Stock Market Spillover of China under Belt and Road Initiative: Evidence from 68 Countries

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Abstract. This paper examines the spillover effects of China's equity market in the context of the Belt and Road Initiative (BRI), utilizing 68 MSCI country indices and an E-GARCH-X model. The study specifically addresses non-synchronous trading times, an aspect often overlooked in current research. Contrary to findings in other recent literature, this study indicates that spillover effects in both return and volatility from and on China's equity market have not significantly deviated from those observed in 2013, the year the BRI was initiated. This underscores the initiative's focus on infrastructure rather than direct impacts on equity markets. The research highlights the importance of market development level over BRI participation in determining spillover effects, affirming the continued value of diversification in global portfolios.

Keywords: Spillover effect; International Finance; Belt and Road Initiative; EGARCH-X.

1 Introduction

The Belt and Road Initiative (BRI), initiated by China in 2013, is a massive global development strategy aimed at enhancing regional connectivity and fostering a brighter economic future through infrastructure building and expanding trade links between Asia, Africa, and Europe. The BRI encompasses a wide range of projects, including infrastructure development (such as ports, roads, and railways), energy investments (like oil and gas pipelines), and technology initiatives. It is seen as a means for China to promote its global influence by investing in and developing trade routes that will also help other countries improve their infrastructure and economic potential. The "Belt" refers to the Silk Road Economic Belt, a network of overland corridors including roads, bridges, and railways intended to create new economic corridors linking China to Central and Western Asia, the Middle East, and Europe. The "Road" is somewhat of a misnomer as it refers to the 21st Century Maritime Silk Road, a sea route connecting China's coastal regions to Europe and the South Pacific through the South China Sea and the Indian Ocean.

After a decade, it is both interesting and necessary to review the project's impact on the global financial market. Examining the spillover effect that China transmits to other

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countries is one straightforward way to assess the importance of the Chinese financial market in the global arena. Moreover, monitoring the spillover effect from China on other countries can serve as a measure of systematic risks. If the spillover is substantial, the embedded systematic risks are also significant, potentially reducing economic resilience around the globe, especially in those less developed BRI participant countries. A moderate recession in China might lead to a substantial crisis in these economies.

Generally, spillover effects can be classified into return spillover and volatility spillover. Return spillover, or the intertemporal correlation among returns (first moment), is also known as the "lead-lag" effect in asset pricing. Assets involving large entities or high liquidity tend to have a leading effect on returns, while those that do not tend to have lagging effects [1], [2], [3], [4]. Sometimes this effect is even asymmetric depending on good news and bad news [5]. This field is also crucial for testing the market efficiency hypothesis because an efficient market should not exhibit such cross-or-autocorrelation patterns [6]. On the other hand, volatility spillover, the intertemporal correlation among volatilities (second moment), is more empirically studied than return spillover. Common methodologies for studying volatility spillover include the VAR and GARCH families. One notable VAR approach is the Diebold-Yilmaz spillover index, which utilizes the generalized forecast error variance decomposition (GFEVD) of a VAR system and summarizes the normalized results into an index [7]. This allows for easy interpretation of how significant one variable in the VAR system, typically the variance of an asset, is in explaining the variance of other variables in future periods. Compared to VAR family approaches, GARCH family approaches offer a more straightforward representation of model parameters, directly accessing both the mean and variance spillover using maximum likelihood or quasi-maximum likelihood estimation. DCC and BEKK are two common specifications for testing volatility spillover effects [8], [9].

Building on these approaches, some recent studies have discussed the impact of the BRI on China's financial spillover to other parts of the world. Feng et al. [10] discussed the tail risk spillover network along the BRI countries, finding that cross-border investment, international trade, and economic freedom are important causes of risk transmission. Hsu and Chien investigate the effect of BRI on the dynamic correlation between the stock market volatilities of China and 20 other countries from 1997 and 2020 [11]. After estimating the dynamics correlation using DCC-GARCH, they found BRI significantly boosts the comovement among risk when controlling for numerous factors. However, a serious problem is embedded within these studies. As we know, the different market has different opening and closing times. Without clarifying the lag alignment between markets creates serious logical inconsistency.

