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

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Abstract

China's stock market (the "A share market") has a lower correlation with the global market and is less affected by international financial contagions than any other major economy. The inclusion of mainland China stocks into an international portfolio increases its Sharpe ratio. However, we find that Chinese stocks providing the most diversification benefits also carry the most policy risk for international investors. Holding Chinese stocks listed in Hong Kong does not reap the same diversification benefits. While global market integration and the increase in foreign ownership can diminish diversification benefits, mainland China stocks still provide valuable diversification opportunities for international investors up till the most recent time in late 2010s.

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1. Introduction

Theoretical models of portfolio selection suggest that diversification can reduce risk and that the degree of risk reduction depends on the return correlations (e.g., Markowitz, 1952). Risk reduction can be facilitated by diversifying portfolios internationally (e.g., Grubel, 1968; Levy and Sarnat, 1970). The 2008 global crisis revealed the 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 the stock market in 1990, and its economy has also grown dramatically since then. By 2019, China's stock market was the second largest in the worldwide with over $8.7 trillion market capitalization. The stock price in China is as informative about future profits as those in the US market (Carpenter, Lu, and Whitelaw, 2021).[1] Despite tensions between China and the US, foreign investors show great interest in the China A-share market.[2] However, their actual exposure remains small. Voluntary trading suspensions and Chinese-style initial public offerings (IPOs) (Qian, Ritter, and Shao, 2021), such as the recent cancellation of Ant Financial's IPO, raise additional concerns about accessing China A shares. China's shadow banks that fueled leveraged stock investing and 2015-2016 stock market turbulence sharpen investors' fears over the financial system's fragility.[3] In this paper, we conduct a comprehensive analysis of the value of China's stock market for international portfolio diversification and the role of policy risks in affecting diversification benefits.

Foreign investors can gain exposure to China through passive instruments such as buying emerging market indices, or China exchanged-traded funds (ETFs). However, Chinese

[1] Increasingly, papers study the characteristics of Chinese capital markets. Hu, Pan, and Wang (2020) review the institutional and empirical facts about the Chinese capital market. While Hu, Chen, Shao, and Wang (2019) find no robust value effect based on book-to-market cross returns in China's stock market, Liu, Stambaugh, and Yuan (2019) construct size and value factors for China considering the special characteristics.

[2] For example, see https://medium.com/william-blair-investment-management/china-a-too-big-to-ignore-132359bd5f40 and other reports by William Blair (2018).

[3] Allen, Qian, Tu, and Yu (2019) investigate China's shadow banking system. See also "Shadow lending crackdown looms over China's stock market," Financial Times, June 25, 2015.

exposure through the available emerging market index is limited. For example, J.P. Morgan Asset Management points out that "Global and emerging market equity investment managers are not always a reliable source of China exposure; some actually have zero exposure."[4] With China's financial market opening up, it is becoming easier for foreign investors to invest directly in Chinese stocks. Before 2003, foreign investors could only trade "offshore China" stocks through Chinese firms listed on the Hong Kong Stock Exchange (H shares) or American Depository Receipts (ADR) traded in the US. In contrast, B shares offered a way for foreign investors to access China's domestic stock market. However, "offshore China" stocks or B shares are dominated by state-owned enterprises or large stocks.[5] While A shares give greater access to small and mid-companies from various industries, which are important drivers of China's economic growth, they were off-limits to many of the international investors. Since 2003, foreign investors can access A shares through a qualified foreign institutional investors (QFII) program via license application and quotas. The 2005-2007 split-share structure reform further improved the tradability of A shares. QFII quotas were removed from June 2020 with a simplified process for routine repatriations to attract more foreign capital. The introduction of Stock Connect programs in 2014 and 2016 provides a new mechanism for foreign investors to invest A shares via Hong Kong.[6]

To investigate the attractiveness of China for international portfolio diversification, we first examine correlation benefits from investing in China's stock market and compare such benefits from investing in other developed markets or emerging markets. Using a cross-country sample from January 1995 to December 2017, we find that China's stock market has the lowest correlation with other markets compared with all other developed and emerging

[4]https://am.jpmorgan.com/us/en/asset-management/institutional/insights/portfolio-insights/equity/understanding-the-opportunity-in-chinese-equities/

[5]By the end of 2018, only 99 companies had B-shares, and the liquidity was much lower than that of A-shares.

[6]Stock Connect programs have lowered the transaction cost of accessing China A-shares to approximately 0.31%, including stamp duty, brokerage, and other fees. See https://www.sc.com/hk/invest/shanghai-hongkong-stock-connect-fees-levis.html. The inclusion of China A shares in the MSCI Emerging Markets Index and MSCI ACWI since June 2018 and the opening up futures trading for foreign investors in November 2020 could boost A shares access further.

markets. To analyze the time-series changes in correlations, we further employ the dynamic conditional correlation model of Engle (2002). We find that while cross-sectional correlations have been increasing, the correlations of emerging markets increased more than those of developed markets in the last two decades, consistent with the previous literature (e.g., Christoffersen, Errunza, Jacobs, and Langlois, 2012). However, the correlations of China with other markets remain low and stable throughout the sample period. The results suggest that China's stock market may offer valuable diversification benefits for international investors.

We next take the perspective of international investors with a well-diversified portfolio-(e.g., the MSCI World index, which includes 23 developed markets), as the benchmark portfolio and investigate whether adding China or other emerging market indices to their benchmark portfolio generates incremental performance benefits. We measure the incremental performance benefits as the change in Sharpe ratio. We find that adding China to the MSCI World index can increase the annual Sharpe ratio by 0.089. The increase in the Sharpe ratio is greater than that from other emerging markets. In addition, international investors have better access to China's stock market during the more recent period. To address the concern that the diversification benefit could be largely due to inaccessibility, we conduct additional analyses with a more recent sample period of 2006 to 2017 and continue to find lower correlation and a greater Sharpe ratio from China's stock market. Therefore, we find evidence that China's stock market offers international investors significant diversification benefits.

Diversification benefits are most valuable during economic downturns. Therefore, we further investigate whether China's stock market is less affected by negative global financial shocks. Specifically, we first identify global index shocks and compare the cumulative market returns of emerging markets around global index shocks. We find that unlike other emerging markets, China's stock market does not experience significant negative returns around global index shocks. In addition, we compare the dynamic conditional correlation of emerging markets with the global index during the index shock week and that prior to the shock week. We find that while all other emerging markets become more correlated with the global

market around global shocks, China does not show a significant increase in the correlation coefficient. Moreover, we follow Bae, Karolyi, and Stulz (2003) and use *coexceedance* to measure financial contagion. We define bottom coexceedance as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail returns of the indices. Our results suggest that China has the lowest coexceedance with other markets among all developed and emerging markets. These results provide additional evidence that China is less vulnerable to financial contagion and can provide valuable diversification benefits for international investors during global shocks.

Despite the diversification benefits, concerns on policy risks may prevent international investors from accessing China's stock market.[7] On the one hand, governments are likely to provide "insurance" against downside risk. Cieslak and Vissing-Jorgensen (2020) refer to this as the "Fed put" in the US, where the government responds to stock market slumps with a sequence of policy easings. In China, government interventions occur mostly after the stock market decline. There is likely more "government put" in China than in other countries.[8] On the other hand, government intervention faces a tradeoff between ensuring financial stability and improving price efficiency. Frequent interventions can distort market prices and raise concerns about trading freedom (Brunnermeier, Sockin, and Xiong, 2020; Song and Xiong, 2018). For example, the recent cancellation of Ant Financial's IPO surprised investors and chilled other IPO hopefuls. In July 2015, more than 1,400 companies suspended their Shanghai- and Shenzhen-trading shares, raising additional concerns about the ability to exit during the market plunge. Additional analysis suggests that while trading suspensions were more frequent before 2009 (see Figure 1), the average number of trading suspensions decreased in the most recent decade. In May 2016, China's two bourses introduced tougher

[7]We interpret policy risks as uncertainty in government policies that may affect the firm operation or cash flows and relevant institutional features that may affect investors' ability to transfer investment or capital gains.

[8]For example, during 2015, China's stock market crash, a state-backed "national team" was called on to support the market.

restrictions on voluntary trading suspensions to protect the interests of investors.

While country-specific policy risk can generate comovement among shares trading in the same country, it may reduce shares comovement with the international market and contribute to international diversification benefits. If policy changes largely move share stock prices, then stock prices would be less related to economic fundamentals. As a result, return patterns in the A share market would deviate from those in the global market. Would policy risk explain the low correlation between the A share market and the global portfolio?

