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

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Abstract

We find that China's stock market provides valuable diversification benefits for international investors. It has low correlation with the global market, and is resistant to international financial contagion. These diversification benefits can be explained by the unique features of China's stock market: frequent government interventions, disconnection with the real economy, and low foreign ownership. The recent Shanghai-Hong Kong and Shenzhen-Hong Kong stock connect programs have minimal impact on these diversification benefits. We further find more trading suspensions but more diversification and better performance for A-share stocks with high policy sensitivity.

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1. Introduction

Recent global financial crisis revealed the importance and complication of international asset allocation. One new element is rising markets which present opportunities for alternative investment. In 1989, China did not have a stock market and its economy was much less significant in the world (ranked #11 after Spain). China introduced stock market in 1990 and its economy also grew dramatically since then. China's stock market is the second largest in the world with over $8.7 trillion market capitalization in 2017.[1] While the stake of international investors is still small, China's stock market has attracted increasing global attention, especially after the recent inclusion of China A-share into the MSCI Emerging Market Index. Despite the concerns over China's economic growth and trade war, international investors' buying of Chinese stocks remains very robust.[2]

Like other emerging markets (EMs), China can provide diversification benefits for international investors. The benefits of international diversification have relied largely on the existence of low cross-country correlations. However, major stock markets are more correlated in the last few decades, reducing potential diversification benefits (Christoffersen, Errunza, Jacobs, and Langlois, 2012). Stock markets are even more correlated and subject to contagions in market downturns when the diversification benefits are most needed. Early studies find novel evidence of contagion in developed markets (DMs) (e.g., Ang and Bekaert, 2002; Longin and Solnik, 2001). Recent studies find that contagion also affects EMs (e.g., Baur, 2012; Christoffersen et al., 2012), although the severity is less. However, China can be an exception considering its special features. In this study, we examine whether China's stock market would be a better choice for diversification and a safe haven for international investors during global shocks.

Using a cross-country sample from January 1995 to December 2017, we first find that

[1] See `http://wdi.worldbank.org/table/5.4#`

[2] For example, Charlie Munger, Vice Chairman of Berkshire Hathaway, described China's stock market as "a happier hunting ground" for value investors at 2017 Annual Meeting. Also see "Foreign Investors Keep Buying Chinese Stocks as Markets Go Wild." *Bloomberg*, August 9, 2018, `https://www.bloomberg.com/news/articles/2018-08-09/foreign-investors-keep-buying-chinese-stocks-as-markets-go-wild`.

China's stock market has the lowest correlation with other markets, compared with all other DMs and EMs. To analyze the time series change of correlations, we further use dynamic conditional correlation (DCC) model of Engle (2002) and Tse and Tsui (2002). The results show that the correlations of EMs increase more than DMs in the last two decades, probably because of market liberalization of EMs. More importantly, all markets show uptrend correlations, except for China. Therefore, while diversification benefits from international investment are decreasing, investing in China can provide as much diversification as twenty years ago for international investors.

We further use various measures to investigate global financial contagion. We first identify global index shocks and compare the cumulative market returns (CR) of EMs around global index shocks. We find that different from other EMs, there is no significant negative CRs for China around global index shocks. In addition, we compare DCC of EMs with the global index during index shock week and that prior to the shock week. We find that while all other EMs are more correlated with the global market around global shocks, China does not show significant increase in the correlation. Moreover, we use *coexceedance* to measure financial contagion following Bae, Karolyi, and Stulz (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. Our results suggest that most EMs have lower bottom coexceedance than DMs. China again has the lowest coexceedance, suggesting that China is less likely to experience extremely negative returns simultaneously with other markets. To measure the diversification benefits, we also construct portfolios that contain the global index and EMs, and compare Sharpe ratios (SR) of the optimal portfolios. We find that adding China to the global index can increase its SR more than other EMs and the increase in SR cannot by replicated by investing in other EMs. Therefore, all the results suggest that China is not vulnerable to financial contagion and can provide valuable diversification benefits for international investors during global shocks.

The high diversification benefits of China's market can potentially be explained by its special features. First, since Chinese government has larger control over financial market than other governments, stock market performance can be more dependent on government policy. The government tends to intervene whenever the market is extremely volatile. Government intervention can decrease correlation of China with the global market and prevents it from the "wake-up call" channel of contagion documented in the literature (Goldstein, 1998). Second, as the largest exporter and second largest importer, China's economy is highly correlated with the global economy. However, China's stock market is disconnected with the real economy because of the problematic IPO process, inefficient investment and poor corporate governance (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 documented in Bekaert, Ehrmann, Fratzscher, and Mehl (2014). Third, while common ownership can explain international stock returns and generate global contagion (Bartram, Griffin, Lim, and Ng, 2015; Elliott, Golub, and Jackson, 2014), China's stock market has very low foreign ownership because of capital control and can withstand the "common ownership" channel of financial contagion.

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 stock return with the global index return. 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 global index. First, 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 is based on correlation of stock return with China's Economic Policy Uncertainty (EPU) Index. As the main regulatory body of China's stock market, China Securities Regulatory Commission (CSRC) has a huge impact on market performance. In the spirit of Liu, Shu, and Wei (2017), our second measure is based on the three-day cumulative abnormal return (CAR) of the stock 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 26.09% of the average correlation.

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 the real economy. Our results suggest that stocks more connected with the real economy are also more correlated with the global market. Last, we exploit the Qualified Foreign Institutional Investors (QFII) holding data to test the effect of foreign ownership on stock's connectedness with global market. As expected, the correlation of QFII held stocks is 0.006 higher than that of other stocks, which is equivalent to 13.04% of the average correlation. Overall, we find that stocks are more correlated with the global market if they are less policy sensitive, more connected with the real economy, and held by foreign investors.

With the liberalization of China's financial market, one concern is that the low correlation may not persist when A-share market has more international investors. However, when comparing the correlation and coexceedance of QFII held stocks with the other sample markets, we find that they are still much lower, suggesting that they can still provide more diversification benefits than other markets. To further address this issue, we divide our sample into sub-samples based on their policy sensitivity. We show that stocks with low policy sensitivity increase much more in correlation with the global market after they have QFII ownership than stocks with high policy sensitivity, suggesting that market access alone cannot explain the low correlation of China. We further show that stocks in the Shanghai-Hong Kong Stock Connect Program (SH-HK Connect) and Shenzhen-Hong Kong Stock Connect Program (SZ-HK Connect) do not increase in correlation with global market after the launch of the programs. This again suggests that the diversification can persist even there are more international investors in China. Moreover, using A-H cross-listed stocks, we find that the diversification benefits provided by A-share stocks are significantly higher than overseas listed stocks.

Despite of the diversification benefits, concerns on policy risks can prevent international investors from accessing China's stock market. On the one hand, effective government interventions can stabilize the market and keep the market "in order". On the other hand, frequent interventions can distort market prices and raise concerns on trading freedom (Song and Xiong, 2018). For example, during the 2015 China's stock market crash, a state-backed "national team" were called on to support the market. However, government temporarily banned betting on stocks to fall, halted IPOs, curbed trading with borrowed money and froze dozens of trading accounts. All of these reduce investors' opportunities to exit the market at the right time. Moreover, because of the frequent stock trading suspension in China, trading freedom lies in the center among concerns of international investors. Therefore, we test the relation of stock's policy sensitivity and probability of trading suspension. We find that while policy-sensitive stocks are more likely to be suspended for trading in general, the effect disappears during crisis period when the diversification is most needed by international investors. We also show that policy-sensitive stocks have higher stock return and SR than other stocks, suggesting that the potential policy risk is compensated by even higher return. In this sense, China's stock market can still be attractive for investors looking for portfolio diversification or long-term performance.

Our paper contributes to the literature on international diversification and contagion (e.g., Christoffersen et al., 2012; Bae et al., 2003; Bekaert et al., 2014). Previous papers have documented global contagions through real business relationship such as trade credit of foreign direct investment (Lin and Ye, 2017) or subsidiaries of multinational firms (Bena, Dinc, and Erel, 2018). We will focus on contagions through stock markets and emphasize the difference between real sector and stock market contagions. Furthermore, we contribute to the increasing literature on China's stock market. Carpenter, Lu, and Whitelaw (2018) also document the low correlation of China's stock market with international markets. We investigate China's stock market from the perspective of well-diversified global investors and extend by investigating the dynamics of the correlation overtime and comparing the vulnerability to global contagions across markets. We also explicitly explore the sources of the diversification benefits. There are also a number of works focus on the role of government interventions. Huang, Miao, and Wang (2016) find government intervention in 2015 China's stock market crash increased the value of rescued firms by busting stock demand and decreasing default probability. However, there are still concerns about the long-run costs of the Chinese government intervention. Jin, Wang, and Zhang (2018) find implicit government guarantees increase bond value, and have real effects on corporate investment and financing policies. The reduction in implicit guarantees decrease bond value, investment, and debt issuance, and increase precautionary cash savings. Different from these works, we focus on the implications of government interventions for international investors.

The rest of this paper is organized as follows. Section 2 provides institutional background of China's stock market. Section 3 presents the data and summary statistics. The empirical results are reported in section 4 and 5. Section 6 concludes.

2. China's Stock Market

In 1989, China did not have a stock market and its economy was much less significant in the world (ranked #11 after Spain). China introduced stock market in 1990 and its economy also grew dramatically since then. China's stock market has been the second largest in the world with over $8.7 trillion market capitalization in 2017 and has increasingly attracted global attention. China's stock market is shaped by several key features.

First, 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. With the aim of stabilizing financial market, Chinese government tends to intervene whenever the market is extremely volatile. On the one hand, effective government interventions can stabilize the market and keep the market "in order". On the other hand, frequent interventions can distort market prices and raise concerns on trading freedom (Song and Xiong, 2018). For example, anecdotal evidence suggests that government aimed to preserve the market stability during major political events. Trading guidance was issued to institutional investors, and even to individual investors through their brokers. During the 2015 China's stock market crash, a state-backed "national team" were called on to support the market. However, government temporarily banned betting on stocks to fall, halted IPOs, curbed trading with borrowed money and froze dozens of trading accounts. All of these reduce investors' opportunities to exit the market at the right time. In addition to trading freedom, government policies may be in favor of particular groups of firms, such as the SOEs (e.g., Cong, Gao, Ponticelli, and Yang, 2018). 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).

