An Empirical Analysis of Volatility in China's Green Bond Market*

Boyuan Chen†

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Abstract

With the worldwide increasing concern of environmental problems, green bond is designed as a new source to help finance green and sustainable projects. This thesis is intended to quantify the volatility pattern of the Chinese green bond market and examine whether there exists long-term or short-term volatility transformation between the Chinese green bond market and the Chinese stock market/conventional (traditional) bond market applying the DCC-GARCH model. It's found that the volatility of the Chinese green bond market is driven by its own "experience", and there exists a long-term volatility transformation phenomenon among the Chinese green bond market and the other two benchmark markets. Also, the relatively small optimal hedge ratio between the green bond market and the equity market indicates that the green bond market lacks sufficient hedging protection capability against the equity market. The results provided in this thesis might give investors some insights into this emerging but promising market, which might also have implications for portfolio optimization and risk management from the perspective of hedging.

Keywords: Chinese green bond, conventional bond market, equity market, DCC-GARCH modeling, volatility transformation.

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†B.A. Candidate in Economics, Research Institute of Economics and Management, Southwestern University of Finance and Economics, Liulin Campus, Chengdu, Sichuan, 611130. Correspondence Email Address: chenboyuan@smail.swufe.edu.cn

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1 Introduction

Green bond is defined as a financial instrument to finance "green" and sustainable projects and provide investors with fixed-income payments. The green bond market has experienced significant growth over the past decade, expanding from about $4.2 billion in 2012 to almost $300 billion in 2020, since its establishment in 2007. The green bond has become a crucial instrument in the contemporary financial realm for tackling the effects of climate change and associated difficulties. In the past few years, China has made remarkable advancements in constructing an eco-friendly financial system, as the nation places more emphasis on preserving the environment and cultivating a sustainable economy, and one of the priorities in building a green financial system is to mature the green bond market and incentivize green financial instrument offerings. With the support of investors and policies, in the year 2021, With a three-year compound annual growth rate of 37.8%, China has become the second-largest global issuer of green bonds, following the United States.[1]. With the market rapidly growing in size and expectations of continued expansion, it is crucial to evaluate the market's volatility risks. Firstly, investors are becoming more conscious of the potential dangers of climate change on their investments, and they are starting to disclose these risks by using methods like the *Task Force on Climate-related Financial Disclosures (TFCD)*[2]. In addition, stakeholders are urging the investment industry to adopt more rigorous environmental,

[1] See "China's Green Bond Market: Growing Issuance and Historical Outperformance." MSCI, Feb. 24, 2022 and "2021 Annual Report of China Domestic Green Bond Market." CCXI Green Finance, Jan. 11, 2022 for detailed information.

[2] The TFCD has released guidelines for financial disclosure related to climate issues, with the goal of helping companies provide more valuable information to enable informed capital allocation. See Task Force on Climate-related Financial Disclosures Website for detailed information.

social, and governance (ESG) measures. Green bonds enable investors to influence the business approach of bond issuers and function as a means to reduce the hazards linked with climate change. In addition, they offer fixed returns on investment and contribute to diversifying investors' portfolios.

The research questions of interest in this thesis are as follows: How does the volatility pattern of the Chinese green bond market perform, compared to the aggregate conventional Chinese bond market? Do the Chinese green bond market and China's overall bond market have any short- or long-term spillover effects? Since in portfolio compositions, bonds are more stable assets compared to stocks and can offset the risks of stocks, the volatility transfers between the equity market and green bond market is also a research target; What's more, To what extent does a "shock" or "experience" in the green bond market contributes to the volatility of the aggregate bond market and equity market in China and *vice versa* is also focused on in the thesis.