To examine the role of policy risks in diversification benefits, in the spirit of Liu, Shu, and Wei (2017), we measure stocks' policy sensitivity based on the three-day cumulative abnormal return (CAR) of stocks around announcements of new regulatory documents issued by the China Securities Regulatory Commission, the main regulatory body of China's stock market. A larger absolute announcement return suggests higher policy sensitivity. We further construct two firm-level variables, *Correlation* and *Global beta*, to measure the connectedness of stocks with the global market. Then, we regress the stock connectedness measures on a proxy for stocks' policy sensitivity. The results suggest that the correlation with the global market for more policy-sensitive firms is 0.014 lower than that of a less sensitive firm, which is a 30.43% decrease relative to the average correlation.[9] In addition, we show that policy-sensitive stocks have higher stock returns and Sharpe ratios than other stocks, suggesting that a higher return compensates the potential policy risk.[10] In this sense, China's stock market is attractive for investors looking for portfolio diversification. Policy-sensitive stock brings both risks and rewards to international investors.

We conduct additional analysis based on A-H cross-listed stocks to better understand

[9]Given the mean Correlation for our sample firm is 0.046 (Table 1 Panel B), the coefficient of -0.014 suggests that compared with the least sensitive firms (Policy sensitivity=0), the correlation with the global market for the most policy sensitive firm (Policy sensitivity=1) is 0.014 lower, which is 0.014/0.046=30.43% of the average correlation. Alternatively, this number suggests that a one standard deviation increase in Policy sensitivity (0.268 from Table 1 Panel B) is associated with a 0.268×(-0.014)=-0.0038 change in the stock's correlation with the global market. Given the mean Correlation of 0.046 in Table 1 Panel B, this 0.0038 decrease in correlation represents 0.0038/0.046=8.26% decrease relative to the mean.

[10]A number of papers document that political risk is priced (e.g. Pástor and Veronesi, 2013; Liu et al., 2017; Brogaard, Dai, Ngo, and Zhang, 2020). We emphasize the role of policy-sensitive stocks in generating diversification benefits for international investors.

the sources of policy risks and their contributions to diversification benefits. From the international investors' perspective, policy risks may come from two sources: policy risks that affect firms' operation or cash flows or policy risks that affect firms' cost of financing or discount rate. Cross-listed stocks share identical firm fundamentals and thus provide a good laboratory to separate the above channels. In the sample of 98 cross-listed stocks, we find that A share stocks have a significantly lower correlation with the global market than their H share-listed counterparts. A share stocks provide greater diversification benefits than H share stocks. This result suggests that firm fundamentals alone cannot explain the low correlation of the A share market with the global market. Factors related to institutional features in listing markets that affect firm financing costs and discount rates play a greater role in explaining policy risks and the resulting diversification benefits.

With the global integration of capital markets, foreign investors may obtain better access to China's stock market. Regulators' efforts to moderate frictions through regulatory cooperation help integrate equity markets and boost cross-border equity investment (Silvers, 2020). The increase in common foreign ownership after the moderation of frictions may improve the comovement between Chinese stocks and the global market, resulting in decreased diversification benefits. To test the role of market integration in affecting diversification benefits from A share stocks, we identify A share-listed stocks held by QFII and use the QFII indicator as a proxy for foreign ownership. We find that, compared with non-QFII stocks, QFII stocks indeed have greater correlation and coexceedance with the global market. However, the correlation and coexceedance of QFII stocks are still much lower than those from other markets. Including both QFII holding and policy sensitivity measures in the regression analysis, we find that policy sensitivities have a larger economic magnitude in explaining the low correlation of China's stock market with other markets than that of foreign ownership.

This study contributes to three strands of literature. First, there is interrelated literature on international diversifications, stock comovements and contagions (e.g. Bekaert, Hodrick, and Zhang, 2009; Barberis, Shleifer, and Wurgler, 2005; Christoffersen et al., 2012). Given

the more integrated global market, some recent works attempt to search for investments that have relatively lower correlations with international markets and approaches to obtain this exposure (e.g., Eun, Huang, and Lai, 2008; Eun, Lai, de Roon, and Zhang, 2010; Bae, Elkamhi, and Simutin, 2019). While information-induced home bias may prevent investors from developing a globally diversified portfolio, investors can capture the information advantage of other countries by investing international equity funds with home-biased managers (Jagannathan, Jiao, and Karolyi, 2020). Unlike previous works, this study focuses on the role of China in international portfolio diversification, which has been much less studied thus far. We also explore contagions to China through stock markets and document that China's stock markets are relatively resistant to international financial contagion compared with other markets, which is new to the literature. While Bekaert, Harvey, Lundblad, and Siegel (2011) emphasize the role of a country's political risk profile in explaining the variation in equity market segmentation, we explore firm-level policy risk exposure of Chinese stocks and the resulting diversification benefits for international investors.

Furthermore, we contribute to the increasing literature on China's stock market (e.g., Huang and Zhu, 2015; Huang, Miao, and Wang, 2019; Allen, Qian, Shan, and Zhu, 2020; Liu, Wang, and Wei, 2021). In particular, Carpenter et al. (2021) also document the low correlation of China's stock market with international markets. Different from them, we investigate China's stock market from the perspective of well-diversified global investors and extend it by investigating the dynamics of the correlation over time and comparing the vulnerability to global contagions across markets. We also explicitly explore the role of policy risks in affecting diversification benefits. Our results are consistent with Carpenter, Whitelaw, and Zou (2020) that compared with A share stocks, H shares are not a better investment for global investors. However, their work focuses on the determinants of the A-H premium.

The rest of this paper is organized as follows. Section 2 provides a literature review and hypothesis development. Section 3 presents the data and summary statistics. Section

4 examines the diversification benefits of stocks listed in the China A share market for international investors. Section 5 investigates the role of policy risks in explaining the low correlation and diversification benefits of China's stock market. Section 6 concludes.

2. Literature and Hypothesis Development

International portfolio diversification provides benefits that outweigh various costs. The benefits have relied largely on the low correlations among international assets (Grubel, 1968; Levy and Sarnat, 1970). The low international correlation can be explained by country-specific variations caused by differences in policies, institutional and legal regimes, and regional economic shocks (Heston and Rouwenhorst, 1994; Griffin and Karolyi, 1998). In addition, investor demand can explain additional variations in international correlations. Stocks with less common ownership provide more diversification benefits (Barberis and Shleifer, 2003; Barberis et al., 2005).

However, recent studies find that as international capital markets become more integrated, the correlations of major stock markets increase over time, reducing international diversification benefits (Longin and Solnik, 1995; Solnik and Roulet, 2000; Christoffersen et al., 2012). Stock markets are even more correlated and subject to contagions in market downturns when diversification benefits are most needed, particularly for developed markets (e.g., Ang and Bekaert, 2002; Longin and Solnik, 2001; Baur, 2012). As the largest emerging market, China's stock market has been largely ignored by international investors. Allen et al. (2020) posit the disconnection between China's economic growth and its stock market performance. Institutional features, including listing and delisting policies, and corporate governance issues, can explain the underperformance of the Chinese stock market. The disconnection between economic growth and stock market performance may have resulted in a low correlation between the Chinese stock market and other markets. Meanwhile, tight capital control restricts foreign investors from participating in the Chinese stock market, making the A share market

a segmented market.[11] The unique features of China's stock market, particularly the role of government policies and low foreign ownership, can potentially make China's stock market even more attractive to international portfolio diversification.

Hypothesis 1: China's stock market provides more diversification benefits for international investors than other markets, especially during market downturns.

Government policies can have a large impact on China's financial market (Brunnermeier et al., 2020). To stabilize the financial market, the Chinese government tends to intervene when the market is extremely volatile. Active government intervention during an economic downturn can also exempt China from the crisis "wake-up call" and enable China's stock market to resist financial contagions from other markets.[12] In addition, as part of the reform and opening of China's financial markets, the Chinese government frequently performs regulatory experiments (Carpenter and Whitelaw, 2017). Markets often react violently to the experiments. While government policies may help stabilize the market in the short run, they may also increase China's idiosyncratic volatility and make it less correlated with the global market. Firms that are more sensitive to policy change may see their stock price change more independent of variation in the global market.

Hypothesis 2: Stocks with high policy risks in China provide greater diversification benefits to international investors.

While stocks with high policy risks may generate greater diversification benefits, concerns about policy risks can prevent foreign investors from accessing the A share market. Policy risks can affect investors by changing firm cash flows and/or investors' investment risks because of the institutional features of the listing market.[13] A-H cross-listed shares can help to distinguish the sources of policy risks and their contributions to diversification benefits. If firm cash flows or other fundamentals explain the low correlation of the China A share

[11] See more detailed discussions in Forbes, Fratzscher, Kostka, and Straub (2016).

[12] "Wake-up call" is one channel of financial contagion documented in the previous literature. Crisis initially restricted to one market can provide new information and wake-up investors to reassess the vulnerability of other markets (Goldstein, 1998).