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 each year, firms normally need to wait for years to be listed on A-share market. State-owned enterprises (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. The problematic IPO process can also partly explain the underperformance of China's domestically listed firms. (Allen et al., 2018). Because of the difficulty of IPO in Mainland China, many Chinese firms choose to be listed overseas, mainly in Hong Kong and US. As of 2018, over 1000 Chinese firms are listed overseas, with 414 in Hong Kong and 523 in US.

Third, China's stock market is dominated by domestic 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 Exchange. 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. To open the financial market, Chinese government introduced the QFII program in 2002 and Renminbi Qualified Foreign Institutional Investors (RQFII) program in 2011 that allows foreign institutional investors to trade A-shares directly. 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 has been relaxing regulation on QFII and RQFII in recent years, including increasing quotas and expanding investor eligibility. As of January 2019, the total quota of QFII is $300 billion with $101 billion already granted, and the total quota of RQFII is around $277 billion with $93 billion already granted.[3] Although the quotas are already large, they are never fully fulfilled, suggesting the potential concern of investing in China of international investors.

Because of the restrictions on QFII and RQFII, only large institutional investors have access to these programs. Thus, most global investors have been investing on Chinese firms traded in Hong Kong and US to get exposure to China. As shown in Carpenter and Whitelaw (2017), both the largest and oldest ETF traded in US hold equities traded outside of China. The first ETF tracking broad A-share index was introduced in 2010 and has not gained significant traction. To further open the stock 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 Programs allow international and Mainland

[3] See the official document of CSRC on `http://www.csrc.gov.cn/pub/newsite/zjhxwfb/xwdd/201901/t20190131_350598.html`.

Chinese investors to trade securities in each other's markets through the trading and clearing facilities of their home exchange.[4] The SH-HK Connect includes constituent stocks in the SSE 180 Index and SSE 380 Index and all A-H cross-listed stocks. The SZ-HK Connect 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. The main differences between the programs and QFII are that they allow retail investors to trade A-share directly and has much higher quota. With the stable increase of the Stock Connect Program, MSCI finally agreed to add China A-share to its flagship emerging market index in June 2017. FTSE Russell also decided to add A-share to its key emerging market index in September 2018. In the meanwhile, US traded ETF on A-share increase dramatically, with the largest ETF has a $1.2 billion asset under management as of January 2019.[5] However, since global investors still have various concerns of investing in China, particularly policy risk, foreign investment represents a small fraction of China's stock market until now.

Fourth, China's stock market has more and longer trading suspension than other markets. The rapid economic and political development in China leads to a large number of corporate events including merger and acquisition, asset reorganization and capital restructuring in the last two decades. Information related to these corporate activities are generally price sensitive. Therefore, Chinese regulators consider stock trading suspension as an important means to alleviate the issues caused by information asymmetry during corporate events. The main reasons of suspension include shareholder meeting and financial report release, material events, asset reorganization, and unusual stock price movement. The duration of suspension ranges from a few hours to several months. As companies are not required to suspend stock trading for shareholder meeting and report release anymore from 2012, this suspension reason was seldom used afterwards. Since companies can suspend trading voluntarily, some

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

[5]See `https://etfdb.com/etfs/country/china/#etfs&sort_name=assets_under_management&sort_order=desc&page=1` for the list of China ETF.

of them have been abused suspension to prevent stock price decline or even manipulate stock price, especially during market crash. For example, during the 2015 stock market crash, more than half of A-share companies suspended their stocks. The frequent and long trading suspension has been a major concern for international investors as it prevents them from withdrawing money on time.[6] From 2016, both CSRC and the two stock exchanges have released new regulations in order to curb the misuse of trading suspension.[7] These new regulations requires companies to be more prudent when applying trading suspension, shorten suspension duration, and disclose information timely. Figure 1 plots the average number of times of suspension each A-share stocks has from 2003 to 2017. It shows that trading suspension tends to decrease in recent years, especially after 2015.

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.[8] 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,

[6] See "Chinese stock suspensions a 'visceral' issue for investors", *Financial Times*, June 5, 2018, https://www.ft.com/content/cb84f678-67bc-11e8-8cf3-0c230fa67aec

[7] See http://www.csrc.gov.cn/pub/zjhpublic/zjh/201811/P020181106685802073496.pdf, http://www.sse.com.cn/lawandrules/sserules/listing/stock/c/c_20160527_4121001.shtml, and http://www.szse.cn/disclosure/notice/t20181228_563857.html for the documents issued by CSRC, SSE, and SZSE.

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

to proxy the performance of global market. Therefore, our market-level sample includes 9 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.[9] Our 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 firm-level sample includes 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 EPU Index during 1995 to 2017 from the EPU Index website.[10] We hand-collect the announcement dates of new regulatory documents issued by CSRC from their official website. The first regulatory document is issued in 2001 and 137 documents are issued during 2001 to 2017.[11] For the Stock Connect Program, 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 Connect and 833 stocks in the SZ-HK Connect. 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 sample markets. In general, EMs have much higher return and volatility than DMs. Hong Kong has the highest return and volatility among DMs and 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

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

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

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

than 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. 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. The average correlation of A-share stocks with the Index is as low as 0.046. Since our measures of policy sensitivity and connection with real economy are based on rankings from 0 to 1, their means are all around 0.5. The average $QFII$ is 0.106, suggesting that only very small part of A-share stocks have QFII holdings. The mean of $Trade\ suspension$ is 1.602, suggesting that an A-share stock is suspended for trading 1.602 times every year for the reason other than shareholder meeting and financial report release. Most firm characteristics are comparable to those in recent studies (e.g. Giannetti, Liao, and Yu, 2015; Liu et al., 2017), except that our sample has more SOEs because the sample period is longer and most Chinese listed firms are SOEs before the Split-Share Structure Reform in 2005.

4. Diversification Benefits of China's Stock Market

4.1. Correlations of Stock Markets

The diversification benefits from international investing is determined by the cross-country correlations (Christoffersen et al., 2012). However, recent studies show that international diversification benefit is decreasing because markets are more correlated in the last few decades and financial contagion makes international investors more vulnerable to global shocks. In this section, we investigate the diversification benefits of China's stock market and compare China with other markets. We first report cross-market correlations in Panel A of Table 2. All correlations are calculated using weekly USD returns and 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. 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 two decades. But the pattern does not change, with China still has the lowest correlations. The results suggest that compared to the other markets, China can potentially provide more diversification benefits for international investors.

The unconditional correlation provides an overall picture of long-term connectedness of the sample markets. However, it cannot capture the pattern of connectedness over time. Therefore, we further use a DCC model of Engle (2002) and Tse and Tsui (2002) to investigate time-varying connectedness. Specifically, we follow Christoffersen, Errunza, Jacobs, and Jin (2014) and fit univariate AR(2)-GARCH(1,1) models to the weekly returns of each sample market. The autoregressive model of order two, AR(2), can pick up the potential return dependence of each market. The GARCH(1,1) can 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 the other 18 markets for each sample market in Figure 2. Consistent with Christoffersen et al. (2014), most sample markets have an uptrend correlation. Moreover, most EMs' correlations increase more than DMs', possibly because of market liberalization in EMs. However, we find only marginal increase in China's correlations across years. The results suggests that although the global market is increasingly correlated, China keeps having low correlation with the other markets. We then calculate time-series mean of the three average correlations for each market. The results are reported in Panel B of Table 2. The average DCC with all markets show similar pattern with unconditional correlation reported in Panel A, suggesting that our DCC model estimates fit our data well. We again observe the lowest correlation for China with only 0.097. The last two columns show the average correlation of each market with DMs and EMs, respectively. We find that most markets have much higher correlations with DMs than with EMs. However, China has similar correlations with DMs and EMs. To conclude, while the diversification benefit of investing in EMs is decreasing, China is an exception.

4.2. Financial Contagion of Stock Markets

In this subsection, we investigate whether stock markets are vulnerable to financial contagion, which decreases the benefits of international diversification. Since testing contagion is difficult because of the spurious relationship between correlation and volatility (Longin and Solnik (2001)), we use different measures to examine the cross-market financial contagion.

Since markets vulnerable to contagion should have large negative return when the global market is under shock, we first examine CR of the 10 EMs around global index shocks. We define the global index is under shock when it is in the bottom 5% tail returns during 1995-2017. Based on the 1150 weekly observations of the global index during 1995-2017, we identify 57 index shock weeks. Then for each EM and each index shock, we calculate the CR during the shock week (0), from one week before to one week after the shock (-1, 1), and from three weeks before to three weeks after the shock week (-3, 3). Finally, we take average across all the shocks for each EM and each window. As we can see from Panel A of Table 3, most EMs have large and significantly negative CRs around global index shocks. For example, the seven-week CRs of Indonesia and Turkey are -10.213% and -9.995%, respectively. Although the two markets have relatively low correlations with the global market from the previous analysis, they still suffer from large negative returns during global shocks. On the contrary, CRs of China are not significant for all the three windows. Therefore, while most EMs are vulnerable to contagion, China can be an exception and provide valuable diversification benefits during global economic downturns.

To examine whether EMs are more correlated with the global market during global index shocks, we further conduct an event study test on the DCC of EMs with the global index. 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 with the Index at time t is defined as 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. At last, we take average across the 57 event weeks for each event window. 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. 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 from global market.

As discussed in Bae et al. (2003), correlations may not be appropriate for an evaluation of the differential impact of large returns. In this subsection, we use *coexceedance* to measure contagion. Following 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 simultaneously and 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 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. We further plot the average coexceedance with the other 18 sample markets for each market in Figure 3. It provides more intuitive results that China's coexceeance is much lower than other markets. In Panel C of Table IA1, we also investigate the cross-market bottom coexceedances for the more recent period from 2006 to 2017. It shows that both DMs and EMs are more vulnerable to financial contagion in the last decade. 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 examine diversification benefits of EMs using SR. We first calculate SR of the Index each year based on weekly USD return. Then we construct portfolios that contain the Index and each of the 10 EMs and calculate SR of the optimal portfolios. Since most EMs including China have short-selling constraints, we do not allow short-selling when constructing the portfolio. Last we calculate difference of SR between the Index and the optimal portfolios to test whether investing in the EM can increase SR for global investors.