Addressing their methodological issues by abandoning the multivariate specification of the GARCH model and applying E-GARCH-X models, this paper investigates the spillover effect from China on other stock markets, both BRI participants and non-participants. Utilizing 68 MSCI country indices over 15 years, I found that the spillover effects, both return and volatility, have not significantly changed over time both for BRI participants and non-participants. This result is intuitive, as the BRI is designed not for equity markets but for infrastructure and general economic development. Moreover, BRI investments are mostly generated with strict scrutiny and financial control.

It would be surprising to observe significant changes before and after. On one hand, these results imply that global portfolio diversification is still valuable since the spillover effects of China on other financial markets remain limited.

The remainder of the paper is organized as follows: Chapter 2 discusses the empirical methodology and data used in this study; Chapter 3 illustrates the results of the tests and the reasoning behind them; Chapter 4 summarizes all findings and content presented previously.

2 Methodology

2.1 Empirical models

Two main obstacles in implementing GARCH specifications for spillover analysis are: 1) addressing non-synchronous trading times, and 2) maintaining asymptotic constraints for GARCH, including ensuring the positive definiteness of conditional variance and keeping the spectral radius of the sum of ARCH and GARCH terms strictly less than 1. Given the limited methods available for addressing both obstacles simultaneously in multivariate GARCH, I opted for a univariate specification.

In this study, an Exponential-GARCH(1,1)-X model with skewed-t distributed innovations is used. The covariate in this model is the standardized residuals of another asset, constructed to test for both return and volatility spillover effects. Incorporating covariates within GARCH models is highly useful for increasing the predictability of conditional covariance and exhibits good asymptotic characteristics [12]. EGARCH, first proposed by Nelson [13], relaxes many restrictions of the simple GARCH model, including positive definite constraints, allowing for the estimation of negative spillover coefficients, if present.

The model is illustrated in equations (1), (2), and (3).

$$R_{\mathrm{j},t} = \mu_t + \varphi R_{\mathrm{j},t-1} + \lambda_0 R_{\mathrm{i},t-1} + \sum_{i=1}^{N} \lambda_i R_{\mathrm{i},t-1} D_{(2007+i)} + \varepsilon_{j,t};\ i \neq 6 \tag{1}$$

$$\varepsilon_{j,t} = \sigma_{\mathrm{j},t}\eta_t;\ \eta_t \sim norm(0,1);\ \varepsilon_{j,t} \sim sstd(0,1,T,\nu) \tag{2}$$

$$\ln\left(\sigma_{\mathrm{j},t}^2\right) = \omega_t + a(z_{t-1}) + \gamma(|z_{t-1}| - E|z_{t-1}|) + \beta \ln\left(\sigma_{\mathrm{j},t-1}^2\right) + \theta_i \hat{\epsilon}_{\mathrm{i},t-1}^2 + \sum_{i=1}^{N} \theta_i \ln\left(\hat{\epsilon}_{i,t-1}^2\right) D_{(2007+i)};\ i \neq 6 \tag{3}$$

R_j and R_i are returns for index j's and i's stock index, respectively. σ_j^2 is the conditional variance for index j, and η_t is a white noise innovation series with standard normal distribution. Due to the prevalent fat-tail distribution in stock returns, I assume the $\varepsilon_{j,t}$ follow a skewed-t distribution, whose shape and skewness are also parameters that need to be estimated. Using skewed t distribution with EGARCH can better capture the information in stock returns than most conventional setups [14]. a and β denote the typical exponential ARCH term and exponential GARCH term, showing the short-term and long-term persistence in volatility. γ denotes the asymmetrical effect of the innovation on return, with a negative coefficient indicating that bad news has a higher impact on the volatility. λ_i are the return spillover coefficients, and θ_i are the volatility spillover coefficients. $D_{(2007+i)}$ represents the year dummy variables from 2008 to 2023, excluding the base year 2013.