[13] Cosset and Suret (1995) explore policy risks in a cross-country setting of 36 countries from 1982 to 1991, whereas China is not in the sample due to lack of development in the stock market.

market with other markets, then we should expect no difference in the correlation coefficients of the A share-listed part and the H share-listed part for A-H cross-listed stocks. However, if it is the institutional features of the listing markets related to discount rate and investors' investment risks that explain the low correlation of A share market, then we should expect lower correlation coefficients of the A share-listed part than the H share-listed part, and correspondingly larger diversification benefits of the A share-listed than the H share-listed for the cross-listed sample.

Hypothesis 3: A share stocks in mainland China provide greater diversification benefits to international investors than H share stocks listed in Hong Kong.

3. Data and Descriptive Statistics

We start to construct our market-level sample with the G20 countries, accounting for 85% of global economic output and 80% of global investment.[14] Then, we drop the European Union (EU) since the largest four markets of the 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 the Hong Kong stock market to the sample, as it is closely connected with China's A share market and many Chinese firms are listed on the Hong Kong Exchange.[15] We collect data on China's market from the China Stock Market and Accounting Research Database (CSMAR). The market return from CSMAR includes all stocks traded in the A-share market. We use the MSCI country index collected from DATASTREAM to measure the performance of other markets. The MSCI country index typically accounts for 85% of the market capitalization in a country. Finally, we use the MSCI World Index, which includes 23 DMs, to proxy for the performance of

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

[15]By the end of 2018, firms that are headquartered in mainland China account for over 60% of the total market capitalization of the Hong Kong stock market.

the global market.[16] 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. According to the World Bank, the 19 stock markets account for more than 90% of global market capitalization.[17] Our sample period is from January 1995 to December 2017. We also conduct analyses for a more recent subperiod from January 2006 to December 2017 for comparison.

Our firm-level sample includes A share firms listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange from 1995 to 2017. Financial firms are excluded because their financial statements are compiled under different accounting standards. To construct the stock-level policy sensitivity measure, we hand collect the announcement dates of new regulatory documents issued by the China Securities Regulatory Commission (CSRC) from its official website. The first regulatory document was issued in 2001, and 137 documents were issued from 2001 to 2017.[18] Then, we calculate an individual firm's stock price reaction to these announcements as a measure of the stock's policy sensitivity. We also use regulatory documents issued by the Ministry of Finance of China, State Administration for Market Regulation of China, and the announcements of People's Bank of China to adjust reserve requirement ratio (RRR) to construct an alternative measure.[19] As a robustness check, we also construct stock-level policy sensitivity measure based on extreme changes in China's Economic Policy Uncertainty (EPU) Index.[20] All other firm-level and macroeconomic data of China are also obtained from CSMAR.

Panel A of Table 1 reports summary statistics of annualized weekly returns in USD and

[16]The latest country weight of the MSCI World Index is 67.95% for the US, 6.63% for Japan, 4.11% for the UK, 3.31% for France, 3.2% for Canada, and 14.8% for other DMs.

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

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

[19]See `http://www.mof.gov.cn/gkml/bulinggonggao/czbl/`, and `http://www.samr.gov.cn/zw/zcfg/xzfg/`

[20]We collect monthly China's EPU Index from 1995 to 2017 from `http://www.policyuncertainty.com/china_monthly.html`, which is developed by Davis, Liu, and Sheng (2019).

Sharpe ratio for sample markets. In general, emerging markets have much higher returns and volatilities than developed markets. The mean weekly return of stocks listed in mainland China is 0.151, with a standard deviation of 0.288. Russia has the highest return and volatility among all markets. In contrast, Japan has the lowest return among all markets, with volatility also among the lowest. Although Russia and Turkey have higher returns than China, their volatilities are also higher. Emerging markets such as South Africa, India, and Mexico have volatility similar to that of China but lower returns. In particular, China's market has the largest Sharpe ratio. Therefore, from the perspective of an international investor, China provides attractive reward-to-volatility 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 MSCI World Index is as low as 0.046. Since our measure of policy sensitivity is normalized ranking, which ranges from 0 to 1, its means are all approximately 0.5. The average $QFII$ is 0.131, suggesting that only a small part of A share stocks are held by qualified foreign institutional investors. The mean of *Trade suspension* is 1.602, suggesting that an A share stock's trading is suspended an average of 1.602 times for reasons other than shareholder meetings and financial report releases. The average firm asset size and firm age are 2.4 billion CNY and 11.58 years, respectively. Other firm characteristics are comparable to those in recent studies (e.g. Giannetti, Liao, and Yu, 2015; Liu et al., 2017), except that our sample includes more SOEs because the sample period starts from 1995 and SOEs account for a larger share of the sample in earlier years of the sample period.

4. Diversification Benefits for International Investors

4.1. Correlations

The diversification benefits from international investing are determined by cross-country correlations (Christoffersen et al., 2012). However, recent studies show that international diversification benefits have been decreasing over time because markets have become more correlated in the last few decades, and financial contagion makes international investors more vulnerable to global shocks. In this section, we investigate whether China's stock market provides diversification benefits to global investors. We also compare the diversification benefits from China with other markets.

We first report cross-market stock return correlations in Panel A of Table 2. All correlations are calculated using weekly USD returns and statistically significant at the 1% level. Consistent with previous studies, correlations between developed markets are generally higher than those between emerging markets. Japan, among all developed markets, has the lowest correlations with other markets. Markets in the EU have high correlations with each other, as EU economies are closely connected. The correlations of emerging markets vary greatly across markets. South Africa, Brazil, and Mexico have the highest correlations with other markets, while China has the lowest correlations with both developed markets and emerging markets. For example, the correlation of China with the US is only 0.038. It is worth noting that China has a higher correlation with Hong Kong (0.114) than with most other developed markets.

However, the low correlation with China and other markets could be due to the inaccessibility of China's stock market to international investors. The Chinese stock market was off-limits to foreign investors prior to the introduction of qualified foreign institutional investors in 2002. In addition, prior to 2005, two-thirds of Chinese domestic equity shares were not tradable. To address the concern of inaccessibility, we conduct additional analyses with the more recent sample period from 2006 to 2017. The results are presented in Panel A of

Internet Appendix Table IA1. It shows that correlations of all 19 markets have increased in the last two decades. However, the pattern does not change, with China still having the lowest correlations with other markets. The results suggest that adding China into the global portfolio can generate the most diversification benefits for international investors compared with other markets.[21]

The unconditional correlation depicts the long-term connectedness of the sample markets. However, it cannot capture the pattern of connectedness over time. Therefore, we further use a dynamic conditional correlation model of Engle (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 return of each sample market. The autoregressive model of order two, AR(2), can pick up the potential return dependence of each market. GARCH(1,1) can pick up the second-moment dependence. The model specification and results of the model estimates are summarized in Internet Appendix A and Table IA3 and Table IA4.

We first estimate the dynamic conditional correlation model for each pair of sample markets. Then, for each market in each week, we calculate three average correlations with other markets: the average correlation with all other 18 markets, the average correlation with all 9 developed markets (or the other 8 developed markets for a developed market), and the average correlation with all 10 emerging markets (or the other 9 emerging markets for an emerging market). We plot the time series of average dynamic conditional correlation 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 until the 2008 credit crisis. Moreover, most emerging markets' correlations increase more than developed markets, possi-

[21]Previous studies find that large stocks in different markets tend to move together (Eun et al., 2008; Huang, 2007). Therefore, we perform another robustness using the return of the Shanghai Stock Exchange 180 Index (SSE180 Index) to measure China's market return. The index includes large stocks from different industries traded on the Shanghai Stock Exchange. The results in Internet Appendix Table IA2 show that although correlations of China with other markets are higher than those in the main results, they are still much lower than the other markets, suggesting that our results remain robust to the size factor in market integration and international diversification.

bly because of market liberalization in emerging markets. However, we find only a marginal increase in China's correlations over the years. Given the increasing connectedness of other markets, China keeps having a low correlation with the rest of the world. We then calculate the time-series mean of the three average correlations for each market. The results are reported in Panel B of Table 2. The average dynamic conditional correlations with all markets show a similar pattern with unconditional correlations in Panel A, suggesting that the dynamic conditional correlation 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 developed markets and emerging markets. We find that most markets have much higher correlations with developed markets than with emerging markets. However, China has similarly low correlations with developed markets and emerging markets. The analysis in the more recent sample period from 2006 to 2017 in Panel B of Internet Appendix Table IA1 shows similar pattern.

4.2. Sharpe Ratios

In this subsection, we examine the diversification benefits of China and other emerging markets to the global portfolio using the Sharpe ratio. We use the MSCI World Index (the World Index), which includes 23 DMs, to proxy for the performance of the global market and first calculate the annual Sharpe ratio of the World Index based on weekly returns in USD. Then, we construct portfolios that contain the World Index and each of the 10 emerging markets and calculate the Sharpe ratio of the optimal portfolios. We do not allow short selling when constructing the portfolio, as most emerging markets, including China, have short selling constraints. Last, we calculate the difference in the Sharpe ratio between the World Index and the optimal portfolios to test whether investing in an emerging market can increase the Sharpe ratio for global investors.