The results are presented in Panel A of Table 4. We also report the significance level of the difference and the weight of each EM in the optimal portfolios. The results suggest that all EMs can provide diversification benefits, as evident by the significant increase in SR. On average, the 10 EMs can increase SR of the Index by 0.059. While the increase in SR is significant for all EMs, it is the largest for China, suggesting that the economic size of diversification benefits of China is the largest. Moreover, since the weight of China is lower than other markets, the optimal portfolio should be more feasible for China. We also perform the test for the more recent period from 2006 to 2017 and the results are reported in Panel A of Table IA2. While most EMs provide less diversification compared to the full sample period, China can increase SR of the Index 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.

Next, since all EMs can increase SR for international investors, we further test whether the diversification benefits provided by China can be replicated by investing in other EMs. For each EM, we first calculate SR of the optimal portfolio that contain the Index and the other 9 EMs each year. Then we calculate SR of the optimal portfolio that contain the Index and all of the 10 EMs. Last we calculate difference of SR between the two portfolios to test whether adding each EM can further increase the SR. The results are reported in Panel B of Table 4. We find that the increase in SR are marginal and less significant for most EMs, suggesting that the diversification benefits of most EMs can be replicated by investing in other markets. On the contrary, China can still significantly increase SR of the portfolio by 0.051. We also perform the test for the more recent period from 2006 to 2017 and the results are reported in Panel B of Table IA2. We again find that China can provide even more diversification in the recent decade. To conclude, although other EMs can also provide diversification benefits, they cannot replicate the large benefits provided by China. Therefore, underweighting China can bring high opportunity cost to international investors.

5. Dissecting the Diversification Benefits

5.1. *Government Intervention*

In this section, we employ firm-level data to investigate explanations for the low correlation of China's stock market. First, 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 2015 China's stock market crash, a state-backed "national team" were called on to support the market. 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 has more willingness and flexibility to deal with shocks, investors may not reassess upward the vulnerability of China when crisis happens in other markets.

To examine the effect of government intervention on stock's connectedness with global market, we estimate the following regression model:

$$Connectedness_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}, \qquad (1)$$

where $Connectedness_{it}$ is the connectedness of stock i with global market in year t, $Policy\ sensitivity_{it}$ is a variable constructed to measure stock i's policy sensitivity in year t, and ω

and λ are firm and year fixed effect, respectively. Standard errors are two-way clustered by industry and year in all regressions throughout the paper. We use two variables to measure stock's connectedness with the global market. First, *Connectedness* is measured using the correlation of stock i with the Index in year t based on weekly USD return (*Correlation*). Second, *Connectedness* is measured using global beta (*Global beta*), which is estimated using the following regression model:

$$R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i, \tag{2}$$

where $R^u_{i,k}$ is USD return of stock i in week k, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index. We estimated the model for each stock in each year.

Two variables are used 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 EPU Index. We first calculate the correlation of stock i's monthly return with EPU Index 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. Therefore, our second measure, *Policy sensitivity*2, is based on stock's reaction to release of regulatory documents of 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:

$$R_{i,k} - R_{f,k} = \alpha + \beta_i \times (R_{m,k} - R_{f,k}) + \epsilon_i, \tag{3}$$

where $R_{i,k}$ 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 in 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). Since the first CSRC regulatory document is issued in 2001, the sample period for this measure is from 2001 to 2017.

The regression results are reported in Table 5. The dependent variables are *Correlation* in column (1) and (2). Column (1) shows that the coefficient on *Policy sensitivity*1 is -0.012, suggesting that *Correlation* of the most policy-sensitive firms is 0.012 lower than the least sensitive firms. The difference is large and equivalent to 26.09% of the average *Correlation*. Column (2) shows similar results when we use *Policy sensitivity*2 as the main explanatory variable. We use *Global beta* to measure stock's connectedness with global market in column (3) and (4). The coefficients are -0.054 on *Policy sensitivity*1 and -0.062 on *Policy sensitivity*2. They are statistically significant and also economically large as the average *Global beta* is only 0.135. We also find that firms with larger size and higher tangibility are more correlated with the global market. To conclude, Table 5 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 EPU Index and absolute CAR without ranking to measure firm's policy sensitivity. The results are reported in Panel A of Table IA3 and consistent with the main results.

5.2. Disconnection with the Real Economy

As the largest exporter and second largest importer in the world, 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) also 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 the 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 one-quarter lagged stock return when calculating correlation of stock return with GDP growth rate. Then we estimate regression model (1) again using *Economy connection* as the main explanatory variable.

The regression results are reported in Table 6. Coefficients on *Economy connection* are significantly positive at 1% level in all columns. Column (1) shows that the coefficient on *Economy connection*1 is 0.011, suggesting that $Correlation$ of stocks that are most connected with the real economy is 0.011 higher than the least connected, which is equivalent to 23.91% of the average $Correlation$. The effect is even stronger when we use *Economy connection*2 in column (2). Column (3) and (4) show similar results when we use *Global beta* to measure stock's connectedness with the global market. Therefore, consistent with our expectation, stocks that are more connected with the real economy are also more correlated with global market. This is because performance of these firms are more dependent on China's real economy, which is highly connected with global market. These firms may also have more international business, export, and import. However, since A-share market is overall disconnected with the real economy, China's market potentially has low correlation with 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 B of Table IA3 and consistent with the main results.

5.3. Foreign Ownership

It is well known that China's stock market is dominated by domestic investors because of capital control. Chinese investors are also restricted to invest in other markets. Since common ownership is also an important factors in explaining international stock returns (Bartram et al., 2015), China's market potentially has 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.

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 use regression model (1) again and the results are reported in Panel A of Table 7. Column (1) shows that QFII held stocks have 0.006 higher *Correlation* than the others, which is equivalent to 13.04% of the average correlation. Coefficient on $QFII$ is also significantly positive in column (3) when we use *Global beta* as the dependent variable, although is has lower significance level. In general, stocks held by QFII are more connected with global market. We also run a unified regression that includes all three factors, *Policy sensitivity*, *Economy connection*, and $QFII$ as a robustness test. The results are reported in Table IA4. Both the magnitude and significance level of the coefficients are consistent with previous results.

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

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

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. The regression results are reported in Panel A of Table 7. Consistent with previous results, the coefficients on $In\ QFII_i \times Post$ are significantly positive at 1% level in both column (2) and (4). Stocks have 0.01 higher $Correlation$ and 0.039 higher $Global\ beta$ after they have QFII holdings. Therefore, we conclude from Table 7 that stocks with foreign ownership are more connected with the global market. However, only 10.6% A-share stocks ever have QFII holding as shown in Table 1 and the holdings are normally small because of capital control. This can partly explain its low connectedness with global market. It also has important implication for international investors that investing on A-share stocks with less foreign ownership may provide more diversification benefits.

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. To address this concern, we divide all A-share stocks into two portfolios every year based on whether they have QFII holding and compare connectedness of the two portfolios with the global market. The results are reported in Panel B of Table 7. Although the correlation, DCC, and coexceedance of QFII held stocks are significantly higher than other stocks, they are still much lower than the other sample markets. Moreover, the increases in SR after adding each portfolio to the Index are comparable for QFII and non-QFII held stocks, suggesting that QFII held stocks can still provide similar diversification benefits to international investors. This also suggests that market access alone may not explain the low correlation of China.

To further address this issue, we perform sub-sample analysis by dividing our sample into high and low policy sensitivity groups based on *Policy sensitivity*1 and high and low real economy connection groups based on *Economy connection*1. The results are reported in Panel C of Table 7. We find that although the coefficients on $In\ QFII \times Post$ are similar for high and low real economy connection groups as shown in column (3) and (4), they are very different for high and low policy sensitivity groups in column (1) and (2). Specifically, stocks with low policy sensitivity have large and significant increase in *Correlation* after they are held by foreign investors, but stocks with high policy sensitivity only have small and less significant increase. This suggests that beside market access, government intervention may be more important in explaining the low correlation of China's market.

Foreign ownership in A-share market has been increasing steadily after the launch of SH-HK Connect and SZ-HK Connect. To investigate the effect of the Stock Connect on stock's correlation with global market, We estimate the following DID regression:

$$Connectedness_{it} = \beta_0 + \beta_1 \times HK\ connected_i \times Post + Controls_{it} + \omega + \lambda + \epsilon_{it}, \qquad (5)$$

where $HK\ connected_i$ is a dummy variable which is equal to 1 if stock i is in the SH-HK Connect or SZ-HK Connect 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 Panel A of Table 9. The sample includes all A-share stocks in SSE from three years before to three years after the introduction of SH-HK Connect (2012-2017) and stocks in SZSE from one year before to one year after the introduction of SZ-HK Connect (2016-2017). Column (1) and (3) show results for the full sample. Coefficients on $HKconnected_i \times Post$ are small and not significant, suggesting that connected stocks are not more correlated with global market after the introduction of the programs. We also perform the sub-sample analysis for SH-HK Connect. The results are reported in column (2) and (4) and similar to the full sample results. In Panel B, we again divide all stocks into two portfolios every year from 2015 to 2017 based on whether they are in the Stock Connect

Program. And we compare connectedness with the global market of the two portfolios. We find that connected stocks have higher correlation and average DCC with the global market than the other stocks. As a result, their increase in SR of the Index is also lower. However, their bottom coexceedance is the same with the other stocks, suggesting that they are not more vulnerable to financial contagion even they are more open to international investors. Moreover, stocks not in the Stock Connect Program perform much better than connected stocks from 2015 to 2017. This suggests that if international investors can access stocks not covered by the Program, they can have not only more diversification benefits, but also higher return. We also compare DCC with the Index of connected stocks and the other stocks in Figure 4. It shows that their DCC are comparable after the introduction of the Stock Connect Program. Therefore, market openness itself may not explain the low correlation of China's market. Even China has been more open to international investors, the low correlation may still persist.