The model implements robust standard errors to correct for potential serial correlation and will be estimated using Quasi-Maximum Likelihood Estimation (QMLE). This model partly resembles the structure of GARCH-BEKK-X, which includes past conditional variance information of both the index itself and others, along with an exogenous covariate.

In this study, the primary focus is on the λ_i and θ_i. The effects in the base year, 2013, are indicated by the subscript 0, and the year-specific moderating effects are shown by the coefficients with the year dummy. If the spillover effect changed after 2013, the year the BRI was initiated, the coefficients related to the year dummy variables (λ_i and θ_i, where $i \neq 0$), will be significant.

2.2 Data

For this analysis, I utilized 68 MSCI country indices obtained from the Wind Financial Terminal. Unlike other studies, which predominantly focus on developed and emerging markets, our study also includes frontier markets, which are less developed than emerging markets. The dataset includes indices from 23 frontier, 23 emerging, and 23 developed markets. Of these, 45 markets (including China) are participants in the Belt and Road Initiative (BRI), encompassing all 23 frontier, 17 emerging, and 5 developed markets. An advantage of using MSCI indexes is that the close prices of all countries' market indexes are reported synchronously at 18:30 Eastern Daylight Time (EDT), making all data not suffer from the problem of non-parallel trading time.

All returns are logarithmic standardized returns, calculated as: $r_t = \ln(P_t) - \ln(P_{t-1})$; $R_t = (r_t - \mu)/\sigma$. In this way, the data are suitable for comparative analysis across different assets and periods. Additionally, with less extreme value, the estimation of GARCH will be much easier. Table 1 illustrates the summary statistics of all 68 log-standardized returns. Column 2 shows the classification tag for each country, with F, E, and D being frontier, emerging, and developed respectively. The number after FED indicates whether the country is a BRI participant (1=participant).

Table 1. Currency information and summary statistics for the market indexes

Country	TAG	Mean	SD	Min	Median	Max
Morocco	F1	-0.025	1.011	-9.918	-0.001	5.495
Bahrain	F1	-0.056	1.297	-23.435	0.000	7.931
Kuwait	F1	-0.011	1.233	-22.612	0.000	8.714
Oman	F1	-0.018	1.093	-17.333	0.000	10.867
Bulgaria	F1	-0.044	1.636	-18.315	0.000	11.377
Kazakhstan	F1	-0.010	2.227	-24.523	0.000	17.764
Romania	F1	-0.005	1.803	-31.624	0.018	12.534
Ukraine	F1	-0.110	2.657	-48.608	-0.027	30.492
Lebanon	F1	0.006	3.959	-159.499	0.000	160.022
Kenya	F1	-0.013	1.191	-7.135	0.000	9.904