The results are presented in Panel A of Table 3. We also report the significance level of the difference and the weight of each emerging market in the optimal portfolios. As shown, all

emerging markets can provide diversification benefits, as evidenced by the significant increase in the Sharpe ratio. On average, the 10 emerging markets can increase the Sharpe ratio of the World Index by 0.059. While the increase is significant for all emerging markets, it is the largest for China, suggesting that China's economic magnitude of diversification benefits is the largest. Moreover, the weight of China in the optimal portfolio is the lowest among all emerging markets, implying that the optimal portfolio should be more feasible for China.

Next, since all emerging markets can increase the Sharpe ratio for international investors, we further explore whether the diversification benefits provided by China can be replicated by investing in other markets. We first calculate the Sharpe ratio of the optimal portfolio that contains the World Index and all 10 emerging markets. Then, we exclude each market from the whole portfolio and recalculate the Sharpe ratio of the new portfolio (which contains the World Index and the other 9 markets). The difference in the Sharpe ratio between the two portfolios measures the marginal diversification benefits contributed by each market. The results are reported in Panel B of Table 3. As shown, the marginal Sharpe ratio contributed by most emerging markets is small and less significant, suggesting that the diversification benefits of most emerging markets can be fully replicated by investing in other markets. In contrast, China still contributes the largest marginal increase in the Sharpe ratio to the portfolio by 0.051. Therefore, although other emerging markets can provide diversification benefits to the global portfolio, they cannot replicate as large benefits as provided by China.

We also conduct the test using a more recent sample period from 2006 to 2017. The results are reported in Panels C and D. It shows that while the other emerging markets provide fewer diversification benefits than the full sample period, China can still significantly increase the Sharpe ratio of international investors. Therefore, China is an exception among emerging markets in terms of generating diversification to global investors. Underweighting China would bring high opportunity costs to international investors.

4.3. Financial Contagion

In addition to diversification benefits, investigating the low correlation of a market also has important implications for the contagion effect in market downturns. Presumably, a market with low correlation with other markets would also waterproof shocks from other markets. We further examine whether it is the case for China. Testing contagion is difficult because of the spurious relationship between correlation and volatility (Longin and Solnik, 2001). We construct different measures to examine cross-market financial contagion.

We first examine the cumulative returns of the 10 emerging markets around World Index shocks. As discussed above, the MSCI World Index includes 23 DMs. We define a World Index shock when the World Index return is in the bottom 5% tail during the sample period. Based on the 1150 weekly observations of the World Index during 1995-2017, we identify 57 index shock weeks. The shocks were heavily concentrated on the burst of the Internet Bubble from 2001 to 2002 (10 shock weeks), the global financial crisis and the European debt crisis from 2008 to 2011 (28 shock weeks). Then, for each emerging market and each index shock, we calculate the cumulative returns 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 the average across all the shocks for each emerging market and each window. As Panel A of Table 4 shows, all emerging markets, except China, have large and significantly negative cumulative returns around global index shocks. For example, Indonesia and Turkey's [-3, +3] cumulative returns 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. In contrast, the cumulative returns of China are not significant for all three windows. Therefore, while most emerging markets are vulnerable to contagion, China can be an exception and stay isolated from global financial market shocks.

An alternative measure for contagion to global market shock is the dynamic conditional correlation. We apply the dynamic conditional correlation measure in the event study setting

with the global index shock. Specifically, in the spirit of Chae (2005) and Schiller (2017), we measure contagion using *abnormal dynamic conditional correlation* (ADCC) of emerging markets with the World Index around global shocks. ADCC of market i with the World Index at time t is defined as the difference between dynamic conditional correlation in week t and the average dynamic conditional correlation over an estimation window from 30 to 5 weeks prior to week t. Then, we calculate the average ADCC over the weeks during the event window for each index shock. Lastly, we take an average across the 57 event weeks. The results are reported in Panel B of Table 4. Similar to cumulative returns around global index shocks, all markets, except China, have large and significantly positive ADCCs during the event window. For instance, the ADCC of Russia in the event week is 0.052, equivalent to a 10% increase in its average dynamic conditional correlation. The ADCC of China is insignificant in both the [-1, +1] and [-3, +3] windows and becomes negative in the event week. Therefore, unlike other markets, China is not more correlated with the global market during global shocks. Our results from the ADCC again suggest that financial contagion from global market shocks is less of a concern for China, as the A share market stays less affected by global market downturns.

As discussed in Bae et al. (2003), correlations may not be appropriate for an evaluation of the differential impact of large returns. Thus, we use *coexceedance* as the third measure for stock market contagion. Following Bae et al. (2003), we define bottom coexceedance as the ratio of the number of weeks when two market indexes both experience 5% bottom tail returns to the total number of weeks in the 5% bottom tail for each individual index. The bottom coexceedance for each pair of markets has a maximum value of 1. A large coexceedance of a pair of markets suggests that they are very likely to experience market downturns simultaneously and, thus are both vulnerable to financial contagion.

Panel C of Table 4 reports cross-market bottom coexceedances. The results show a similar pattern with the cross-market correlation coefficients in Table 2. Each pair of markets has a bottom coexceedance, and each market has a coexceedance of 1 with itself. Devel-

oped markets tend to have higher coexceedances than emerging markets. For example, the coexceedance of the US and the UK is 0.544, but that of China and Turkey is only 0.07. However, some emerging markets, such as South Africa, Brazil, and Mexico, have very large coexceedances, with some of them being even greater than developed markets. 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 emerging markets have lower correlations with other markets, they may be even more vulnerable to financial contagion. In contrast, 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 that of other markets. In Panel C of Internet Appendix Table IA1, we also investigate the cross-market bottom coexceedances for the more recent period from 2006 to 2017. It shows that both developed and emerging markets have been more vulnerable to financial contagion in the last decade. While the coexceedances of China also increase, they are still the lowest among all markets. Collectively, all three measures of contagion suggest that China is not the least vulnerable to global financial contagion; thus, it can be a safe haven for international investors when the global market is under shock.

5. Policy Risks and Diversification Benefits

5.1. Policy Risks

5.1.1. Policy Risks and Diversification Benefits

In this section, we employ firm-level data to investigate explanations for the low correlation of China's stock market. Government policy in China may have a substantial impact on market performance. Stocks that are more sensitive to local policy/regulation change should be less correlated with markets outside China. We estimate the following regression model

to examine whether stocks more sensitive to government policy are less connected with the global market:

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

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 effects, respectively. Standard errors are two-way clustered by industry and year in all regressions throughout the paper. We construct two measures for stock connectedness with the global market. The first measure is the correlation of stock i with the World Index in year t estimated from weekly USD return ($Correlation$). The second measure is *Global beta*, which is estimated using the following regression model:

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

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

Our policy sensitivity measure is based on individual stock reactions to the release of regulatory documents by the China Securities Regulatory Commission, the regulatory authority of China's stock market. Since the first regulatory document was issued in 2001, the sample period for this measure was from 2001 to 2017. Following Liu et al. (2017), we first calculate the [-1,+1] three-day cumulative abnormal returns of stock i around announcements of new regulatory documents based on the following market model:

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

where $R_{i,k}$ is the return of stock i in week k, $R^c_{f,k}$ is China's risk-free rate, and $R_{m,k}$ is China's market return. We estimate β_i every year for stock i using weekly returns, and we

use a one-year lagged beta to calculate abnormal returns. Second, we rank all A share stocks based on the sum of the absolute value of these cumulative abnormal returns in year t. Last, we convert the rank into a number between zero and one using the formula rank/(number of firms + 1). By construction, a larger number represents the greater policy sensitivity of a stock. We divide the sample firms into high and low policy sensitivity firms and report summary statistics for the two groups in Panel A of Table 5. It shows that policy-sensitive firms tend to be small, growth and non-SOE firms. They also have less foreign ownership and higher stock returns.

The regression results are reported in Panel B of Table 5. The dependent variable is *Correlation* in column (1). It shows that the coefficient on *Policy sensitivity* is -0.014, suggesting that *Correlation* of the most policy-sensitive firms is 0.014 lower than that of the least sensitive firms. The difference is large and equivalent to 30.43% of the average *Correlation* (0.046, Table 1, Panel B). We use *Global beta* to measure stock connectedness with the global market in column (2). The coefficient on *Policy sensitivity* is -0.062, and it is statistically significant. It is also economically large compared to the average *Global beta*, 0.135. Coefficients of control variables show that firms with larger sizes and higher tangibility are more correlated with the global market.