5.4. A-H Cross-listed Stocks

As discussed in Section 2, over 1000 Chinese firms are listed overseas, mainly in Hong Kong and US, because of the difficulty of IPO in China. Given it is difficult to access A-share market, international investors have long been investing on overseas listed Chinese firms to get exposure to China. Also, most China ETF still hold stocks traded outside China. However, although overseas listed firms also provide exposure to China, they may not provide as much diversification benefits as A-share stocks, because they do not share the three special features of China's stock market we analyzed above. To investigate this issue, we use A-H cross-listed stocks to perform a sub-sample analysis. The cross-listed stocks have the same fundamentals but traded under different regulations and potentially by different groups of investors. We

As of 2017, there are 98 A-H cross-listed stocks. We construct two portfolios using these A-share stocks and their counterpart H-share stocks to compare their connectedness with the global market. The results are reported in Table 8. A-share stocks have both lower correlation and lower average DCC than H-share stocks and the differences are significant at 1% significance level. This suggests that A-share stocks should provide more diversification than H-share stocks although they have the same fundamentals. The last column shows that A-share stocks are also less vulnerable to global financial contagion, as evident by the significantly lower bottom coexceedance. We also plot time-series DCC with global market for the two portfolios in Figure 5. It shows that while A-share stocks are increasingly correlated with global market, H-share stocks have always been more correlated with global market than A-share stocks, providing further support for our argument. Moreover, compared to DCC of the overall A-share market shown in Figure 2, these cross-listed A-share stocks are much more correlated with global market, possibly because they are more attractive to international investors and their price tend to move together with their counterpart H-share stocks. This also suggests that the other A-share stocks can provide even more diversification benefits than cross-listed stocks.

5.5. Policy Risks of China's Stock Market

China has made progress in opening financial markets to foreign investors. Institutional investors have long been using QFII and RQFII programs to access China's stock market. The recent SH-HK Connect and SZ-HK Connect further relax the capital control. However, foreign investors have never fulfilled quotas of these programs, suggesting that concerns on risks, especially policy risks, may prevent international investors from investing in China's stock market. On the one hand, effective government interventions can stabilize the market and keep the market "in order". On the other hand, frequent interventions can distort market prices, make the market more volatile, cause excessive speculation, and raise concerns on trading freedom (Song and Xiong, 2018). For example, the dramatic revision in restrictions on margin financing led to China's stock market bubble in 2015. After the market crashed, Chinese government took various actions to support the market, but it temporarily banned betting on stocks to fall, halted IPOs, curbed trading with borrowed money and froze dozens of trading accounts. All of these reduce investors' opportunities to exit the market at the right time.

Another policy-related risk in China, the frequent stock trading suspension, also raises international investors' concern on trading freedom. Although our previous analysis suggests that policy-sensitive stocks can provide more diversification benefits, investors may not be able to realize the benefits if they cannot withdraw their money on time, especially during crisis when the benefits are needed the most. To address this concern, we examine whether policy-sensitive stocks are more likely to be suspended using the following regression model:

$$Trade\ suspension_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}, \qquad (6)$$

where $Trade\ suspension_{it}$ is the number of times of trading suspension of stock i in year t and the other variables are defined as above. $Trade\ suspension$ includes all types of suspensions except suspensions because of shareholder meeting and financial report release, as all firms are required to suspend trading during shareholder meeting and report release before 2012 and this reason is seldom used after the rule is made obsolete in 2012. The sample period is from 2002 to 2017. The regression results are reported in Table 10. Column (1) and (2) show that coefficients on both policy sensitivity measures are significantly positive. Therefore, policy-sensitive stocks are more likely to be suspended for trading, suggesting that they may have more concern on trading freedom. However, the sub-sample analysis in column (3) and (4) suggest that policy-sensitive stocks do not have higher probability of being suspended during crisis period, including the global financial crisis and Euro debt crisis. This means that trading suspension may not be a particular concern for policy-sensitive stocks during crisis. Therefore, although policy-sensitive stocks have more trading suspension that may compromise diversification benefits, this effect is weak during crisis when the diversification is most needed. Moreover, Figure 1 shows that trading suspension has been decreasing in recent years, suggesting that is should be a minor concern in the future.

Given China's stock market is heavily affected by policy, it can have higher policy risks than other markets. Thus, while policy-sensitive stocks can provide more diversification benefits, one concern is that they may have higher policy risk that can decrease realized return, as policy uncertainty can generate greater stock price volatility (Pástor and Veronesi, 2013). To address this concern, we examine the relation of policy sensitivity and stock performance using regression model (6) with $Performance$ as the dependent variable. We use stock return and SR to measure $Performance$. The regression results are reported in Table 11. Overall, 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.

6. Conclusions

Recent studies find that stock markets are increasingly correlated and more vulnerable to financial contagion, which decrease international diversification benefits. However, China is an exception because of 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 stock market can provide more diversification benefits for international investors. Second, 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 less policy-sensitive, more connected with real economy, and held by QFII. Thus, the special features of China's stock market can explain the low correlation of China's market: frequent government intervention, disconnection with the real economy, and small foreign ownership. Further analysis shows that market access alone cannot explain the low correlation of China's stock market. Thus, the low connectedness may persist even China is gradually opening its stock market. Fourth, although policy-sensitive stocks can have higher policy risk and lower trading freedom that may compromise diversification benefits, we show that they also have higher return and SR.

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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 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: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock i in week k, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index.
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).
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).

Table A1 Continued

Variable	Definition
Economy connection2	The ranking of correlation of the stock's one-quarter lagged quarterly return with GDP growth rate. We first calculate the correlation of the stock's one-quarter lagged 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).
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.
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.
Trade suspension	The number of times of trading suspension excluding suspensions because of shareholders meeting and release of financial reports.
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.

Appendix B. Model Specification and Estimates

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

$$R_{i,t} = \mu + \phi_{1i}R_{i,t-1} + \phi_{2i}R_{i,t-2} + \epsilon_{i,t}, \tag{7}$$

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 $\epsilon_{i,t}$:

$$\begin{aligned} \epsilon_{i,t} &= \sigma_{i,t} z_{i,t} \\ \sigma^2_{i,t} &= \omega_i + \alpha_i \epsilon^2_{i,t-1} + \beta_i \sigma^2_{i,t-1} \end{aligned} \tag{8}$$

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

$$\Sigma_t = D_t \Gamma_t D_t, \tag{9}$$

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):

$$\tilde{\Gamma}_t = (1 - \lambda_1 - \lambda_2)\tilde{\Gamma} + \lambda_1 (z_{t-1} {z'}_{t-1}) + \lambda_2 \tilde{\Gamma}_{t-1}, \tag{10}$$

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

$$\Gamma_{ij,t} = \tilde{\Gamma}_{ij,t} / \sqrt{\tilde{\Gamma}_{ii,t} \tilde{\Gamma}_{jj,t}}, \tag{11}$$

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

$$CL(\lambda_1, \lambda_2) = \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{j>i} \ln f(\lambda_1, \lambda_2; z_{it}, z_{jt}) \tag{12}$$

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

Panel A reports summary statistics of annualized weekly USD returns of the 19 sample markets and MSCI World Index over the period from January 1995 to December 2017. Panel B reports summary statistics of firm-level variables used in the study for all non-financial listed A-share firms from 1995 to 2017. 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
MSCI World 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
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
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
QFII	37,967	0.106	0.308	0	0	0
In QFII	37,967	0.586	0.492	0	1	1
Trade suspension	31,992	1.602	2.355	0	1	2
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 Stock 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. All correlations are significant at 1% significance level. 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 Stock Markets

This table reports financial contagion of the 19 sample markets using different measures for the period from January 1995 to December 2017 based on weekly USD return. 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 shock weeks 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. 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. Then we calculated the mean of ADCC over the weeks in every event window. Last we take average across all global index shocks for each event window to calculate average ADCC. 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 diversification benefits of the 10 emerging markets (EMs) measured by Sharpe ratio (SR) based on weekly USD return over January 1995 to December 2017. In Panel A, we first calculate SR of the MSCI World Index (the Index) each year. Then we calculate SR of the optimal portfolios constructed by the Index and each of the 10 EMs. Last we calculate the difference of SR between the Index and the optimal portfolios to test whether adding each EM to the Index increase the SR. We report the increase in SR and the significance level from t-tests. We also report weight of each EM in the optimal portfolios. In Panel B, for each EM, we first calculate SR of the optimal portfolio constructed by the Index and the other 9 EMs every year. Then we calculate SR of the optimal portfolio constructed by the Index and all of the 10 EMs. Last we calculate the difference of SR between the two portfolios to test whether adding each EM to the portfolio can further increase SR. We report increase in SR and the significance level from t-tests. We also report weight of each EM in the optimal portfolios. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

	Panel A: global index with one EM		Panel B: global index with all EMs	
Market	Increase in SR	Weight	Increase in SR	Weight
China	0.089***	0.335	0.051***	0.227
South Africa	0.035**	0.417	0.001	0.030
South Korea	0.054***	0.412	0.005	0.068
India	0.056***	0.413	0.006**	0.064
Indonesia	0.062***	0.421	0.009**	0.110
Brazil	0.050***	0.435	0.002*	0.032
Mexico	0.056***	0.549	0.006*	0.104
Russia	0.078***	0.540	0.012**	0.102
Turkey	0.067***	0.421	0.012*	0.072
Argentina	0.052***	0.422	0.012**	0.074

Table 5: Government Intervention and Low Correlation of A-share Market

This table reports the effect of government intervention on A-share stock's connectedness with the global market using the following model: $Connectedness_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ is the connectedness of stock i with the global market in year t, $Policy\ sensitivity_{it}$ is a variable constructed to measure stock i's policy sensitivity in year t, and ω and λ are firm and year fixed effect. In column (1) and (2), *Connectedness* is measured using the correlation of stock i with the MSCI World Index (the Index) in year t based on weekly USD return (*Correlation*). In column (3) and (4), *Connectedness* 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: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock i in week k, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index. *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. *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 defined in Appendix A. All variables are winsorized at 1% to 99% except dummy variables. The standard errors are two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