Mauritius	F1	-0.014	1.203	-15.299	0.000	13.144
Nigeria	F1	-0.051	1.571	-36.294	0.000	8.479
Tunisia	F1	-0.009	0.942	-6.718	-0.028	5.394
Vietnam	F1	0.003	1.439	-7.153	0.000	5.441
Serbia	F1	-0.040	1.707	-16.218	-0.027	18.895
Argentina	F1	0.000	2.557	-51.131	0.000	12.976
Sri Lanka	F1	-0.019	1.474	-17.189	0.000	16.627
Jordan	F1	-0.040	1.317	-45.674	0.000	9.230
Pakistan	F1	-0.057	1.484	-12.858	-0.002	8.630
Russia	E1	-0.362	20.460	-1282.725	0.000	23.976
Egypt	E1	-0.027	1.827	-38.223	0.000	11.084
Indonesia	E1	0.007	1.674	-14.576	0.000	15.633
Malaysia	E1	-0.010	0.927	-6.002	0.000	7.203
Thailand	E1	0.007	1.432	-14.576	0.000	9.733
Qatar	E1	-0.009	1.293	-13.892	0.000	11.259
U.A.E	E1	-0.010	1.599	-17.273	0.000	18.628
China	E1	-0.004	1.636	-12.837	0.000	14.042
Mexico	E0	-0.001	1.624	-11.183	0.021	15.159
Philippines	E1	0.009	1.421	-14.511	0.000	7.986
Brazil	E0	-0.026	2.251	-19.433	0.000	16.618
Chile	E1	-0.014	1.619	-16.736	0.000	16.369
Taiwan	E0	0.015	1.315	-7.228	0.000	8.232
Colombia	E0	-0.016	1.798	-21.900	0.000	15.941
Czech Republic	E1	-0.021	1.698	-16.747	0.008	19.721
Greece	E1	-0.090	2.638	-25.061	0.000	17.173
Hungary	E1	-0.010	2.276	-20.349	0.017	20.311
India	E0	0.014	1.525	-15.623	0.018	19.486
South Korea	E0	0.005	1.753	-20.672	0.000	24.987
Peru	E1	0.001	1.895	-16.503	0.000	13.028
Poland	E1	-0.029	1.985	-17.650	0.000	14.234
South Africa	E1	-0.007	1.926	-13.566	0.036	12.353
Turkey	E1	-0.014	2.256	-19.144	0.031	25.942
Israel	D0	-0.011	1.263	-11.696	0.012	9.831
Australia	D0	-0.004	1.564	-15.975	0.047	8.808
Austria	D1	-0.026	2.010	-16.647	0.044	13.354
Belgium	D0	-0.012	1.544	-18.224	0.002	10.664
Canada	D0	0.000	1.439	-14.245	0.044	12.205
Denmark	D0	0.029	1.480	-13.512	0.036	10.713
Finland	D0	-0.014	1.643	-12.085	0.005	10.292
France	D0	0.002	1.594	-14.903	0.044	11.844
Germany	D0	-0.003	1.582	-15.094	0.032	11.589
Hong Kong	D0	0.000	1.261	-12.567	0.004	10.449
Ireland	D0	-0.015	1.904	-18.931	0.011	13.599
Italy	D1	-0.016	1.830	-20.544	0.031	12.470
Japan	D0	0.004	1.284	-9.513	0.018	11.467

Netherlands	D0	0.009	1.535	-12.090	0.042	10.527
New Zealand	D1	0.000	1.374	-10.066	0.011	10.202
Norway	D0	-0.017	1.948	-14.225	0.014	15.394
Portugal	D1	-0.025	1.565	-13.832	0.002	11.820
Spain	D0	-0.016	1.760	-17.217	0.000	16.005
Sweden	D0	0.004	1.815	-14.810	0.017	14.052
Switzerland	D0	0.013	1.157	-11.325	0.022	9.735
U. K.	D0	-0.007	1.429	-14.205	0.042	12.161
U. S.	D0	0.029	1.283	-12.922	0.035	11.043
Singapore	D1	-0.008	1.229	-9.809	0.001	8.563

3 Results

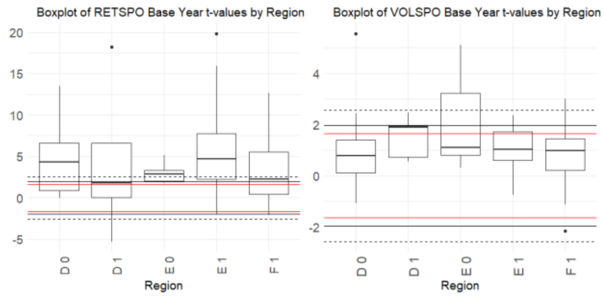

Fig. 1. T-value of the coefficients of the return and volatility spillover effects from China

Figure 1 displays the distribution of the T-values for the coefficients associated with both return and volatility spillover effects from China to other countries in the base year 2013, categorized by region type (Developed, Emerging, Frontier, where "1" denotes BRI participants, and "2" denotes non-participants). The critical values for 90%, 95%, and 99% confidence levels (C.L.) are represented by the red solid line, black solid line, and black dashed line, respectively.