We also construct two alternative measures of policy sensitivity as a robustness check. The first one is similar to our main measure except that we not only use regulatory documents issued by the China Securities Regulatory Commission but also use documents issued by the Ministry of Finance of China, State Administration for Market Regulation of China, and announcements of the People's Bank of China to adjust the reserve requirement ratio (RRR). This expands our sample of 137 regulatory documents to 255 documents or announcements. The regression results are reported in Panel A of Internet Appendix Table IA5. They are consistent with our main results, and some coefficients are even larger in magnitude. Another alternative measure is based on stock returns around extreme changes in the EPU Index of China. The results are reported in Panel B of Table IA5 and are also consistent with the main

results. However, since the EPU data are at a monthly frequency, the stock price reaction based on monthly abnormal returns might be less indicative.

To conclude, the results in this section suggest that stocks that are more sensitive to policy announcements are less correlated with the global market. This implies that government intervention in the stock market explains the low connectedness of the Chinese stock market with other markets. On the one hand, policy sensitivities could be associated with more volatile price changes at policy announcements; on the other hand, they may lower the stock's connectedness with foreign markets and thus provide more diversification benefits to international investors.

5.1.2. Policy Risks and Stock Performance

Do policy-sensitive stocks deliver better or worse performance? Pástor and Veronesi (2013) posit that stocks that have higher policy risk may have lower realized returns, as policy uncertainty generates greater stock price volatility. We examine the relation of policy sensitivity and stock performance using regression model (1) with $Performance$ as the dependent variable. We use annual stock returns and the Sharpe ratio to measure $Performance$. The regression results are reported in columns (3) and (4) of Panel B of Table 5. Overall, coefficients on *Policy sensitivity* are significantly positive. In particular, the Sharpe ratio of A-share stocks increases with policy sensitivity, suggesting that the higher risks of policy-sensitive stocks are compensated by even higher returns. This result is consistent with Claessens, Feijen, and Laeven (2008), and Fisman (2001) that policy-sensitive firms may also have more political connections with the government, which provides valuable resources to the firm. Collectively, the results in Table 5 suggest that policy-sensitive stocks are less connected to foreign markets and thus provide more diversification benefits to international investors. Moreover, they perform better than other A share-listed stocks.

5.2. Cross-Listed Stocks

Thus far, we document that the Chinese stock market has a low correlation with other markets and provides diversification benefits to international investors. The policy sensitivities of A share-listed stocks contribute to diversification benefits. From an asset pricing perspective, the effect of policy risks on return correlation may come from two sources. The first is related to firm fundamentals, i.e., firms' operation and cash flows could be differently affected by policy changes. The other is related to institutional features of listing markets that may affect firms' cost of financing or investment risks for investors. To distinguish these two mechanisms, we examine a special set of firms: firms cross-listed in the A share market and Hong Kong market. For an A share-HK pair, the two stocks share exactly the same firm fundamentals but are separately traded in two markets with different institutional features. Therefore, firm fundamentals are well controlled in this subset of firms.

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 6, Panel A. A-share stocks have lower correlation and lower average dynamic conditional correlation than H-share stocks, and the differences are significant at the 1% significance level. The last column shows that A-share stocks are also less vulnerable to global financial contagion, as evidenced by the significantly lower bottom coexceedance. We also plot the time-series dynamic conditional correlation with the global market for the two portfolios in Figure 4. It shows that while A-share stocks are increasingly correlated with the global market, H-share stocks have always been more correlated with the global market than their A share-listed counterparts. The results suggest that the cash-flow channel may not be the driving factor explaining the low connectedness of China's stock market. Instead, institutional factors and the investor base of the A share market have greater explanatory power.

Moreover, dividing these A-H cross-listed stocks into high- and low-groups based on their policy sensitivity measures for the A share-listed part, we find that the A-H correlation

difference is larger for the high-sensitivity group (Table 6, Panel B). This result further corroborates our interpretation that policy risks explain and contribute to the diversification benefits of the A share market.

5.3. Global Market Integration and Foreign Ownership

In addition to policy risks, do other factors help explain the low correlation of China's stock market? "Common ownership" can generate extra comovement among stocks because of investors' trading pattern (e.g., Brealey, Cooper, and Kaplanis, 2010; Barberis et al., 2005). Previous literature documents that "common ownership" is an important channel of financial contagion (e.g., Elliott, Golub, and Jackson, 2014). When some investors fire sale assets because of exogenous shocks, other investors' portfolio value will also decrease if they have common holdings. Compared with other major economies, China A shares are less accessed by foreign investors. The relatively low foreign ownership might explain the low correlation of China's stock market with the global market. However, with the opening up of China's capital market to global investors, increasing foreign ownership can increase the correlation and decrease the diversification benefits from China A shares. In this section, we consider two important programs through which foreign investors access China's stock market, the QFII and the Stock Connect Program, to examine whether and how foreign ownership explains the low correlation of China's stock market.

5.3.1. Foreign Ownership through QFII

Before 2002, foreign investors could only access China's stock market by trading B shares in mainland China, which represents a tiny fraction of the total market capitalization. As one step in opening the financial market, the Chinese government introduced the QFII program in 2002 and the Renminbi Qualified Foreign Institutional Investors (RQFII) program in 2011, which allows foreign institutional investors to trade A shares directly. QFII holding also benefits firms through better corporate governance and less political pressure (Huang and

Zhu, 2015). However, QFII and RQFII are not ideal for most international investors due to licensing requirements, quotas, and repatriation restrictions (Carpenter and Whitelaw, 2017). Therefore, the 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.[22] The quotas are never fully fulfilled, suggesting potential concerns of international investors in investing in China.

We extract QFII holding data in CSMAR and identify stocks that are held by QFII. We define $QFII_{it}$ as a dummy variable to represent stock i that has QFII holdings in year t. We estimate the model below to examine the effect of foreign holdings on stock return connectedness:

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

The regression results are reported in Panel A of Table 7. Column (1) shows that stocks held by QFII has 0.006 higher *Correlation* than others not held by QFII, which is equivalent to 13.04% of the average correlation. The coefficient on $QFII$ is also significantly positive in column (3) when we use *Global beta* as the dependent variable, although it has a lower significance level. In general, stocks held by QFII are more connected with the global market.

To mitigate the selection issue, we estimate the following difference-in-differences (DID) regression model to explore whether stocks' connectedness with the global market increases after they have QFII holdings:

$$Connectedness_{it} = \beta_0 + \beta_1 \times In\ QFII_i \times Post_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}, \tag{5}$$

where $In\ QFII_i$ is a dummy variable that is equal to 1 if stock i ever has QFII holdings

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

during 1995 to 2017, and 0 otherwise; *Post* is a dummy variable that is equal to 1 if the stock-year observation is after stock i starts to have QFII holdings for the first time, and 0 otherwise. Other control variables are the same. The regression results are reported in columns (2) and (4) of Table 7 Panel A. Consistent with previous results, the coefficients on $In\ QFII \times Post$ are significantly positive at the 1% level in both columns (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 Panel A that stocks with foreign ownership are more connected with the global market. However, only 13.1% of A-share stocks ever have QFII holdings, as shown in Table 1, and the holdings are usually small because of capital control. This can partly explain the low connectedness of the whole A share market with the global market. As a result, international investors that invest in A share stocks continue to enjoy diversification benefits, and such benefits will be larger for stocks with less foreign ownership.

Furthermore, we test whether the level of policy sensitivity can moderate the increase in correlation through foreign ownership by adding the interaction term of $QFII$ with *Policy sensitivity* in equation (4). The regression results reported in Panel B of Table 7 show that the coefficients on $QFII \times Policy\ sensitivity$ are not significant for *Correlation* and marginally significant for *Global bata*. The mixed results could be because that only 13.1% of A-share firms are held by QFII. While large-cap stocks have received the dominant share of foreign investment (Eun et al., 2008), the high policy sensitive firms tend to be small and have less foreign ownership. However, diversifying into small-cap stocks with greater policy sensitivities, which currently have less QFII holding, could be an effective way to further improve the diversification benefits. In addition, while the coefficients on $QFII$ are not significant after adding the interaction term, the coefficients on *Policy sensitivity* are significantly negative in all model specifications.

5.3.2. Stock Connect Program

Because of the restrictions on QFII and RQFII, only large institutional investors have access to these programs. Thus, most global investors interested in China have been investing in Chinese firms traded in external markets, mainly Hong Kong and the US, to obtain exposure to China. As discussed in Carpenter and Whitelaw (2017), both the largest and oldest ETF traded in the 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, the Chinese government launched the Shanghai-Hong Kong Stock Connect Program in November 2014 and the Shenzhen-Hong Kong Stock Connect Program in December 2016. The programs allow international and local investors in mainland China to trade securities in each other's markets through the trading and clearing facilities of their home exchange.[23] The SH-HK Connect includes constituent stocks in the Shanghai Stock Exchange (SSE) 180 Index and SSE 380 Index and all A-H cross-listed stocks. The SZ-HK Connect includes constituent stocks with a market capitalization greater than 6 billion CNY in the Shenzhen Stock Exchange Component Index, constituent stocks in the Shenzhen Stock Exchange Small/Mid Cap Innovation Index, and all A-H cross-listed stocks. The main differences between the programs and QFII are that the Connect Programs allow retail investors to trade A-share directly and have a much higher quota.