	Dep. Var: *Correlation*		Dep. Var: *Global beta*	
	(1)	(2)	(3)	(4)
*Policy sensitivity*1	-0.012***		-0.054***	
	(0.003)		(0.012)	
*Policy sensitivity*2		-0.014**		-0.062**
		(0.006)		(0.030)
Firm size	0.004***	0.004**	0.018**	0.019**
	(0.002)	(0.002)	(0.008)	(0.009)
Volatility	-0.242***	-0.242***	0.974**	1.591***
	(0.055)	(0.062)	(0.410)	(0.464)
ROE	-0.006	-0.002	0.008	0.015
	(0.005)	(0.005)	(0.025)	(0.027)
Leverage	-0.000	-0.001	-0.019	-0.034
	(0.006)	(0.006)	(0.029)	(0.032)
B/M	0.002	-0.002	-0.050*	-0.061*
	(0.006)	(0.007)	(0.029)	(0.032)
Tangibility	0.038***	0.027*	0.135*	0.114
	(0.015)	(0.015)	(0.075)	(0.081)
Firm age	0.010*	0.012*	0.024	0.031
	(0.005)	(0.007)	(0.022)	(0.030)
AH cross-listed	0.002	-0.013	-0.060	-0.092
	(0.027)	(0.026)	(0.079)	(0.077)
SOE	0.002	-0.001	0.005	-0.002
	(0.003)	(0.004)	(0.015)	(0.017)
Constant	-0.279***	-0.039	-1.772***	-0.470**
	(0.036)	(0.043)	(0.172)	(0.209)
N	33,615	30,051	33,615	30,051
Adj. R^2	0.470	0.473	0.438	0.416

Table 6: Disconnection with Real Economy and Low Correlation 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 using the following model: $Connectedness_{it} = \beta_0 + \beta_1 \times Economy\ connection_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ is the connectedness of stock i with the global market in year t, $Economy\ connection_{it}$ is a variable constructed to measure stock i's connection with the real economy in year t, and ω and λ are firm and year fixed effect. In column (1) and (2), *Connectedness* is measured using the correlation of stock i with the MSCI World Index (the Index) in year t based on weekly USD return (*Correlation*). In column (3) and (4), *Connectedness* 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: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock i in week k, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index. *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 in year t; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). *Economy connection*2 is constructed the same as *Economy connection*1 except that we use the one-quarter lagged stock return when calculating the correlation. 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 two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

	Dep. Var: *Correlation*		Dep. Var: *Global beta*	
	(1)	(2)	(3)	(4)
*Economy connection*1	0.011***		0.038***	
	(0.003)		(0.013)	
*Economy connection*2		0.024***		0.077***
		(0.003)		(0.014)
Firm size	0.005***	0.005***	0.020**	0.021***
	(0.002)	(0.002)	(0.008)	(0.008)
Volatility	-0.262***	-0.265***	0.852**	0.844**
	(0.056)	(0.055)	(0.415)	(0.415)
ROE	-0.007	-0.007	0.003	0.003
	(0.005)	(0.005)	(0.025)	(0.025)
Leverage	-0.001	-0.000	-0.021	-0.020
	(0.006)	(0.006)	(0.029)	(0.029)
B/M	-0.000	-0.003	-0.060**	-0.068**
	(0.006)	(0.006)	(0.029)	(0.029)
Tangibility	0.038***	0.037**	0.135*	0.131*
	(0.015)	(0.015)	(0.075)	(0.075)
Firm age	0.010*	0.011**	0.024	0.028
	(0.005)	(0.005)	(0.022)	(0.022)
AH cross-listed	0.002	0.002	-0.060	-0.059
	(0.027)	(0.026)	(0.080)	(0.078)
SOE	0.002	0.002	0.008	0.006
	(0.003)	(0.003)	(0.015)	(0.015)
Constant	-0.295***	-0.303***	-1.834***	-1.859***
	(0.036)	(0.036)	(0.174)	(0.173)
N	33,621	33,621	33,621	33,621
Adj. R^2	0.469	0.470	0.437	0.437

Table 7: Foreign Ownership and Low Correlation 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 results of the full sample. Column (1) and (3) report results using the following regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times QFII_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ is the connectedness of stock i with the global market in year t, $QFII_it$ 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, and ω and λ are firm and year fixed effect. Column (2) and (4) report results using the following difference-in-difference regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times In\ QFII_i \times Post + Controls_{it} + \omega + \lambda + \epsilon_{it}$, 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, and $Post$ is a dummy variable which is equal to 1 after stock i first has QFII holdings and 0 otherwise. In column (1) and (2), *Connectedness* is measured using the correlation of stock i with the MSCI World Index (the Index) in year t based on weekly USD return (*Correlation*). In column (3) and (4), *Connectedness* 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: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock i in week k, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index. The sample includes all non-financial A-share firms from 1995 to 2017. Panel B compares connectedness with global market of QFII held stocks and the other stocks from 2003 to 2017. We divide all A-share stocks into two groups every year based on their $QFII$. Then we calculate the weekly market-weighted USD return of each group as the portfolio return. We compare correlation and average dynamic conditional correlation (DCC) of the two portfolios with the Index, and average bottom coexceedances of the two portfolios with the other 18 sample markets, and the diversification benefits of the two portfolios. Average DCC is the time series average of the weekly DCC of the portfolio with the Index. 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. To measure diversification benefits, we calculate the increase in SR of the Index after adding each portfolio into the Index. We also report significance levels of the differences between the two portfolios from t-tests. Panel C report results for high and low policy sensitivity sub-samples and high and low real economy connection sub-samples. We divide all stocks into high and low policy sensitivity groups each year based on *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). We then divide all stocks into high and low real economy connection groups each year based on *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). All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Table 7 Continued

Panel A: full sample regression	Dep. Var: *Correlation*		Dep. Var: *Global beta*	
	(1)	(2)	(3)	(4)
QFII	0.006**		0.021*	
	(0.003)		(0.012)	
In QFII $\times$ *Post*		0.010***		0.039***
		(0.003)		(0.012)
Firm size	0.004**	0.004**	0.018**	0.017**
	(0.002)	(0.002)	(0.008)	(0.008)
Volatility	-0.256***	-0.252***	0.873**	0.889**
	(0.055)	(0.056)	(0.415)	(0.415)
ROE	-0.007	-0.007	0.002	0.003
	(0.005)	(0.005)	(0.025)	(0.025)
Leverage	0.000	0.001	-0.019	-0.016
	(0.006)	(0.006)	(0.029)	(0.029)
B/M	0.002	0.002	-0.052*	-0.051*
	(0.006)	(0.006)	(0.029)	(0.029)
Tangibility	0.036**	0.037**	0.129*	0.131*
	(0.015)	(0.015)	(0.075)	(0.075)
Firm age	0.010*	0.009*	0.024	0.021
	(0.005)	(0.005)	(0.022)	(0.022)
AH cross-listed	0.003	0.002	-0.056	-0.058
	(0.027)	(0.027)	(0.081)	(0.080)
SOE	0.002	0.001	0.006	0.004
	(0.003)	(0.003)	(0.015)	(0.015)
Constant	-0.281***	-0.272***	-1.785***	-1.743***
	(0.036)	(0.036)	(0.174)	(0.175)
N	33,621	33,621	33,621	33,621
Adj. R^2	0.469	0.469	0.437	0.437

Panel B: connectedness with global market of QFII held stocks	Correlation	Average DCC	Bottom coexceedance	Increase in SR
QFII	0.076	0.100	0.085	0.109
No QFII	0.061	0.065	0.059	0.114
Difference	0.016*	0.034***	0.025***	0.005

Table 7 Continued

Panel C: sub-sample regression				
	Dep. Var: *Correlation*			
	High policy sensitivity	Low policy sensitivity	High economy connection	Low economy connection
	(1)	(2)	(3)	(4)
$In\ QFII \times Post$	0.008*	0.011***	0.009**	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)
Firm size	0.005**	0.003	0.002	0.004
	(0.003)	(0.002)	(0.002)	(0.002)
Volatility	-0.169**	-0.321***	-0.244***	-0.197**
	(0.086)	(0.080)	(0.086)	(0.080)
ROE	-0.003	-0.007	-0.017**	0.004
	(0.008)	(0.007)	(0.007)	(0.008)
Leverage	0.004	-0.005	-0.005	0.008
	(0.009)	(0.008)	(0.008)	(0.008)
B/M	0.011	-0.006	0.019**	-0.002
	(0.010)	(0.009)	(0.010)	(0.009)
Tangibility	0.042*	0.035*	0.019	0.042*
	(0.024)	(0.020)	(0.021)	(0.022)
Firm age	0.010	0.007	0.006	0.010
	(0.008)	(0.008)	(0.008)	(0.007)
AH cross-listed	0.017	-0.025	0.027	-0.024
	(0.038)	(0.027)	(0.024)	(0.040)
SOE	-0.001	0.002	0.001	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	-0.351***	-0.215***	-0.186***	-0.299***
	(0.056)	(0.051)	(0.053)	(0.051)
N	16,292	17,329	15,970	17,651
Adj. R^2	0.461	0.482	0.474	0.483

Table 8: Connectedness with Global market of A-H Cross-listed Stocks

This table compares connectedness with the global market of A-H cross-listed A-share stocks and their counterpart H-share stocks. We first calculate the weekly market-weighted USD return of the A-share stocks and H-share stocks as the portfolio return. We compare correlation and average dynamic conditional correlation (DCC) of the two portfolios with the MSCI World Index, and average bottom coexceedances of the two portfolios with the other 18 sample markets. Average DCC is the time series average of the weekly DCC of the portfolio with the Index. 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. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

	Correlation	Average DCC	Bottom coexceedance
A-share	0.118	0.110	0.166
H-share	0.350	0.333	0.266
Difference	-0.232***	-0.224***	-0.099***

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 Connect) and Shenzhen-Hong Hong Stock Connect Program (SZ-HK Connect). Panel A reports regression results using the following difference-in-difference regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times HK\ connected_i \times Post + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ 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 firm and year fixed effect. In column (1) and (2), *Connectedness* is measured using the correlation of stock i with the MSCI World Index (the Index) in year t based on weekly USD return (*Correlation*). In column (3) and (4), *Connectedness* 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: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock i in week k, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index. The full sample includes stocks in the Shanghai Stock Exchange from three years before to three years after the introduction of SH-HK Connect (2012-2017) and stocks in the Shenzhen Stock Exchange from one year before to one year after the introduction of SZ-HK Connect (2016-2017). We also report separate results for stocks in the Shanghai Stock Exchange (SSE). Panel B compares connectedness with the global market of stocks in the Stock Connect Programs and those not in the Programs. We divide all A-share stocks into two groups every year based on their *HK connected*. Then we calculate the weekly market-weighted USD return of each group as the portfolio return. We compare correlation and average dynamic conditional correlation (DCC) of the two portfolios with the Index, average bottom coexceedances of the two portfolios with the other 18 sample markets, and the diversification benefits of the two portfolios. Average DCC is the time series average of the weekly DCC of the portfolio with the Index. 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. To measure diversification benefits, we calculate the increase in SR of the Index after adding each portfolio into the Index. We also report significance levels of the differences between the two portfolios from t-tests. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Table 9 Continued