Motivated by the absence of insights about the green bond market in China and the problems mentioned above, I apply a combination of univariate and bivariate ARIMA-DCC GARCH models to make estimations. First and foremost, under the ARIMA mean equation modeling and univariate GARCH(1,1) framework, it's observed that the Chinese green bond market's volatility clustering phenomenon is mainly driven by its "experience" rather than "shocks". After constructing model extensions based on the variance equation of the ARIMA-GARCH model, it's also found that relative to the green bond market and conventional bond market in China, the equity market's volatility needs more time to recover to half of its original volatility after suffering from a "shock", and the volatility of the Chinese green bond market after the Covid-19 pandemic is smaller than that before the epidemic. Additionally, the univariate GARCH analysis reveals the presence of a threshold effect, implying that the green bond market in China demonstrates a faster response to positive innovations. Also, from the conditional covariance parameters estimated in the bivariate DCC GARCH model, it's found that the transmission of volatility among the Chinese green bond market and the other two benchmark markets is mostly driven by long-term structural change in the financial industry. Last but not the least, using the conditional correlation series estimated from the bivariate DCC GARCH model, the optimal hedge ratios between the Chinese green bond market and the other two benchmark markets are calculated, where the optimal hedging ratio between the green bond market and the equity market fluctuates between -1.5 per thousand and 0.5 per thousand, which is relatively small and indicate that the green bond market is still “isolated” compared to other mature financial markets and lack the capabilities to provide sufficient hedging protection against the stock market.

This thesis has a potential marginal contribution to several lines of research. Primarily, this interstate cross-market analysis implements the time series analytic framework to study the volatility mode and risk spillover pattern between the green bond market, conventional bond market, and equity market in China, which is considered the greatest developing economy around the world, in a dynamic perspective. The thesis might fractionally fill the research gap existing in the research fields of financial assets that support environmentally sustainable initiatives or provide a fixed income return, with a regional focus on China. What's more, after the conditional correlations between the Chinese green bond market and the other two benchmark markets are estimated, the dynamic optimal hedge ratio is also calculated, which could also be served as an important indicator for investors to gain more comprehensive insights and adjust their investment behaviors and help portfolio optimizations. The results of the thesis's estimation could have implications for policies that can assist the domestic government in financing eco-friendly projects through the green bond market and contribute to the formation of reasonable public policies and regulations.

This thesis is organized as follows: Section 1 provides some basic facts and an introduction about the topic; section 2 presents a detailed literature review about volatility modeling, fixed-income asset research, and studies on green financial instruments. Section 3 is about data description and variable measurement. Section 4 presents the econometric method to be used and examines the existence of volatility transformation between the green bond market and the other two benchmark markets. Section 5 presents the estimation results and discussions, followed by the conclusion in section 6, reference, and acknowledgment.

2 Literature Review

This thesis might be associated with four main fields of literature. Primarily, since this thesis examines not only the risk volatility patterns of the green bond market itself but also attaches importance to the volatility spillover patterns between the green bond market and other financial markets, this thesis is largely correlated to the literature on the theory of risk & volatility transfer among different economies. The volatility spillover effect between financial markets, also known as financial contagion, has been studied abroad since the 1990s when Calvo and Reinhardt (1996) found changes in market correlations during the Mexican economic crisis; Baijn and Goldfajn (1999) found that the correlations of financial markets in several countries in Asia increased significantly during the financial crisis. Boyer (1999) argues that correlation coefficients that do not take into account conditional heteroskedasticity cannot provide an accurate description of market correlations under extreme conditions; Forbes and Rigobon (2002) use Boyer's (1999) methodology to study the Mexican and Asian financial crises, respectively and do not find volatility spillovers between markets. Rodriguesz (2007) uses the Copula method to study the volatility spillover effect and quantifies the effect while proving its existence. Based on the existing research results, there are 4 main mechanisms of volatility transformation. Masson (1998) proposed the Monsoonal Effect theory, which describes the spread of a crisis resulting from common shocks. For example, the economic policies implemented in major industrial countries can have similar effects and impacts on the economic policies of emerging market countries. The subprime debt crisis acted as a common shock that triggered a significant liquidity crisis, ultimately leading to a full-blown financial crisis. This highlights the monsoon effect as a method of transmitting a crisis. The second theory of volatility transformation is the theory of spillovers. Spillover effects can usually be divided into two kinds. One is the financial spillover effect and the other is the trade spillover effect. Since a country's economic ties with other countries are mainly through trade and finance, financial spillovers and trade spillovers become two important ways of financial volatility transmission. When a financial crisis occurs in a country, the country's exports, foreign direct investment and international capital inflows all decrease significantly. For example, in the financial crisis that occurred in Asia in 1997, Thailand was hit by both financial and trade spillovers. After the Thai baht was hit hard, countries with which it traded were involved in the crisis. The financial crisis greatly reduced the domestic demand of the United States, which is the world's largest importer, and the exports of the countries with which it has close trade relations will undoubtedly be significantly lower. Therefore, under the dual effect of financial spillover and trade spillover, the transmission of the crisis from the financial market to the real economy is faster, increasing the speed and intensity of the crisis infection. The third theory is called pure contagion and it refers to financial volatility induced by factors that cannot be explained by macro-fundamental data. It is mainly concerned with self-fulfilling prophecy[3] and multiple equilibriums theory[4]. Within this framework, a crisis in one country results in a "bad equilibrium" in another economy. This new state is marked by devalued currency, declining asset prices, outflow of capital, and a rise in non-performing loans. In this case, when the financial crisis brought the Icelandic