As the stocks in both programs are adjusted every few months, we keep only stocks in the programs throughout the sample period. This leaves 546 stocks in the SH-HK Connect and 833 stocks in the SZ-HK Connect. To investigate the effect of the Stock Connect on stocks' correlation with the global market, we estimate the following DID regression:

$$Connectedness_{it} = \beta_0 + \beta_1 \times HK\ connected_i \times Post_t + Controls_{it} + \omega + \lambda + \epsilon_{it}, \qquad (6)$$

where $HK\ connected_i$ is a dummy variable that is equal to 1 if stock i is in the SH-HK

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

Connect or SZ-HK Connect, and 0 otherwise; $Post_t$ is a dummy variable that is equal to 1 after the start of each program, and 0 otherwise. The regression results are reported in Panel C of Table 7. The sample includes all A-share stocks in the Shanghai Stock Exchange from three years before to three years after the introduction of the SH-HK Connect (2012-2017) and stocks in the Shenzhen Stock Exchange from one year before to one year after the introduction of the SZ-HK Connect (2016-2017). Columns (1) and (3) show results for the full sample. The coefficients on $HKconnected \times Post$ are small and insignificant, suggesting that connected stocks are not more correlated with the global market after the introduction of the programs. We also perform the subsample analysis for SH-HK Connect. The results are reported in columns (2) and (4) and are similar to the full sample results. We also compare alternative measures, including the dynamic conditional correlation and bottom coexceedance of stocks in/out of the Connect Program. We do not find evidence that connected stocks are significantly more correlated with the global market.

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. Meanwhile, US-traded ETF on A share increase dramatically, with the largest ETF having a $1.2 billion asset under management as of January 2019.[24] However, since global investors still have various concerns about investing in China, particularly policy risk, the foreign investment represents a small fraction of China's stock market until now.

5.3.3. Joint Test of Policy Risk and Foreign Ownership

As the last set of tests, we compare which factor, policy risk or foreign ownership, is more important in explaining the low correlation of the A share market with other markets. We include both policy sensitivity measures and the QFII indicator in the specification, with the same control variables as we used in the previous tests. The results are shown in Table 8.

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

Column (1) shows that a one standard deviation increase in *Policy Sensitivity* (0.268, as shown in Panel B of Table 1) is associated with a 0.0038 decline in the stock's correlation with the global market, which is equivalent to 8.26% of the mean *Correlation* (0.046, as shown in Panel B of Table 1). While a one standard deviation increase in the likelihood of being included in the QFII program (0.337) is associated with a 0.002 (or 4.35% relative to mean *Correlation*) increase in the stock's correlation with the global market.[25] Therefore, the economic magnitude of the policy sensitivity on stock correlation is roughly 2 times that of foreign ownership. Column (2) reports the results for the alternative connectedness measure, *Global Beta*. This shows that the effect of policy sensitivity measures is significant at the 5% level, while the effect of QFII is marginally significant. In terms of economic magnitude, the effect of policy sensitivity is greater than that of foreign ownership.

Collectively, the above results show that policy sensitivity explains the low correlation of A-share stocks with the global market. Other factors, including low foreign ownership, may also explain, but to a lesser extent. Stocks that foreign investors access via the QFII and Stock Connect Program still account for a small percent of the A share market. Given the low foreign ownership of A share-listed stocks, international investors may potentially reap substantial diversification benefits from investing in the A share market.

6. Conclusions

This paper investigates the value of China's stock market for international diversification and the role of policy risks in affecting diversification benefits. We find that Chinese stocks have a lower correlation with the global market compared with all other major markets. From the perspective of international investors, adding Chinese stocks into a well-diversified

[25]To calculate these numbers, a one standard deviation increase in policy sensitivity is associated with a 0.268× (-0.014)=-0.0038 change in the stock's correlation with the global market. Given the mean Correlation of 0.046 in Table 1, Panel B, this 0.0038 decrease in correlation represents a 0.0038/0.046=8.26% decrease relative to the mean. Similarly, the one-standard-deviation increase in the likelihood of being included in the QFII program is associated with a 0.337×0.006=0.002 increase in the stock's correlation with the global market, which is 0.002/0.046=4.35% relative to the mean correlation.

portfolio can further increase its Sharpe ratio. In addition, Chinese stocks are less affected by global financial contagion when diversification benefits are most valuable. We further find that mainland China stocks with high policy sensitivity provide greater diversification benefits. However, concerns about policy risks can prevent international investors from accessing the mainland China stock market. While holding Hong Kong-listed Chinese stocks is less affected by friction-related policy risks such as capital control, it cannot reap the same diversification benefits as that from mainland China stocks. Global market integration can mitigate concerns about policy risks, boost foreign investor holdings, and diminish diversification benefits. The market capitalization of stocks included in the QFII and Stock Connect Program is small relative to the total market size. We find that the effect of foreign ownership in increasing the correlation of China's stock market with the global market is still limited. China's stock market still provides valuable diversification opportunities for international investors until the late 2010s.

Our findings have important implications for international investors and policymakers. In recent years, China's government has made significant efforts to open up China's capital market to foreign investors.[26] Foreign portfolio managers also expressed great interest in China, whereas the value of diversifying into China's stock market has largely not been explored. China's exposure through passive instruments such as emerging market indices and China's ETF is not always reliable and limited to large firms in particular sectors. Foreign portfolio managers' actual exposures to mainland China stocks are small, and some even have zero exposure. Concerns on policy risks help explain why foreign investors forgo the benefits of diversification into Chinese stocks. However, our results suggest that mainland China stocks carrying the most policy risk also provide the most diversification benefits for international investors. Hong Kong-listed mainland China stocks are not perfect substitutes for capturing these diversification benefits. Policymakers may consider the interactions among market integration, policy risks, foreign investor holdings, and investor objectives when mak-

[26]See, for example, "China boosts foreign access to huge onshore capital markets", Financial Times, November 1, 2020.

ing relevant policies. The recent inclusion of A shares into the MSCI index, QFII quota removal and deepening of the Stock Connect Programs provide a new laboratory to study these interactions.

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Appendix A. Variable Definitions

Table A1: Variable Definitions

Variable	Definition
ADCC	Abnormal dynamic conditional correlation, which is defined as the difference between dynamic conditional correlation (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. 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 sensitivity	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. 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).
QFII	A dummy variable which is equal to 1 if the stock has Qualified Foreign Institutional Investor (QFII) holdings in the year 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 1995 to 2017 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.

Table A1 Continued

Variable	Definition
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 from firm foundation.
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.

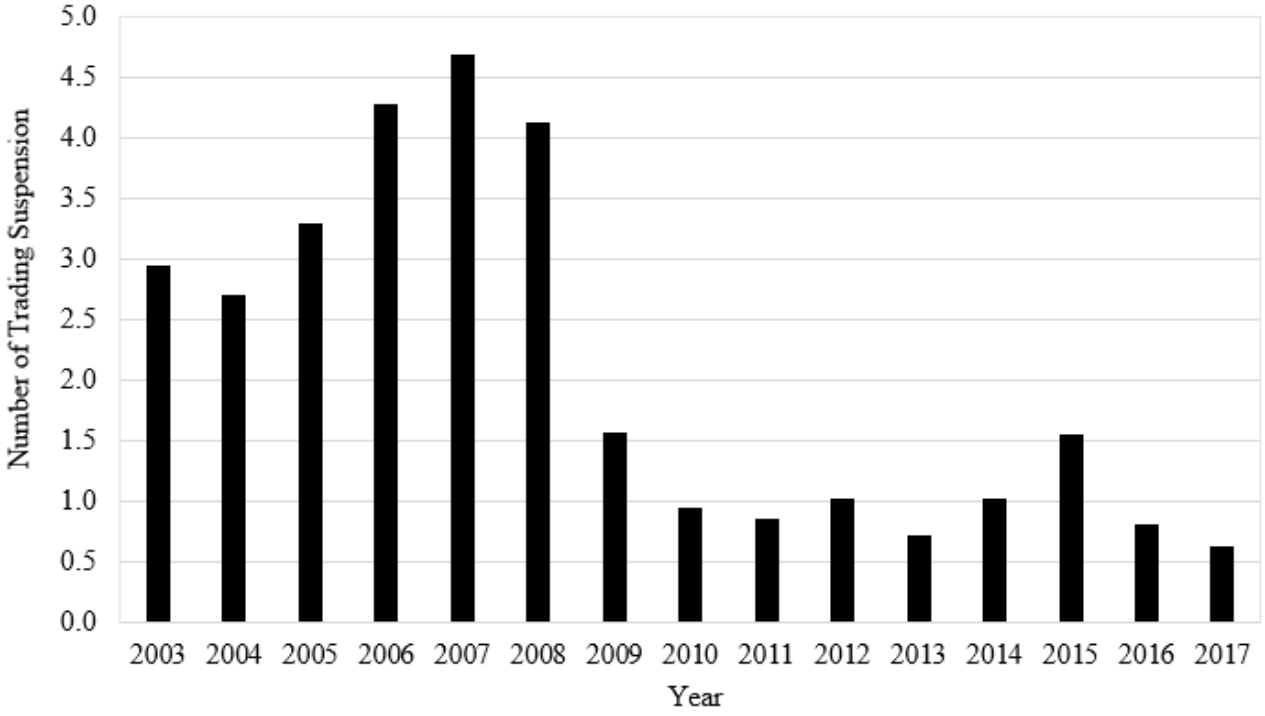


Fig. 1. Trading Suspension of A-share Market

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.