Panel A: regression results	Dep. Var: *Correlation*		Dep. Var: *Global beta*	
	Full Sample	SSE stocks	Full Sample	SSE stocks
	(1)	(2)	(3)	(4)
$HK\ connected \times Post$	0.000	0.012	-0.042	-0.018
	(0.007)	(0.009)	(0.037)	(0.049)
Firm size	-0.018**	-0.020**	-0.053	-0.048
	(0.008)	(0.009)	(0.055)	(0.055)
Volatility	-0.690***	-0.516***	0.418	0.597
	(0.156)	(0.167)	(1.297)	(1.363)
ROE	0.023	0.010	0.179	0.074
	(0.017)	(0.015)	(0.115)	(0.096)
Leverage	0.067***	0.036	0.343**	0.150
	(0.024)	(0.026)	(0.156)	(0.157)
B/M	-0.041*	-0.039	-0.243*	-0.150
	(0.024)	(0.026)	(0.135)	(0.138)
Tangibility	-0.033	-0.053	-0.277	-0.345
	(0.054)	(0.067)	(0.322)	(0.377)
Firm age	-0.137**	-0.163***	-0.774***	-0.717***
	(0.056)	(0.060)	(0.274)	(0.273)
AH cross-listed	0.049***	0.046***	-0.120	-0.132
	(0.014)	(0.016)	(0.213)	(0.219)
SOE	-0.009	-0.014	-0.054	-0.074
	(0.019)	(0.020)	(0.108)	(0.116)
Constant	0.832***	1.016***	3.495**	3.470**
	(0.244)	(0.271)	(1.475)	(1.521)
N	7,724	4,777	7,724	4,777
Adj. R^2	0.633	0.580	0.514	0.489

Panel B: connectedness with global market of stocks in Stock Connect Program	Correlation	Average DCC	Bottom coexceedance	Increase in SR
Connected	0.275	0.070	0.286	0.093
Not connected	0.232	0.060	0.286	0.119
Difference	0.043	0.010***	0	-0.026

Table 10: Policy Sensitivity and A-share Stock Trading Suspension

This table reports the relation of policy sensitivity and A-share stock's trading suspension using the following regression: $Trade\ suspension_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Trade\ suspension_{it}$ is the number of times of trading suspension except suspensions because of shareholders meeting and release of financial reports of stock i in year t, $Policy\ sensitivity_{it}$ is a variable constructed to measure stock i's policy sensitivity in year t, and ω and λ are firm and year fixed effect. $Policy\ sensitivity1$ 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). $Policy\ sensitivity2$ 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) and (2), the sample includes all non-financial A-share firms from 2002 to 2017. In column (3) and (4), the sample includes all non-financial A-share firms during the crisis period (global financial crisis and Euro debt crisis) from 2008 to 2012. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

	Dep. Var: *Trade suspension*			
	Full sample period		Crisis period	
	(1)	(2)	(3)	(4)
Policy sensitivity1	0.143***		-0.062	
	(0.040)		(0.086)	
Policy sensitivity2		0.799***		0.291
		(0.091)		(0.188)
Firm size	-0.282***	-0.293***	-0.324**	-0.207***
	(0.043)	(0.043)	(0.130)	(0.031)
Volatility	20.449***	18.272***	37.729***	33.186***
	(0.855)	(0.897)	(2.301)	(1.892)
ROE	0.202	0.193	0.196	-0.903***
	(0.134)	(0.134)	(0.291)	(0.128)
Leverage	2.644***	2.595***	2.847***	3.481***
	(0.161)	(0.162)	(0.427)	(0.120)
B/M	-1.446***	-1.338***	-1.739***	-2.323***
	(0.122)	(0.123)	(0.307)	(0.129)
Tangibility	-1.861***	-1.796***	-1.663	-1.071**
	(0.282)	(0.282)	(1.209)	(0.449)
Firm age	0.738***	0.623***	1.855***	0.361***
	(0.133)	(0.133)	(0.419)	(0.051)
AH cross-listed	0.175	0.186	0.324	0.454***
	(0.216)	(0.211)	(0.707)	(0.127)
SOE	-0.129	-0.133	-0.274	-0.100
	(0.084)	(0.084)	(0.274)	(0.069)
Constant	4.674***	4.787***	4.115	5.385***
	(0.970)	(0.968)	(3.134)	(0.753)
N	29,031	29,006	8,941	8,932
Adj. R^2	0.381	0.383	0.339	0.393

Table 11: 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 stock i's policy sensitivity in year t, and ω and λ are firm and year fixed effect. We use stock return in column (1) and (2) and Sharpe ratio (SR) in column (3) and (4) to measure $Performance$. $Policy\ sensitivity1$ 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. $Policy\ sensitivity2$ 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 two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

	Dep. Var: Return		Dep. Var: SR	
	(1)	(2)	(3)	(4)
$Policy\ sensitivity1$	0.024***		0.004**	
	(0.009)		(0.002)	
$Policy\ sensitivity2$		0.121***		0.047***
		(0.020)		(0.005)
Firm size	0.130***	0.117***	0.033***	0.032***
	(0.006)	(0.007)	(0.002)	(0.002)
Volatility	9.110***	8.573***	1.231***	1.064***
	(0.236)	(0.262)	(0.042)	(0.045)
ROE	0.272***	0.245***	0.064***	0.059***
	(0.021)	(0.022)	(0.005)	(0.005)
Leverage	0.039	0.042	0.005	0.006
	(0.024)	(0.026)	(0.006)	(0.006)
B/M	-1.141***	-1.150***	-0.294***	-0.303***
	(0.023)	(0.026)	(0.006)	(0.006)
Tangibility	0.140***	0.109*	0.064***	0.061***
	(0.054)	(0.057)	(0.011)	(0.012)
Firm age	0.080***	-0.000	0.019***	0.002
	(0.016)	(0.024)	(0.004)	(0.006)
AH cross-listed	0.075	0.084	0.039**	0.038**
	(0.070)	(0.074)	(0.018)	(0.019)
SOE	0.014	0.005	0.004	-0.000
	(0.011)	(0.012)	(0.003)	(0.003)
Constant	-3.051***	-2.802***	-0.698***	-0.805***
	(0.140)	(0.170)	(0.032)	(0.040)
N	33,068	29,511	33,615	30,051
Adj. R^2	0.707	0.726	0.683	0.694

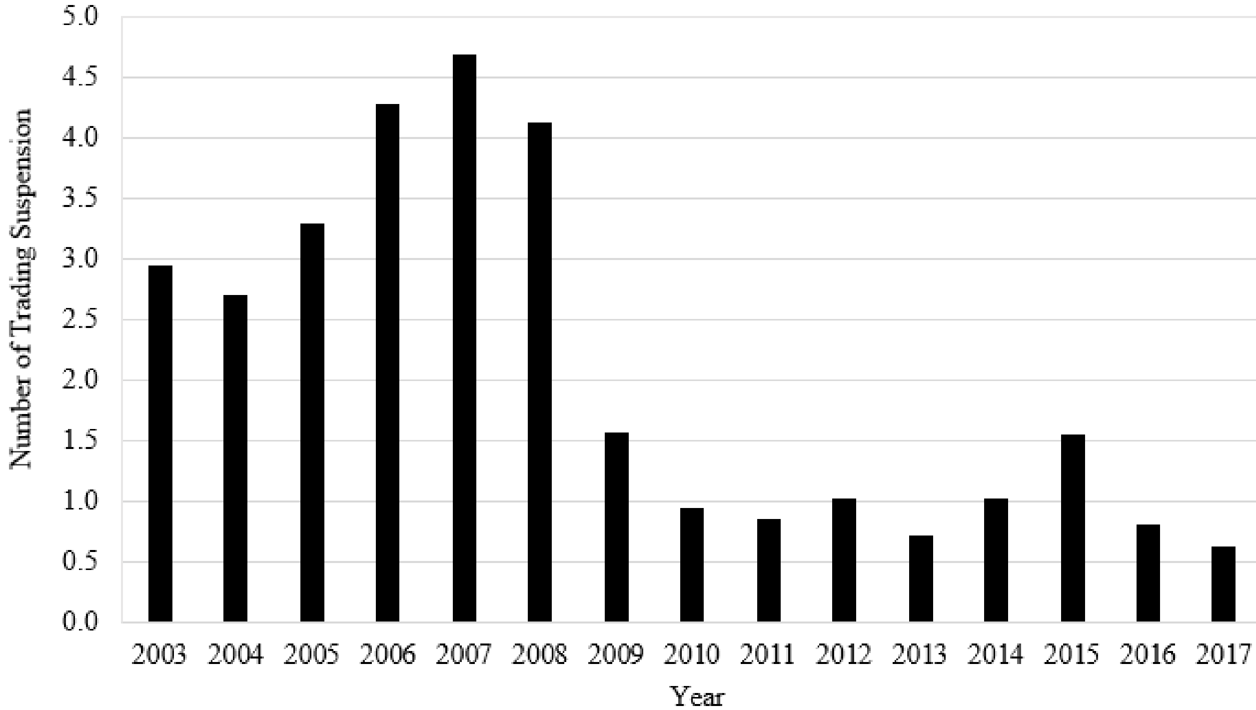
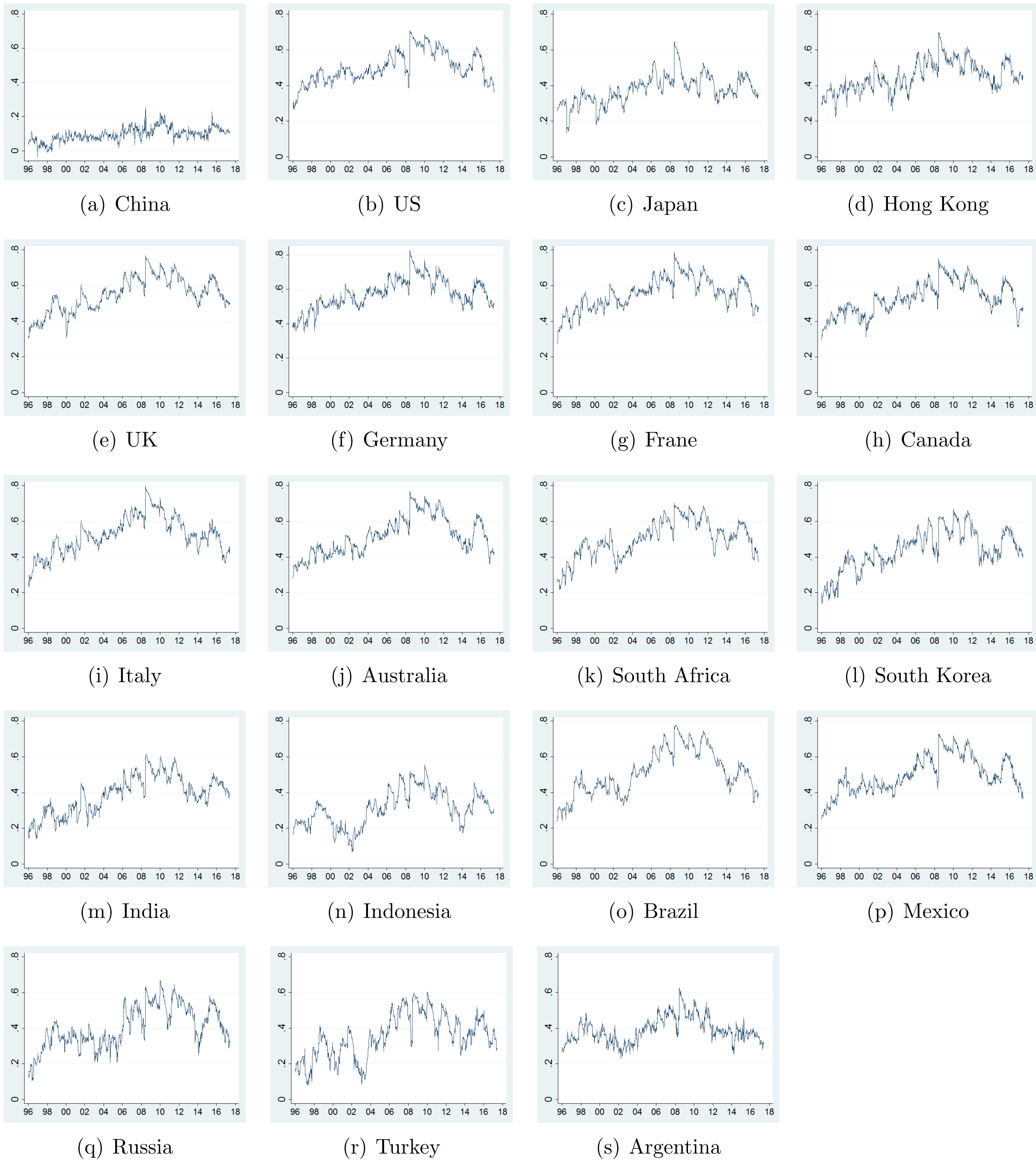