[3]Self-fulfilling prophecy is firstly proposed by Thomas (1928) and it refers to a psychosocial phenomenon in which someone "predicts" or expects something, and the "prediction" or expectation comes true only because the person believes or expects it to happen, and the person's resulting behavior is consistent with the realization of that belief. This suggests that people's beliefs influence their behavior. The rationale behind this phenomenon is that people have consequences for people or events based on their prior knowledge of the subject.

[4]Multiple equilibria in financial markets are dynamic equilibria formed by the interaction of gaming behaviors among market participants. Soros (2015) argues that the market in reality is not as neo-classically conceived - the price mechanism has flexible elasticity to lead supply and demand to general equilibrium, and the market in reality is not entirely regulated by prices, but quantity limits and the cognitive and participation functions of market participants also have a reflexive effect on prices and quantities, thus shaping the market through the expectations of participants. This has a decisive impact on the shaping of the market through the expectations of the participants.

banking system to a complete collapse, the United Kingdom and Germany, the main depository countries, immediately seized the country's assets in both countries, thus avoiding the impact of the Icelandic financial crisis on the financial sector in both countries through a pure contagion effect. The fourth theory refers to the "Herd Behavior". Due to the lack of sufficient information, investors generally believe that a financial crisis in one country will be followed by a similar crisis in other countries. According to Calvo and Mendoza's (2000) research, the tendency to herd can be attributed to information asymmetry and the substantial cost associated with gathering and analyzing information. Agenor and Aizenman (1998) have shown that the majority of small and medium-sized investors are unable to bear the expenses associated with acquiring and analyzing information. Hence, individual investors opt to base their decisions on the actions of other investors, particularly larger ones, and tend to mimic their investment choices. When a financial crisis occurs, and large investors reduce or sell their assets or portfolios, small investors will follow suit and reduce and sell, which leads to the herding effect.

These famous guesses for the mechanism are heavily based on an international financial market perspective. However, this term paper focuses more on the domestic markets of green bond and the other two financial instruments, the volatility transmission generated by the impact of the foreign exchange market can be somehow ignored. Following Kodres and Pristker (1999), the focus of this thesis's volatility transformation mechanism is not through the channel of liquidity demand in international financial markets or the channel of the banking system but pays more attention to investors who make good use of the hedging strategies among different markets. Investors rebalance their portfolio of securities when a shock hits one market, thereby propagating the shock to other markets.