The distributions reveal that the spillover coefficients for all three regions are positive, suggesting that both the return and volatility spillover effects, if statistically significant, tend to be positive. A notable majority of the spillover coefficients for developed and emerging markets are significant. In contrast, only about 50% of the coefficients for frontier markets show significance. This disparity in statistical significance suggests that, in 2013, the spillover effects from China's equity market had a more pronounced impact on developed and emerging markets compared to frontier markets. This outcome aligns with expectations, considering that many frontier markets are relatively isolated from the global financial market. Furthermore, the majority of volatility spillover coefficients are not statistically significant, indicating that the risk transmission from China to these countries was not substantial during the base period.

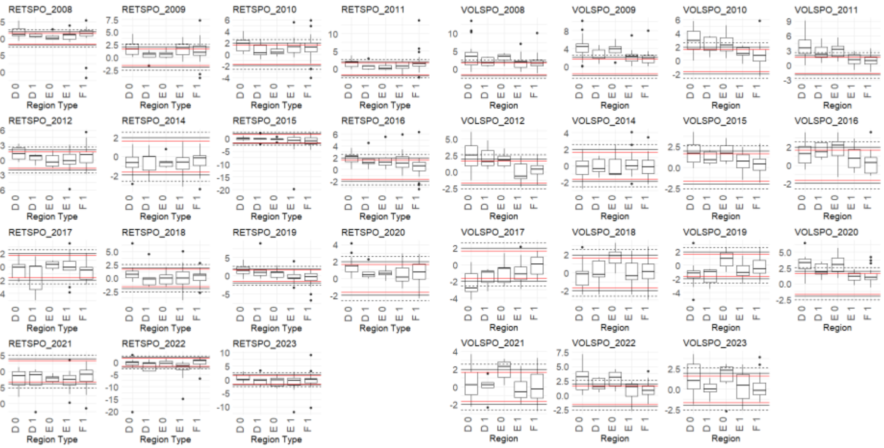

Fig. 2. T-value for the Year dummy for return and volatility spillover effects from China

Figure 2 presents the year-specific coefficients for return and volatility spillover, respectively. Generally, most of the data points fall within the range of statistical insignificance, indicating that spillover effects in years other than 2013 are largely indistinguishable. This result contradicts previous studies yet it remains intuitive because the Belt and Road Initiative (BRI) is primarily designed for international cooperation in infrastructure and trade rather than direct participation in equity trading [10], [11]. Moreover, China's stock market is highly isolated from the rest of the world, reducing the potential spillover effects from China to other parts of the world. Even in developed markets, which are so open, we haven't observed any significant change in the trend of comovement as documented by Bekaert et al. [15], let alone in a less open market like China.

Nevertheless, there are several notable observations. Firstly, there is evidence of stronger positive return spillover for D0 markets from 2008 to 2010. A stronger positive volatility spillover also occurs for D0, D1, and E0 markets during the periods 2008 to 2012, 2020, and 2022. The first period corresponds with the recovery phase following the 2008 financial crisis, while 2020 and 2022 are closely linked to the impacts of COVID-19. This finding is similar to that of previous studies [16], [17]. This observation suggests that previous studies by Hsu and Chien [11], which often designate a single structural breakpoint, might inadvertently attribute the effects of these unique events to the Belt and Road Initiative (BRI), leading to the mistaken conclusion that BRI participation intensifies stock market linkages among participant countries. Secondly, the data shows that whenever year-specific volatility spillover effects are significantly different from zero, the increase is most pronounced in developed market non-participants (D0), followed by developed market participants (D1) and emerging market non-participants (E0). Notably, E0 displays a marginally higher distribution than D1, as indicated by its higher median. This pattern potentially suggests that the level of market development plays a more influential role in the spillover effect than BRI participation status.

