms based on the sum of absolute value of these CARs in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). In column (1), (3), (5), and (7), *Connect* is measured using the correlation of stock i with MSCI World Index (the Index) in year t based on weekly USD return (*Correlation*). In column (2), (4), (6), and (8), *Connect* is measured using global beta of stock i in year t (*Global beta*), which is defined as the loading of weekly excess return of stock i on excess return of the Index: $Return_{ik} - R_{f,k} = \alpha + Global\ beta_i \times (Return_{gm,k} - R_{f,k}) + \epsilon_{ik}$, where $Return_{ik}$ is USD return of stock i in week k, $R_{f,k}$ is USD risk free rate, and $Return_{gm,k}$ is return of the Index. The sample includes all non-financial A-share firms from 2003 to 2017. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are clustered by industry and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Table IA3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
QFII	0.006**	0.023***	0.006**	0.024***	0.005**	0.018**	0.005**	0.019**
	(0.002)	(0.008)	(0.002)	(0.008)	(0.002)	(0.008)	(0.002)	(0.008)
*Economy connection*1	0.013***	0.034***	0.013***	0.037***				
	(0.003)	(0.011)	(0.003)	(0.011)				
*Economy connection*2					-0.003*	0.018*	-0.003*	0.021*
					(0.002)	(0.009)	(0.002)	(0.010)
*Policy sensitivity*1	-0.004*	-0.034**			-0.005**	-0.036**		
	(0.002)	(0.013)			(0.002)	(0.015)		
*Policy sensitivity*2			-0.021**	-0.100***			-0.022**	-0.103***
			(0.008)	(0.029)			(0.009)	(0.032)
Firm size	0.006***	0.017***	0.006***	0.016**	0.006***	0.017**	0.006***	0.016**
	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.007)
Volatility	-0.245***	1.355***	-0.190**	1.676***	-0.300***	1.177**	-0.241**	1.478**
	(0.079)	(0.399)	(0.081)	(0.420)	(0.084)	(0.496)	(0.089)	(0.556)
ROE	-0.002	0.029	-0.002	0.028	-0.004	0.022	-0.004	0.020
	(0.006)	(0.027)	(0.006)	(0.029)	(0.006)	(0.027)	(0.006)	(0.030)
Leverage	-0.007	-0.037	-0.006	-0.033	-0.009	-0.044*	-0.008	-0.039
	(0.007)	(0.025)	(0.007)	(0.027)	(0.006)	(0.023)	(0.007)	(0.025)
B/M	0.007	0.038	0.005	0.029	0.009	0.042	0.007	0.033
	(0.008)	(0.038)	(0.008)	(0.038)	(0.008)	(0.043)	(0.008)	(0.042)
Tangibility	0.028***	0.040	0.026***	0.036	0.028***	0.038	0.025***	0.032
	(0.007)	(0.032)	(0.006)	(0.034)	(0.006)	(0.032)	(0.006)	(0.032)
Firm age	-0.002	-0.009	-0.002	-0.010	-0.001	-0.005	-0.001	-0.006
	(0.002)	(0.013)	(0.002)	(0.012)	(0.002)	(0.013)	(0.002)	(0.013)
AH cross-listed	0.018***	0.013	0.018***	0.014	0.018***	0.011	0.018***	0.012
	(0.005)	(0.013)	(0.005)	(0.013)	(0.005)	(0.014)	(0.005)	(0.014)
SOE	0.001	0.003	0.001	0.003	0.001	0.004	0.001	0.003
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.005)	(0.001)	(0.004)
Constant	-0.184***	-0.507***	-0.171***	-0.459***	-0.173***	-0.494***	-0.160***	-0.442***
	(0.020)	(0.099)	(0.023)	(0.114)	(0.019)	(0.103)	(0.022)	(0.120)
N	27,916	27,916	27,891	27,891	27,513	27,513	27,489	27,489
Adj. R^2	0.461	0.383	0.462	0.383	0.464	0.388	0.465	0.388