What's more, this thesis is also in accord with the research modeling and modifying the volatility of financial instruments and the financial market. Uncertainty is critical to many famous modern finance theories. McKennis (1979) showed that uncertainty in the price volatility of financial market securities varies between forecast periods, with larger or smaller forecast errors usually occurring in clusters. In the majority of asset pricing theorems, the amount of risk premium is shaped by examining the covariance or correlation between the asset's future return and one or multiple benchmark portfolios. (for instance, the market portfolio). However, although the uncertainty of speculative prices is somehow identified and researched by some scholars like Mandelbrot (1963) and Fama (1965), it was not frequently implemented in financial and monetary economics. Before Engle's seminal paper in 1982, conventional methods for analyzing time series data focused on models for the mean, but after his paper, similar techniques were developed for modeling the variance.[5]. Engle modified the time variation in second moments by creating several prominent tools, which are named Autoregressive Conditional Heteroskedasticity (ARCH) model and its annexes. Later, many scholars modified and improved the ARCH-type models, Bollerslev *et al.* (1986) provided a more alternative and flexible time lag structure by conducting the Generalized ARCH model, which shows concern on the time series dependence on the squared residuals ε_t^2. In 1990, Nelson

[5]Referred to Engle (1982), the volatility of the data tends to vary with time, which means it can be measured by conditional variance. The time series data is also supposed to have strong persistence, which is known as volatility clustering. And the fat-tailed distribution can be always be observed in financial data, which indicates higher volatility. See Engle (1982), Dieobold (1986) and Bollerslev *et al.* (1994) for detailed information.

introduced the concept of Exponential GARCH (EGARCH) model. This model, which is asymmetrical, takes into account not only the likelihood of asymmetric shocks but also the differing impacts of "positive" and "negative news" on volatility.Additionally, Bera and Higgins (1993) amended the linear GARCH model into non-linear GARCH model (NGARCH), Glosten *et al.* (1989) proffered the GJR-GARCH model to capture the information that volatility is negatively correlated with perturbations and allow volatility to respond to shocks as a quadratic function. Zakoian (1994) optimized the ARCH model by adding dummies to the variance equation to show the heterogeneous impact of negative and positive shock as Threshold ARCH model, which is denoted as TARCH. However, the error term of TARCH follows the T-distribution rather than normal distribution. Besides TARCH, various economists and mathematicians attempted to make varying assumptions regarding the distribution of the model's error term. For instance, Normal-Poisson mixed distribution proposed by Jorion (1988) and extended exponential distribution proposed by Nelson (1991).

However, the univariate GARCH models mentioned above are not sufficient to study the co-volatilities of markets. Many empirical analyses about the topic of asset pricing or portfolio management can only be meaningful under a multivariate context. Bollerslev, Engle and Wooldridge (1988) proposed the VEC-GARCH model after the multivariate linear ARCH model in Kraft and Engle (1983) is proposed. The VEC-GARCH model demonstrates a mathematical equation involving the squared values of past residuals, the multiplication of residuals from distinct stages, and the conditional covariance matrix. However, it cannot assure that the conditional covariance matrix will always be a positive definite matrix during each stage, and when there are more than two series, there are abundant parameters to estimate. Attanasio and Edey (1988) and Baba, Engle, Kraft and Kroner (1991) have provided a straightforward parameterization for the VEC-GARCH model that ensures positive definiteness, which is called BEKK-GARCH model. Bollerslev (1990) proposed the Constant Conditional Correlation GARCH model to achieve a more efficient way of attaining the covariant relation among variables by reducing the number of parameters. But the drawback of the model is that the conditional correlations among series are assumed to be constant. Although this assumption simplifies the process of inference, and multiple studies have found it to be a reasonable hypothesis based on empirical evidence (e.g. Cecchetti, Cumby and Figlewski, 1988; Kroner and Claessens, 1991; McCurdy and Morgan, 1991), however, it does not align with the reality that financial markets in different sectors can impact each other. Finally, the Dynamic Conditional Correlation GARCH (DCC-GARCH) model tendered by Engle (2002) represents the concern of the time-varying correlations in financial markets and the model combines the adaptable nature of univariate GARCH models with concise parametric models for correlations., which is non-linear but can be estimated in an effective way with 2-step methods based on the likelihood function. The DCC-GARCH model delivers exceptional performance in diverse domains and produces coherent and comprehensible empirical outcomes (e.g. Celik, 2012; Jones and Olson, 2013; Jordà, 2005). Hence, this thesis mainly follows the univariate GARCH models proposed by Bollerslev (1986) and DCC GARCH model conducted by Engle (2002) to research and examine the existence of volatility spillovers and volatility clustering among two financial time series data.