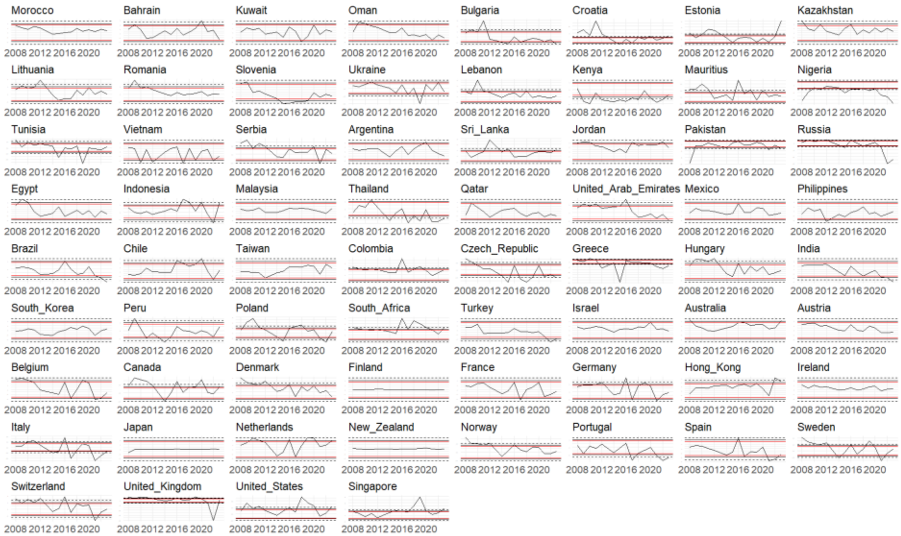

Fig. 3. T-values of Year-specific return spillover from China by country

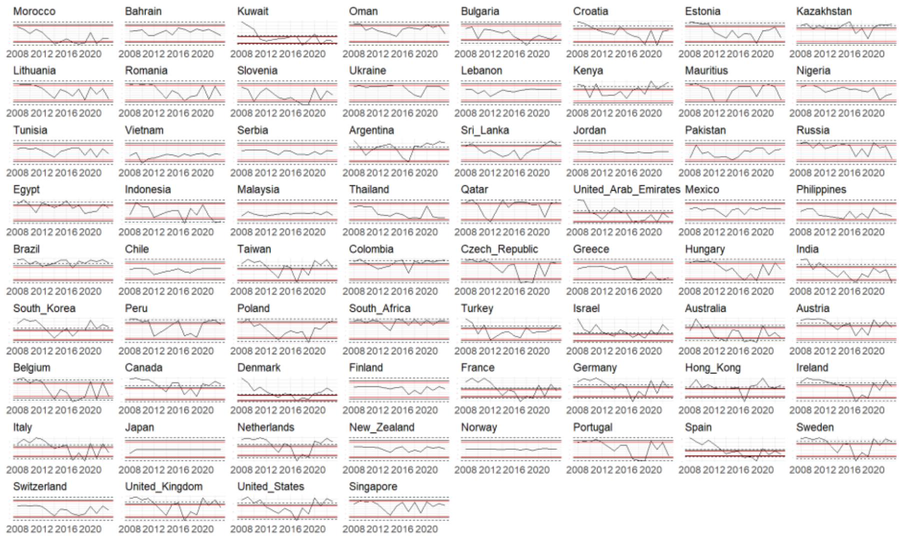

Fig. 4. T-values of Year-specific volatility spillover from China by country

Figures 3 and 4 provide a more detailed examination of the year-specific coefficients. These figures effectively capture the impact of certain significant global events. For instance, during the Greece debt crisis, the Russian-Ukraine conflict, the U.K.'s recession in 2021, and Nigeria's currency shortage in 2023, there is a noticeable decrease in the return spillover effects for these countries, turning sharply negative. Outside of these specific events, however, there are no apparent trends.