Fig. 1. Trading Suspension of A-share Market

This figure plots the average number of times of trading suspension excluding suspension because of shareholder meeting and financial report release of A-share stocks from 2003 to 2017. Data source: CSMAR and DATASTREAM.



(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. 2. Dynamic Conditional Correlations of Stock Markets

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

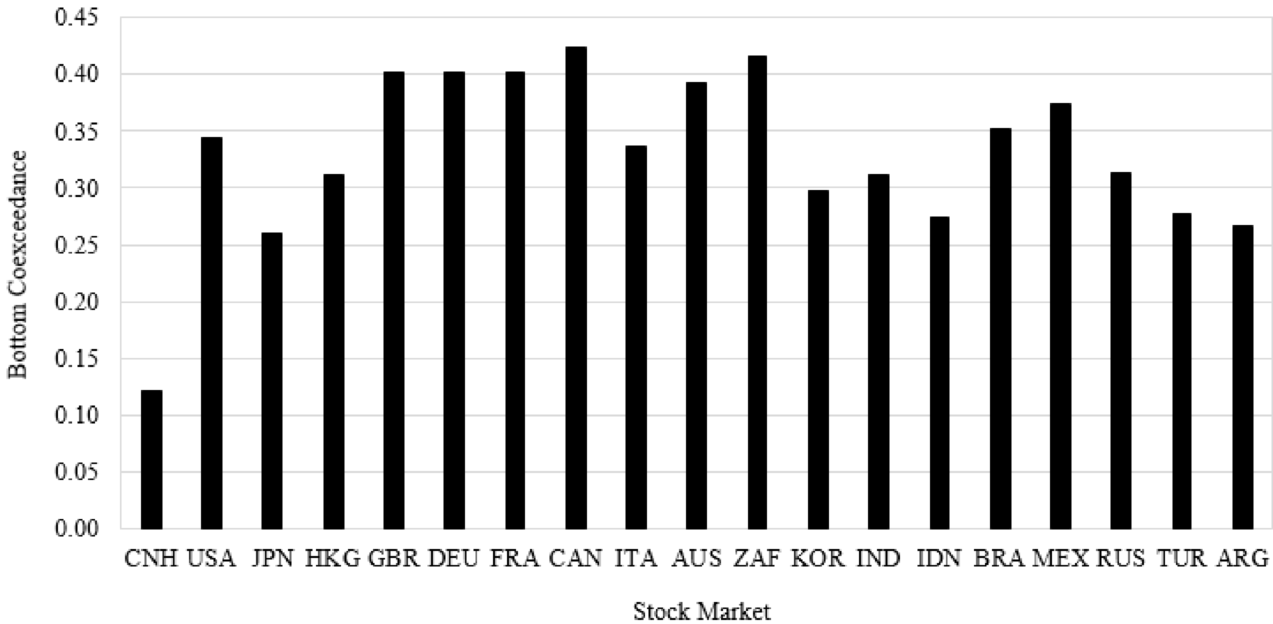
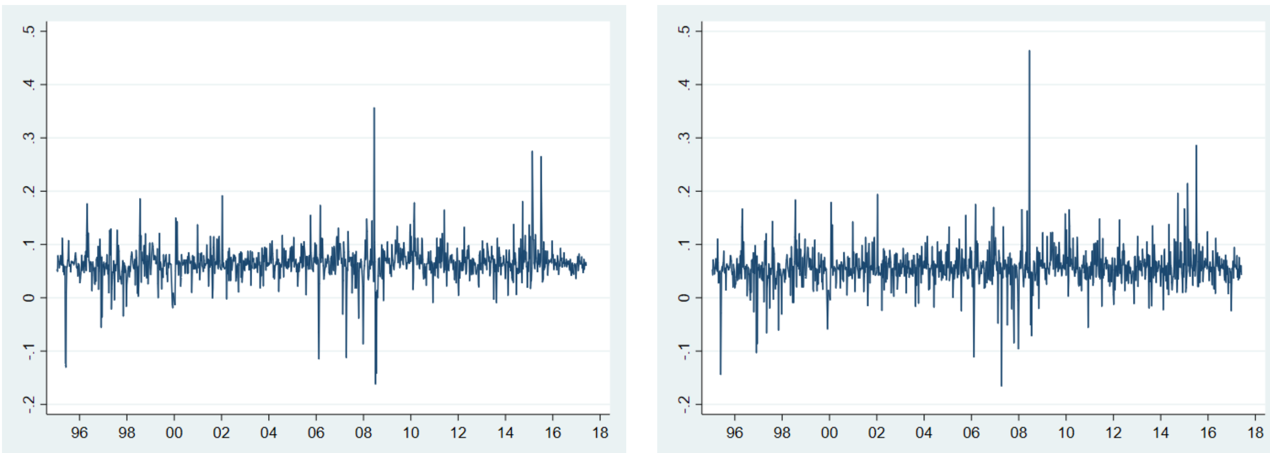


Fig. 3. Bottom Coexceedances of Stock Markets

This figure plots the bottom coexceedances of the 19 sample markets for the period from January 1995 to December 2017. 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. For each market, we report its average bottom coexceedance with the other 18 sample markets. Data source: CSMAR and DATASTREAM.



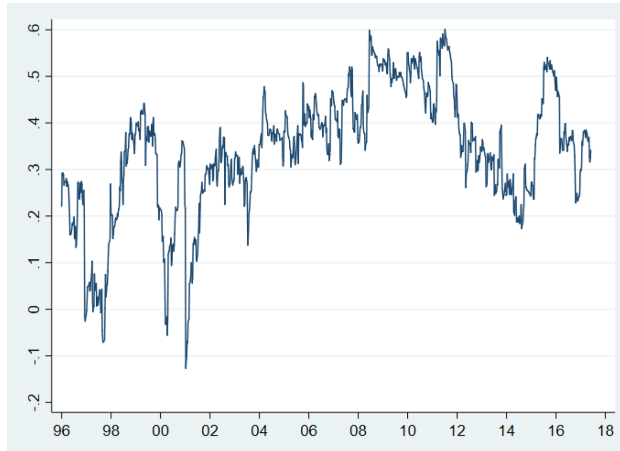
(a) Connected Stocks

(b) Other Stocks

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

This figure compares dynamic conditional correlations (DCC) with MSCI World Index of A-share stocks in the Shanghai-Hong Kong Stock Connect Program and Shenzhen-Hong Kong Stock Connect Program to the other stocks based on weekly return. Data source: CSMAR and DATASTREAM.

(a) A-share Stocks



(b) H-share Stocks

Fig. 5. Dynamic Conditional Correlations of A-H Cross-listed Stocks with Global Market

This figure compares dynamic conditional correlations (DCC) with MSCI World Index of A-H cross-listed A-share stocks to the their counterpart H-share stocks based on weekly return. Data source: CSMAR and DATASTREAM.