Also, this thesis is relevant to the literature focusing on the fixed-income financial market and equity market. Specifically, Campbell and Vuolteenaho (2004) use the VEC-GARCH model to analyze different changes in future cash flows and alternations in discount rates in bond and equity markets. Steeley (2006) conducted an analysis of the relationship between British short-term and long-term bonds and equity and indicates that there exists a negative correlation between the two markets. Christiansen (2010) analyze the volatility transformation effects in U.S. and England's equity markets by employing the bivariate DCC-GARCH model and the result shows that the volatility of each market is driven more by their own past volatility than by that of the other market. This kind of literature focuses on various segments of the bond and equity market, showing somewhat inconsistent results according to the heterogeneity of the region, financial products, and sample periods. The results regarding the volatility of the Chinese green bond market and the risk transfer effect among the green bond market and the other two financial markets in China presented in this thesis could serve as a complement to existing fixed-income asset research.

Additionally, this thesis is also relevant to green financial instrument research. Ortas and Movena (2013) conduct an analysis of 21 clean technology equity indices from the perspective of return and risk and find that these equity indices demonstrating a commitment to clean technology and social responsibility perform better than the whole equity market and they have higher volatility in uprising markets. Pham (2016) investigates the volatility transformation between the green bond market and the aggregate U.S. bond market; Climent and Soriano (2011) unearth that on a risk-adjusted basis, green mutual funds underperform the overall fund market. Additional sources of literature discuss how the fluctuation effects in the green stock market extend to other market sectors, including the traditional stock market, the carbon market, and the oil market, etc. (Matsuda *et al.*, 2012; Nelson, Chang and Witte, 2012). While the literature researching the green bond market has been deeply established, there is almost no literature to study the volatility spillover between the Chinese green bond market and other sectors in financial markets, and most of the emphasis of literature is to analyze the return performance of the equity market. With the Chinese green bond market already taking shape, analysis conducted in this thesis could not only provide additional insights to the strand of literature allied with green financial instruments but also serve as assistance for financial market participants to get a fuller picture of the risks and volatility of the Chinese green bond market from a dynamic perspective, which could potentially help investors refine their investment strategies and assist governments in effectively making use of the green bond market to improve the quality of economic development.

3 Data

This thesis is planned to employ three financial time series data in a selected time period from May 31st, 2017 to April 29th, 2022. To measure the green bond market performance, the daily settlement prices of the CSI Exchange Green Bond Index published by China Securities Index is applied to serve as the indicator of the performance of Chinese green bond market. The behavior of the aggregate conventional bond market is measured by the Standard&Poor (S&P) China Bond Index published by S&P Global. The broad market performance of the Chinese equity market is represented by the S&P China A 300 Index, consisting of more than 2500 stocks listed on the Shenzhen or Shanghai exchanges.

The CSI Exchange Green Bond Index[6] is a tool for tracking the Chinese green bond market, and it consists of green bond listed on Shanghai Stock Exchange and Shenzhen Stock Exchange, excluding ABS, private-placement bond and equity-linked bond. A large majority of bonds subsumed in the CSI index are investment grade, with 73.44% of the bond rated with AAA, 14.95% of the bond rated with AA+ and 2.59% of the bond rated with AA. The mission of the CSI index is to follow the trail of “labeled”[7] green bond market performance. The S&P China Bond Index aims to monitor the progress of government and corporate bonds denominated in the local currency of China. Meanwhile, the S&P China A 300 Index is composed of 300 of the largest and most liquid firms from 24 industry groups of the global industry classification standard, selected to reflect the sector equilibrium of the overall market. The 2 indices offered by S&P Global serve as a benchmark for comparison to analyze the performance of the CSI green bond indices with the broader fixed-income market and equity market. For detailed descriptive statistics

[6] For more detailed information about CSI Exchange Green Bond Index, please refer to the official website of China Security Index.