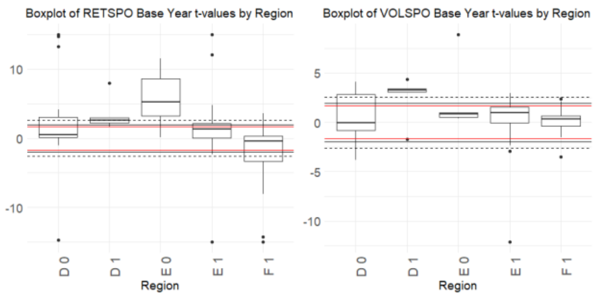

Fig. 5. T-value of the coefficients of the return and volatility spillover effects on China

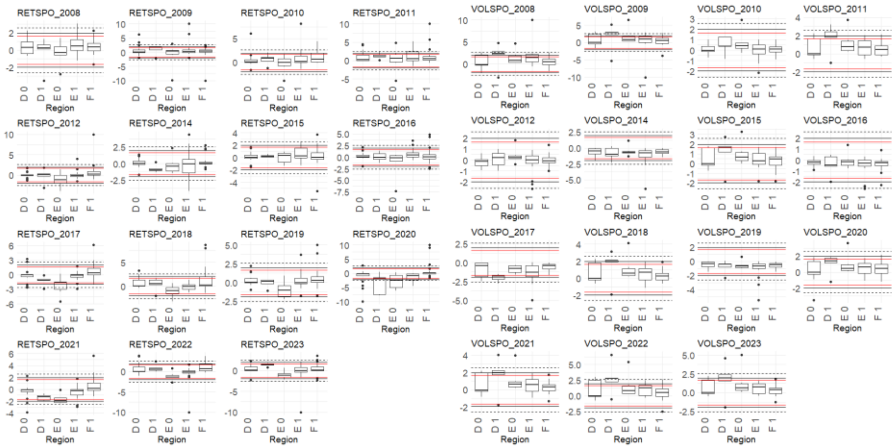

Fig. 6. T-value for the Year dummy for return and volatility spillover effects on China

I have also examined the spillover effect from other countries to China. Figure 5 presents the box plots for the coefficients, similar to Figure 2. When compared to the spillover effects of China on other countries, the effects that China receives from other countries are generally much less significant. Figure 6 illustrates the year-specific spillover effects. Unlike the effects from China to other countries, the effects from other countries on China are generally less significant—even the return spillover, which showed significant yearly effects in previous tests, does not demonstrate significant year-specific effects. These results suggest that China's equity market, as a market which relatively isolated from global equity markets, gives moderate spillover effects to others but receives limited impacts from other countries. China is a relatively leading market in the world rather than a lagged market.

Figures 7 and 8 provide a detailed view of the results from Figure 6. For most countries, the year-specific effects have a t-value within the insignificant range, indicating that the effects in other years are not statistically different from those in the base year, 2013. However, some countries, including the U.S., experienced significantly higher positive return spillover effects on China's equity market during the 2008 financial crisis. Similarly, some countries exhibited significantly higher negative return spillover to

China during 2020, the year the pandemic began. Conversely, the volatility spillover effects do not show significant year-specific trends, except in rare instances, such as 2008-2010 for Qatar, New Zealand, and the United States, and the post-pandemic period for Singapore.