Fig. 2. Dynamic Conditional Correlations of Stock Markets

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

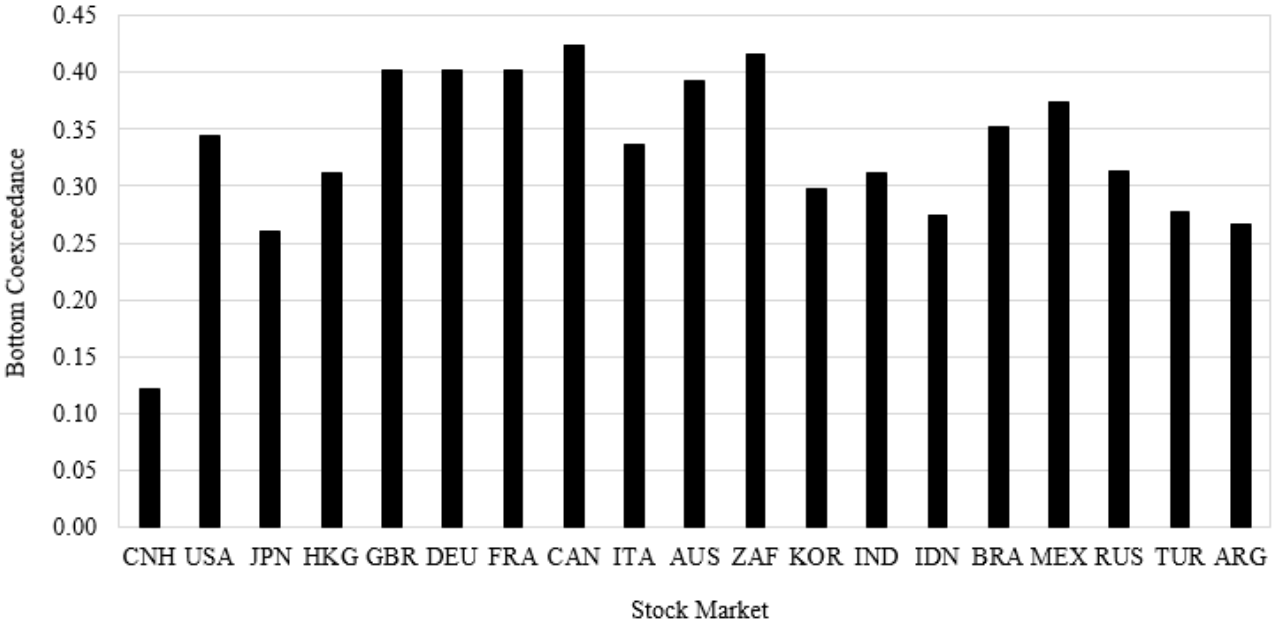
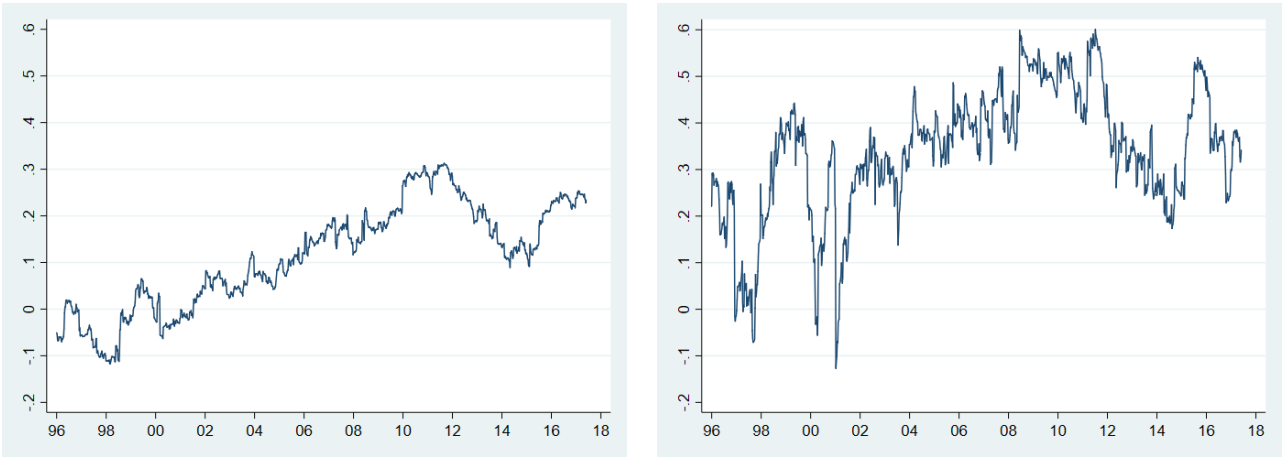


Fig. 3. Bottom Coexceedances of Stock Markets

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) A-share Stocks

(b) H-share Stocks

Fig. 4. Dynamic Conditional Correlations of A-H Cross-listed Stocks with Global Market

This figure compares dynamic conditional correlations 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.

Table 1: Summary Statistics

Panel A reports summary statistics of annualized weekly USD returns and Sharpe ratio (SR) 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 and Sharpe ratio							
Market	N	Mean	S.D.	p25	p50	p75	SR
China	1150	15.132	28.768	-91.237	14.940	119.408	0.445
US	1150	9.462	16.908	-54.184	13.836	74.816	0.421
Japan	1150	3.335	19.917	-85.794	-0.680	81.823	0.050
Hong Kong	1150	6.909	22.637	-85.413	12.974	97.335	0.202
UK	1150	4.220	19.094	-63.610	12.139	78.628	0.098
Germany	1150	7.966	23.737	-80.398	20.813	98.423	0.237
France	1150	7.292	22.099	-76.535	17.557	96.271	0.224
Canada	1150	9.752	21.689	-62.058	19.290	91.410	0.342
Italy	1150	3.860	24.969	-93.495	9.849	106.726	0.061
Australia	1150	7.128	22.277	-73.988	19.090	97.558	0.215
South Africa	1150	7.160	28.229	-99.345	13.415	116.836	0.171
South Korea	1150	11.947	35.571	-117.330	15.500	135.104	0.270
India	1150	8.762	26.504	-106.997	14.340	123.801	0.242
Indonesia	1150	8.364	42.442	-118.339	10.125	128.946	0.142
Brazil	1150	11.499	37.342	-125.765	21.518	157.558	0.245
Mexico	1150	11.646	29.993	-101.271	17.695	130.125	0.310
Russia	1150	20.768	49.431	-136.294	19.635	179.611	0.373
Turkey	1150	17.994	47.386	-159.495	22.684	190.797	0.330
Argentina	1150	15.367	37.890	-132.523	14.460	164.225	0.344
MSCI World Index	1150	6.785	16.106	-54.038	14.545	66.636	0.276

Table 1 Continued

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 sensitivity	32,772	0.508	0.268	0.251	0.504	0.753
QFII	30,797	0.131	0.337	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			
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: 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. The sample period in Panel A and B is from January 1995 to December 2017. In Panel A, we first calculate SR of the MSCI World Index each year. Then we calculate SR of the optimal portfolios constructed by the World Index and each of the 10 EMs. Last we calculate the difference of SR between the World Index and the optimal portfolios to test whether adding each EM to the World 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 World Index and the other 9 EMs every year. Then we calculate SR of the optimal portfolio constructed by the World 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 also report weight of each EM in the optimal portfolios. Panel C and D are the same with Panel A and B, respectively, except that the sample period is from January 2006 to December 2017. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

	Panel A: global index with one EM for 1995 to 2017 sample		Panel B: global index with all EMs for 1995 to 2017 sample	
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

	Panel C: global index with one EM for 2006 to 2017 sample		Panel D: global index with all EMs for 2006 to 2017 sample	
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 4: 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 of the 10 emerging markets (EMs) around index shocks of MSCI World Index and their significance levels from t-tests. We define the World Index is under shock when it has 5% bottom tail returns during the sample period. And we calculate the average cumulative market returns across all global index shock weeks for each EM. Panel B reports average abnormal dynamic conditional correlation (ADCC) of the 10 EMs with the World Index around 5% shocks of the World Index for different windows and their significance levels from t-tests. ADCC of week t is the difference between the dynamic conditional correlation in week t and the average dynamic conditional correlation 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

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 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 4 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 5: Policy Risks, Correlations, and Returns

Panel A reports summary statistics of high and low policy sensitivity firms and compares the differences. The policy sensitivity measure 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). If a firm's policy sensitivity is higher than 0.5, it is in the high policy sensitivity group. Otherwise, it is in the low policy sensitivity group. In Panel B, column (1) and (2) report the effect of policy risks 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 the 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), $Connectedness$ is measured using the correlation of stock i with the MSCI World Index in year t based on weekly USD return ($Correlation$). In column (2), $Connectedness$ 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 World 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. Column (3) and (4) report 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. We use stock return in column (3) and Sharpe ratio (SR) in column (4) to measure $Performance$. 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.