[7] Green bonds can be categorized as either "labeled" or "unlabeled". Labeled green bonds are those where the funds raised are specifically intended for projects that promote environmental benefits. On the other hand, "unlabeled" green bonds are used for climate-aligned projects and initiatives, but do not have formal certifications. However, it’s important to note that some "unlabeled" green bonds can still contribute to environmental improvements, even if they are not formally labeled as "green". For example, certain clean energy technology companies may issue bonds that can have positive environmental impacts.

and the pattern of the first difference form of the 3 series, please refer to Table 1, Fig. 1 and Table 2. All series are taken first difference to be stationary and they are called "return series" in the following chapters.

Table 1: **Descriptive Statistics**

	GB Index	Aggregate Bond Index	A300 Index
Mean	0.023972	0.021338	0.519316
Median	0.030000	0.020000	1.535000
Maximum	0.660000	0.690000	204.6900
Minimum	-0.410000	-0.500000	-273.5500
Std. Dev.	0.067548	0.107095	46.50831
Skewness	0.907870	0.172266	-0.539870
Kurtosis	20.46776	5.926049	5.880188
Jarque-Bera	15626.59	470.1919	478.5854

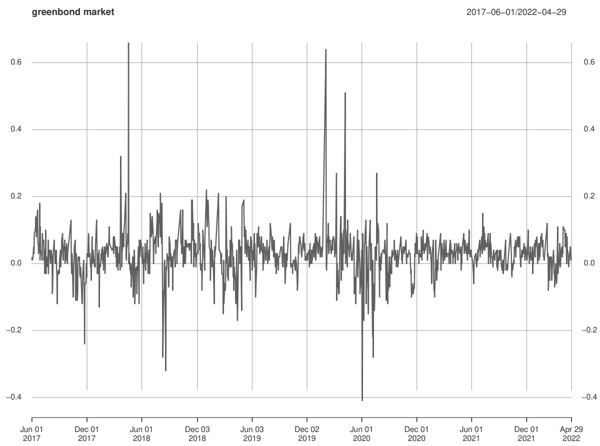
Note: Column 1, 2 and 3 shows the return series of green bond index, bond index and A300 index respectively. The time period of interest is from May 31st, 2017 to April 29th, 2022. All three series are taken first difference and three series all pass the Augmented Dicky-Fuller test.

Table 2: **Augmented Dicky-Fuller Test Results**

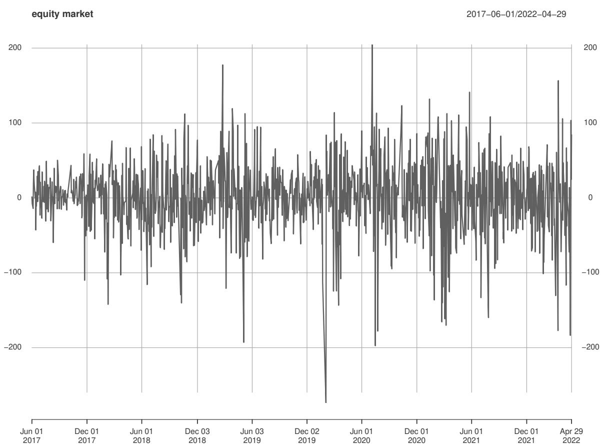
	ADF test results
Return on GB	-8.5357^{***}
Return on CB	-8.6535^{***}
Return on A300	-10.621^{***}

Note: GB = green bond market; CB = conventional bond market; A300 = equity market; $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$.
Note: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$.