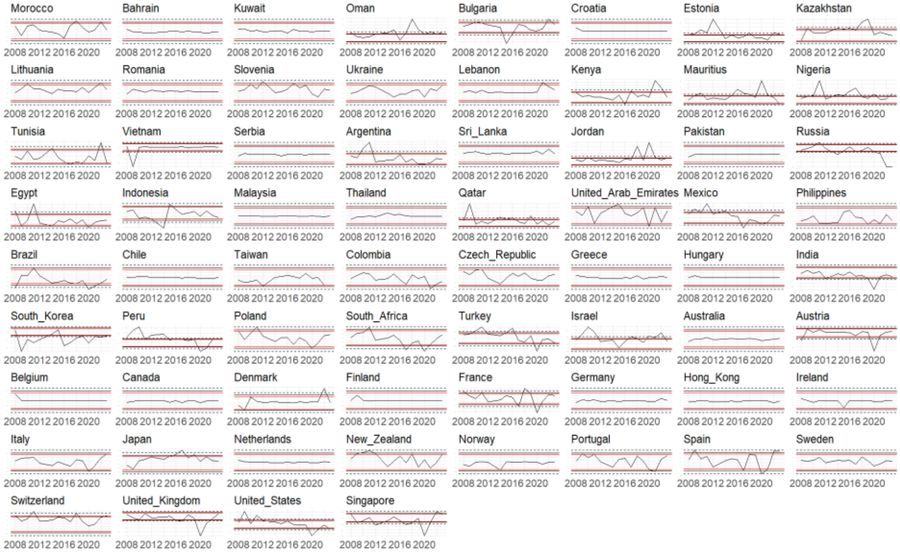

Fig. 7. T-value of Year-specific return spillover to China by country

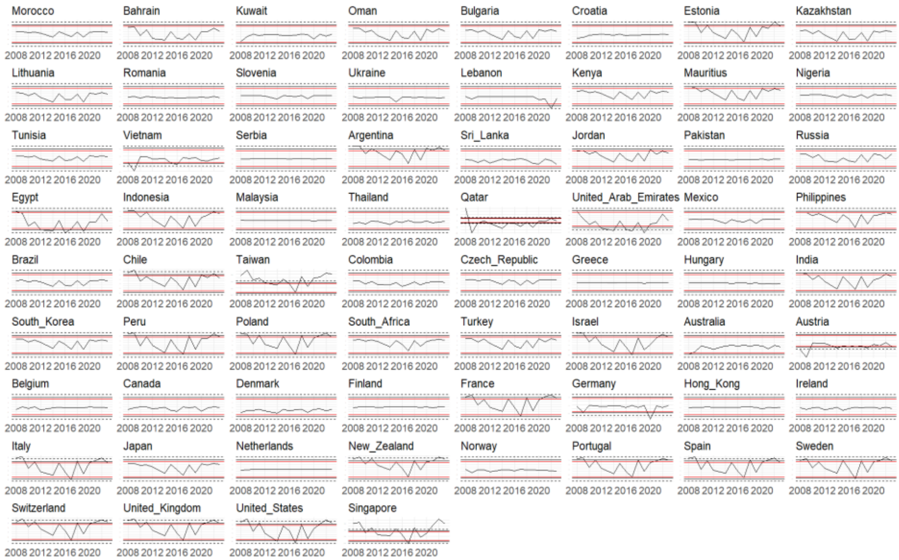

Fig. 8. T-value of Year-specific volatility spillover to China by country

In summary, it is evident that both the return and volatility spillover effects from 2008 to 2023 are not significantly different from those in 2013, the year China initiated its financial internationalization and the Belt and Road Initiative (BRI). The spillover effects in equity markets are influenced by global events rather than local reforms, and the BRI has not significantly altered the interactions between China's equity market and global equity markets.

4 Conclusion

This study provides a comprehensive analysis of the spillover effects of China’s equity market, with a special focus on the impact of the Belt and Road Initiative (BRI). Utilizing 68 MSCI country indices and an E-GARCH-X model, I meticulously explored the nuances of return and volatility spillover effects from and on China’s equity market. A significant aspect of our methodology was addressing the problem of non-synchronous trading times by applying the MSCI market index, a challenge often overlooked in similar studies. Our findings indicate that the spillover effects, both return and volatility, have remained relatively stable over time, without significantly difference from 2013, in which BRI was initiated. This stability highlights the BRI’s focus on infrastructure and broader economic development, rather than direct influences on the interconnection between China’s and the global equity markets.

The result underscores the enduring value of diversification in global portfolios. Despite the BRI’s extensive reach, it has not significantly altered the financial spillover landscape, suggesting that diversification strategies retain their importance in managing portfolio risk. The study reveals that the level of market development and global events, rather than local reforms, such as BRI participation status, is more critical in determining the extent of spillover effects. Developed markets showed a more pronounced response to global events compared to emerging and frontier markets, indicating the nuanced impact of market maturity on financial interconnectedness.

Future studies could explore the use of a structured VAR-GARCH-X model to better address the non-synchronous trading time problem. Additionally, employing a broader set of alternative indices beyond the MSCI could offer a more comprehensive view of global market dynamics. While the BRI has not markedly altered the financial spillover landscape, its long-term economic implications, and its role in shaping global financial interconnectedness remain rich areas for future research.

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