Panel A: summary statistics of high and low policy sensitivity firms

	High	Low	Difference
Firm size	21.509	21.958	-0.449***
B/M	0.465	0.576	-0.111***
SOE	0.502	0.609	-0.107***
QFII	0.110	0.136	-0.026***
Return	0.327	0.131	0.196***

Table 5 Continued

Panel B: regression results

	Dep. Var: *Correlation*	Dep. Var: *Global beta*	Dep. Var: Return	Dep. Var: SR
	(1)	(2)	(3)	(4)
Policy sensitivity	-0.014**	-0.062**	0.121***	0.047***
	(0.006)	(0.030)	(0.020)	(0.005)
Firm size	0.004**	0.019**	0.117***	0.032***
	(0.002)	(0.009)	(0.007)	(0.002)
Volatility	-0.242***	1.591***	8.573***	1.064***
	(0.062)	(0.464)	(0.262)	(0.045)
ROE	-0.002	0.015	0.245***	0.059***
	(0.005)	(0.027)	(0.022)	(0.005)
Leverage	-0.001	-0.034	0.042	0.006
	(0.006)	(0.032)	(0.026)	(0.006)
B/M	-0.002	-0.061*	-1.150***	-0.303***
	(0.007)	(0.032)	(0.026)	(0.006)
Tangibility	0.027*	0.114	0.109*	0.061***
	(0.015)	(0.081)	(0.057)	(0.012)
Firm age	0.012*	0.031	-0.000	0.002
	(0.007)	(0.030)	(0.024)	(0.006)
AH cross-listed	-0.013	-0.092	0.084	0.038**
	(0.026)	(0.077)	(0.074)	(0.019)
SOE	-0.001	-0.002	0.005	-0.000
	(0.004)	(0.017)	(0.012)	(0.003)
Constant	-0.039	-0.470**	-2.802***	-0.805***
	(0.043)	(0.209)	(0.170)	(0.040)
Firm F.E.	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y
N	30,051	30,051	29,511	30,051
Adj. R^2	0.473	0.416	0.726	0.694

Table 6: Diversification Benefits and Policy Risks: Cross-Listed Stocks

Panel A 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 World 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. We also report significance levels of the differences between the two portfolios from t-tests. Panel B first compares policy sensitivity of A-H cross-listed A-share stocks and their counterpart H-share stocks. To measure policy sensitivity, we first calculate the three-day abnormal return of the stock around announcements of new regulatory documents issued by China Securities Regulatory Commission; then we rank all stocks based on the sum of absolute value of these abnormal returns in the year; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). Then Panel B reports A-H correlation difference by policy sensitivity. We divide the cross-listed stocks into high and low policy sensitivity groups by their A-share stocks' policy sensitivity. For each group, we calculate the correlation with the World Index using weekly USD return for A-share stocks and H-share stocks, respectively. Then we take difference of their correlations as A-H correlation difference. Last, we compare the A-H correlation difference between high and low policy sensitivity groups. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Panel A: correlation of A-H cross-listed stocks

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

Panel B: policy sensitivity of A-H cross-listed stocks

	A-share	H-share	Difference
Policy sensitivity	0.476	0.467	0.010***

	High Policy sensitivity	Low Policy sensitivity	Difference
A-H Correlation Difference	0.126	0.110	0.016***

Table 7: Foreign Ownership and Correlations

This table reports the effect of foreign ownership on A-share stock's connectedness with the global market. Panel A reports results for qualified foreign institutional investor (QFII) held stocks. 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 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: $Connectedness_{it} = \beta_0 + \beta_1 \times In\ QFII_i \times Post_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, 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 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 World 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 World Index. The sample includes all non-financial A-share firms from 1995 to 2017. Panel B reports the moderation effect of policy sensitivity on foreign ownership by adding the interaction term of $QFII$ with $Policy\ sensitivity$ in the regression model, where $Policy\ sensitivity$ is a variable constructed to measure stock's policy sensitivity. To measure policy sensitivity, we first calculate the three-day abnormal return of the stock around announcements of new regulatory documents issued by China Securities Regulatory Commission; then we rank all stocks based on the sum of absolute value of these abnormal returns in the year; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). Panel C report 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) using the following difference-in-difference regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times HK\ connected_i \times Post_t + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $HK\ connected_i$ is a dummy variable which is equal to 1 if stock i is in the Programs and 0 otherwise, $Post_t$ 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. 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). All variables are winsorized at 1% to 99% except dummy variables. 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: QFII held stocks	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)
Firm F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	33,621	33,621	33,621	33,621
Adj. R^2	0.469	0.469	0.437	0.437

Table 7 Continued

Panel B: Moderation of policy sensitivity on foreigh ownership		
	Dep. Var: *Correlation*	Dep. Var: *Global beta*
	(1)	(2)
QFII	0.007	-0.053
	(0.009)	(0.037)
Policy sensitivity	-0.014**	-0.082***
	(0.006)	(0.032)
QFII × *Policy sensitivity*	-0.001	0.152*
	(0.017)	(0.079)
Firm size	0.003*	0.018**
	(0.002)	(0.009)
Volatility	-0.240***	1.595***
	(0.062)	(0.464)
ROE	-0.002	0.014
	(0.005)	(0.027)
Leverage	-0.001	-0.032
	(0.006)	(0.032)
B/M	-0.001	-0.057*
	(0.007)	(0.032)
Tangibility	0.026*	0.111
	(0.015)	(0.081)
Firm age	0.012*	0.030
	(0.007)	(0.030)
AH cross-listed	-0.013	-0.083
	(0.026)	(0.077)
SOE	-0.001	-0.002
	(0.004)	(0.017)
Constant	-0.034	-0.434**
	(0.043)	(0.209)
Firm F.E.	Y	Y
Year F.E.	Y	Y
N	30,051	30,051
Adj. R^2	0.473	0.416

Table 7 Continued

Panel C: connected stocks

	Dep. Var: *Correlation*		Dep. Var: *Global beta*	
	Full Sample	SSE stocks	Full Sample	SSE stocks
	(1)	(2)	(3)	(4)
HK connected × *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)
Firm F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	7,724	4,777	7,724	4,777
Adj. R^2	0.633	0.580	0.514	0.489

Table 8: Determinants of Low Correlation of A-share Stocks with Global Market

This table reports the effect of policy sensitivity and foreign ownership on A-share stock's connectedness with the global market using the following regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + \beta_2 \times QFII_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, 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, $QFII_{it}$ 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. In column (1), *Connectedness* is measured using the correlation of stock i with MSCI World Index in year t based on weekly USD return (*Correlation*). In column (2), *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 World 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 World Index. *Policy sensitivity* 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.

Table 8 Continued

	Dep. Var: *Correlation*	Dep. Var: *Global beta*
	(1)	(2)
Policy sensitivity	-0.014**	-0.062**
	(0.006)	(0.030)
QFII	0.006**	0.021*
	(0.003)	(0.012)
Firm size	0.003*	0.018**
	(0.002)	(0.009)
Volatility	-0.240***	1.596***
	(0.062)	(0.464)
ROE	-0.002	0.014
	(0.005)	(0.027)
Leverage	-0.001	-0.033
	(0.006)	(0.032)
B/M	-0.001	-0.058*
	(0.007)	(0.032)
Tangibility	0.026*	0.112
	(0.015)	(0.081)
Firm age	0.012*	0.030
	(0.007)	(0.030)
AH cross-listed	-0.013	-0.091
	(0.026)	(0.078)
SOE	-0.001	-0.003
	(0.004)	(0.017)
Constant	-0.033	-0.450**
	(0.043)	(0.209)
Firm F.E.	Y	Y
Year F.E.	Y	Y
N	30,051	30,051
Adj. R^2	0.473	0.416