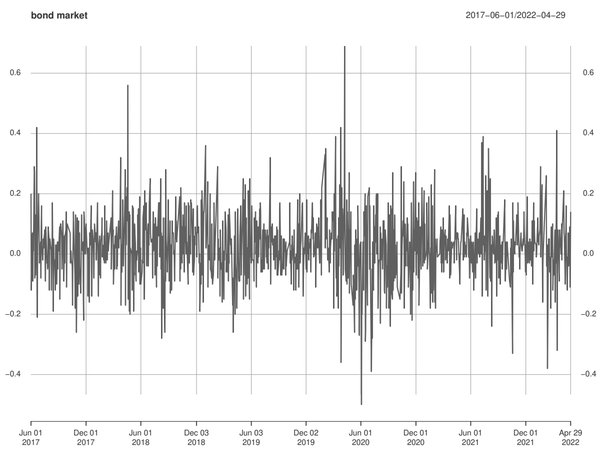
Figure 1: **Return Series of Three Markets**



(a) Green Bond Market's Return



(b) Equity Market's Return



(c) Conventional Bond Market's Return

4 Econometric Specification

To fully understand and address carefully with questions mentioned in the section of introduction, this thesis will start by building a univariate GARCH framework (served as a baseline model) to analyze the volatility pattern and characteristics of the financial time series data. Then, the DCC-MVGARCH (Dynamic Conditional Correlation – Multivariate Generalized Autoregressive Conditional Heteroskedasticity) framework will be applied to analyze the correlation between the volatility of various financial time series (In this thesis, the relationship between the Chinese green bond market and Chinese aggregate bond market and the connection between Chinese green bond market and Chinese equity market is supposed to be studied). By answering these research questions, the results might, to some extent, generate some relevant insights into this accrescent but propitious market and have some implications for portfolio optimization, financial risk management, asset pricing, and public policy formulation.

4.1 Baseline Model Specification

Firstly, by employing the univariate GARCH model, which applies an autoregressive (AR) structure to modify the conditional variance of one specific series, thereby enabling the endurance of volatility shocks over the selected time period. Within this framework, each series' volatility is modified in the following set of functions:

$$Return_t = E_{t-1}[Return_t] + \varepsilon_t,\ where\ \ \varepsilon_t | I_{t-1} \sim\ iid(0,\ \sigma_t^2)$$

This function represents the process of mean equation modification. $E_{t-1}[Return_t]$ represents the conditional expectation of one specific series at time point t following the set of information I_{t-1}. ε_t denotes the error term and σ_t^2 represents the conditional variance of each series at time point t.

$$Return_t = \sum_{h=1}^{r} \varphi_h Return_{t-h} + \sum_{k=1}^{s} \chi_k \varepsilon_{t-k} \tag{1}$$

$$h_{it} = a_0 + \sum_{p=1}^{P} a_i \varepsilon_{it-p}^2 + \sum_{q=1}^{Q} b_j \sigma_{it-q}^2 \tag{2}$$

$$where \;\; a_0 > 0; \;\; a_i > 0 \;\; \forall i \in [1,p]; \;\; b_j > 0 \;\; \forall j \in [1,q]$$

Following Engle (2002) and Bollerslev (1986), function (1) is a representation of the mean equation model specification in an ARIMA perspective. In the sense of economics, the parameters a_i and b_j represents the volatility clustering existence where one period of high volatility level is followed by another period of high volatility level and *vice versa*. The lag terms are all determined by the Akaike information criteria and Schwartz information criteria.

4.2 Baseline Model Extension

After obtaining estimated univariate GARCH results, it's also necessary to do some extensions and heterogeneous analyses so that we could get a deeper perspective on the volatility characteristics/patterns of each market selected.