Internet Appendix

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

March 4, 2019

Table IA1: Correlations and Financial Contagion of Stock 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. All correlations are significant at 1% significance level. 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: Diversification Benefits: Sharpe Ratio from 2006 to 2017

This table reports diversification benefits of the 10 emerging markets (EMs) measured by Sharpe ratio (SR) based on weekly USD return over January 2006 to December 2017. In Panel A, we first calculate SR of the MSCI World Index (the Index) each year. Then we calculate SR of the optimal portfolios constructed by the Index and each of the 10 EMs. Last we calculate the difference of SR between the Index and the optimal portfolios to test whether adding each EM to the Index increase the SR. We report the increase in SR and the significance level from t-tests. We also report weight of each EM in the optimal portfolios. In Panel B, for each EM, we first calculate SR of the optimal portfolio constructed by the Index and the other 9 EMs every year. Then we calculate SR of the optimal portfolio constructed by the Index and all of the 10 EMs. Last we calculate the difference of SR between the two portfolios to test whether adding each EM to the portfolio can further increase SR. We report increase in SR and the significance level from t-tests. We also report weight of each EM in the optimal portfolios. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

	Panel A: global index with one EM		Panel B: global index with all EMs	
Market	Increase in SR	Weight	Increase in SR	Weight
China	0.114**	0.386	0.063**	0.273
South Africa	0.026**	0.514	0.000	0.000
South Korea	0.030**	0.430	0.000	0.005
India	0.051**	0.442	0.004	0.055
Indonesia	0.067***	0.525	0.012	0.152
Brazil	0.046*	0.346	0.001	0.032
Mexico	0.026**	0.479	0.002	0.084
Russia	0.037**	0.545	0.006	0.079
Turkey	0.046**	0.449	0.010	0.092
Argentina	0.054**	0.434	0.016*	0.108

Table IA3: Regression Results of Robustness Tests

This table reports regression results of the robustness tests for Table 5 and 6. Panel A reports the effect of government intervention on A-share stocks' connectedness with the global market using the following regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ is the connectedness of stock i with the global market in year t, $Policy\ sensitivity_{it}$ is a variable constructed to measure stock i's policy sensitivity in year t, and ω and λ are firm and year fixed effect. In column (1) and (2), *Connectedness* 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 (3) and (4), *Connectedness* 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: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta1_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock i in week k, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index. *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. *Policy sensitivity*2 is the sum of 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. Panel B reports the effect of disconnection with the real economy on A-share stock's connectedness with the global market using the following regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times Economy\ connection_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Economy\ connection_{it}$ is a variable constructed to measure stock i's connection with the real economy in year t. *Economy connection*1 is the correlation of stock i's quarterly return with GDP growth rate in year t. *Economy connection*2 the correlation of stock i's one-quarter lagged quarterly return with GDP growth rate in year t. 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 two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Table IA3 Continued

Panel A: government intervention				
	Dep. Var: *Correlation*		Dep. Var: *Global beta*	
	(1)	(2)	(3)	(4)
*Policy sensitivity*1	-0.020***		-0.086***	
	(0.005)		(0.024)	
*Policy sensitivity*2		-0.123*		-0.524
		(0.066)		(0.364)
Firm size	0.004***	0.004**	0.018**	0.019**
	(0.002)	(0.002)	(0.008)	(0.009)
Volatility	-0.239***	-0.237***	0.985**	1.599***
	(0.055)	(0.063)	(0.410)	(0.464)
ROE	-0.006	-0.002	0.008	0.014
	(0.005)	(0.005)	(0.025)	(0.027)
Leverage	-0.000	-0.002	-0.019	-0.035
	(0.006)	(0.006)	(0.029)	(0.032)
B/M	0.002	-0.001	-0.050*	-0.059*
	(0.006)	(0.007)	(0.029)	(0.032)
Tangibility	0.038***	0.027*	0.135*	0.115
	(0.015)	(0.015)	(0.075)	(0.081)
Firm age	0.010*	0.011	0.024	0.028
	(0.005)	(0.007)	(0.022)	(0.030)
AH cross-listed	0.002	-0.013	-0.059	-0.090
	(0.027)	(0.026)	(0.079)	(0.078)
SOE	0.002	-0.001	0.005	-0.002
	(0.003)	(0.004)	(0.015)	(0.017)
Constant	-0.281***	-0.041	-1.783***	-0.480**
	(0.036)	(0.043)	(0.172)	(0.208)
N	33,615	30,051	33,615	30,051
Adj. R^2	0.470	0.473	0.438	0.416

Table IA3 Continued

Panel B: Disconnection with the real economy	Dep. Var: *Correlation*		Dep. Var: *Global beta*	
	(1)	(2)	(3)	(4)
*Economy connection*1	0.008***		0.016**	
	(0.002)		(0.008)	
*Economy connection*2		0.014***		0.046***
		(0.002)		(0.009)
Firm size	0.005***	0.005***	0.018**	0.020***
	(0.002)	(0.002)	(0.008)	(0.008)
Volatility	-0.264***	-0.268***	0.957**	0.925**
	(0.053)	(0.053)	(0.395)	(0.395)
ROE	-0.005	-0.006	0.009	0.007
	(0.005)	(0.005)	(0.024)	(0.024)
Leverage	-0.002	-0.002	-0.035	-0.035
	(0.006)	(0.006)	(0.027)	(0.027)
B/M	0.001	-0.002	-0.047	-0.060**
	(0.006)	(0.006)	(0.028)	(0.029)
Tangibility	0.043***	0.040***	0.169**	0.160**
	(0.014)	(0.014)	(0.072)	(0.072)
Firm age	0.009*	0.010*	0.020	0.021
	(0.005)	(0.005)	(0.021)	(0.021)
AH cross-listed	0.002	0.004	-0.054	-0.051
	(0.027)	(0.026)	(0.080)	(0.077)
SOE	0.001	0.000	0.002	0.000
	(0.003)	(0.003)	(0.015)	(0.015)
Constant	-0.291***	-0.285***	-1.820***	-1.802***
	(0.035)	(0.035)	(0.166)	(0.166)
N	33,461	33,437	33,461	33,437
Adj. R^2	0.473	0.475	0.448	0.449

Table IA4: Determinants of Low Correlation of A-share stocks with Global Market

This table reports the effect of government intervention, disconnection with the real economy, and foreign ownership on A-share stock's connectedness with the global market using the following regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + \beta_2 \times Economy\ connection_{it} + \beta_3 \times QFII + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ is the connectedness of stock i with the global market in year t, $Policy\ sensitivity_{it}$ is a variable constructed to measure stock i's policy sensitivity in year t, $Economy\ connection_{it}$ is a variable constructed to measure stock i's connections with the real economy 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, and ω and λ are firm and year fixed effect. In column (1), (2), (3), and (4), *Connectedness* 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 (5), (6), (7), and (8), *Connectedness* 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: $R_{i,k} - R_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R_{f,k}) + \epsilon_i$, where $R_{i,k}$ is USD return of stock i in week k, $R_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index. $Policy\ sensitivity1$ 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). $Policy\ sensitivity2$ 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). $Economy\ connection1$ 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). $Economy\ connection2$ is constructed the same as $Economy\ connection1$ except that we use one-quarter lagged stock return when calculating the correlation. 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 two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Table IA4 Continued

	Dep. Var: *Correlation*				Dep. Var: *Global beta*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*Policy sensitivity*1	-0.013***		-0.012***		-0.055***		-0.053***	
	(0.003)		(0.003)		(0.012)		(0.012)	
*Policy sensitivity*2		-0.014**		-0.013**		-0.063**		-0.060**
		(0.006)		(0.006)		(0.030)		(0.030)
*Economy connection*1	0.012***	0.006*			0.041***	0.020		
	(0.003)	(0.003)			(0.013)	(0.014)		
*Economy connection*2			0.024***	0.030***			0.078***	0.095***
			(0.003)	(0.003)			(0.014)	(0.015)
QFII	0.007**	0.006**	0.007***	0.006**	0.021*	0.021*	0.022*	0.022*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.012)	(0.012)	(0.012)	(0.012)
Firm size	0.004**	0.004*	0.004***	0.004**	0.018**	0.019**	0.019**	0.020**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)	(0.009)	(0.008)	(0.009)
Volatility	-0.244***	-0.242***	-0.247***	-0.254***	0.964**	1.592***	0.957**	1.555***
	(0.055)	(0.062)	(0.055)	(0.061)	(0.411)	(0.464)	(0.410)	(0.464)
ROE	-0.006	-0.002	-0.006	-0.002	0.008	0.014	0.007	0.014
	(0.005)	(0.005)	(0.005)	(0.005)	(0.025)	(0.027)	(0.025)	(0.027)
Leverage	-0.000	-0.001	0.000	-0.001	-0.019	-0.033	-0.018	-0.034
	(0.006)	(0.006)	(0.006)	(0.006)	(0.029)	(0.032)	(0.029)	(0.032)
B/M	0.002	-0.002	-0.001	-0.006	-0.052*	-0.060*	-0.060**	-0.075**
	(0.006)	(0.007)	(0.006)	(0.007)	(0.029)	(0.032)	(0.029)	(0.032)
Tangibility	0.039***	0.027*	0.037**	0.026*	0.138*	0.114	0.133*	0.110
	(0.015)	(0.015)	(0.015)	(0.015)	(0.075)	(0.081)	(0.075)	(0.081)
Firm age	0.010*	0.012	0.011**	0.012*	0.022	0.029	0.026	0.030
	(0.005)	(0.007)	(0.005)	(0.007)	(0.022)	(0.030)	(0.022)	(0.030)
AH cross-listed	0.001	-0.014	0.001	-0.014	-0.063	-0.093	-0.062	-0.096
	(0.027)	(0.026)	(0.026)	(0.025)	(0.080)	(0.078)	(0.078)	(0.076)
SOE	0.001	-0.001	0.001	-0.002	0.004	-0.003	0.003	-0.004
	(0.003)	(0.004)	(0.003)	(0.004)	(0.015)	(0.017)	(0.015)	(0.017)
Constant	-0.282***	-0.038	-0.289***	-0.056	-1.783***	-0.464**	-1.806***	-0.519**
	(0.036)	(0.043)	(0.036)	(0.043)	(0.173)	(0.210)	(0.173)	(0.209)
N	33,615	30,051	33,615	30,051	33,615	30,051	33,615	30,051
Adj. R^2	0.470	0.473	0.471	0.475	0.439	0.416	0.439	0.417