Firstly, using the estimated a_i and b_j, following the computation methods of Half-life of a GARCH(1,1) model used by Pham (2016) and A. John *et al.* (2019), Half-life (days) could be calculated by using the equation of:

$$Half-life\ (days) = \frac{ln(0.5)}{ln(a_1 + b_1)} \tag{3}$$

and it represents how many days each market takes to recover from the shock and return to half of its original volatility. What's more, based on the univariate GARCH regression results, the threshold effect and Covid-19 impact are examined respectively. To investigate the presence of the threshold effect, the variance equation (function (2)) is revised in the following manner:

$$h_{it} = a_0 + \sum_{p=1}^{P} a_i \varepsilon_{it-p}^2 + \sum_{q=1}^{Q} b_j \sigma_{it-q}^2 + \delta D_{threshold} \varepsilon_{it-p}^2 \tag{4}$$

$$where\ \ D_{threshold} = \begin{cases} 1, if\ \ \varepsilon_{it-p} < 0 \\ 0, if\ \ \varepsilon_{it-p} \geq 0 \end{cases}$$

What's more, one dummy variable is also added into function(2) to examine whether the return of 3 series become more volatile before/after the pandemic. Considering 12/01/2019 as the beginning of the pandemic, the variance equation is updated as follows:

$$h_{it} = a_0 + \sum_{p=1}^{P} a_i \varepsilon_{it-p}^2 + \sum_{q=1}^{Q} b_j \sigma_{it-q}^2 + \lambda D_{pandemic} \tag{5}$$

$$where\ \ D_{pandemic} = \begin{cases} 1, if\ \ date\ \ < 12/01/2019 \\ 0, if\ \ date\ \ \geq 12/01/2019 \end{cases}$$

4.3 Multivariate Model Specification

To explore the Chinese green bond market and the other 2 benchmark markets' fluctuation patterns, functions (1) to (2) can be estimated for each financial market respectively. However, this method neglects the volatility interactions between the Chinese green bond market and the other 2 benchmark markets. To capture the possible volatility spillover effects between 2 markets, the multivariate GARCH model must be introduced. In order to model the time-varying volatility of two series (green bond market (GB) & conventional bond market (CB)), the green bond market (CB) and equity market (EM), respectively), the maximum likelihood estimation (MLE) approaches of Engle's (2002) dynamic conditional correlation GARCH model is applied. Within this framework, the mean equation specification is the same as that in the univariate GARCH part, but the conditional covariance matrix is denoted as $\mathbf{\Sigma_t}$, where $\mathbf{\Sigma_t}$ is defined as:

$$\mathbf{\Sigma_t} = \mathbf{D_t} \times \mathbf{R_t} \times \mathbf{D_t} = \begin{bmatrix} \sigma_{it}^2 & \sigma_{ikt} \\ \sigma_{kit} & \sigma_{kt}^2 \end{bmatrix}, \tag{6}$$

$$where \;\; \mathbf{R_t} = diag(\mathbf{Q_T})^{-1/2} \times \mathbf{Q_T} \times diag(\mathbf{Q_T})^{-1/2}, \tag{7}$$

$$\mathbf{D_t} = \begin{bmatrix} \sqrt{h_{it}} & 0 \\ 0 & \sqrt{h_{kt}} \end{bmatrix}, \tag{8}$$

$$h_{it} = a_{0i} + a_{1i}\varepsilon_{it-1}^2 + b_{1i}h_{it-1}, \tag{9}$$

$$h_{kt} = a_{0k} + a_{1k}\varepsilon_{kt-1}^2 + b_{1k}h_{kt-1}, \tag{10}$$

$$and \;\; \mathbf{Q_T} = (1-\alpha-\beta)\bar{\mathbf{R}} + \alpha z_{t-1}z_{t-1}' + \beta\mathbf{Q_T} - \mathbf{1}, \tag{11}$$

$$in\ \ which\ \ z_t = \begin{bmatrix} \varepsilon_{it}/\sqrt{h_{it}} \\ \\ \varepsilon_{kt}/\sqrt{h_{kt}} \end{bmatrix}, \bar{\mathbf{R}} = E[z_{t-1}z'_{t-1}] \tag{12}$$

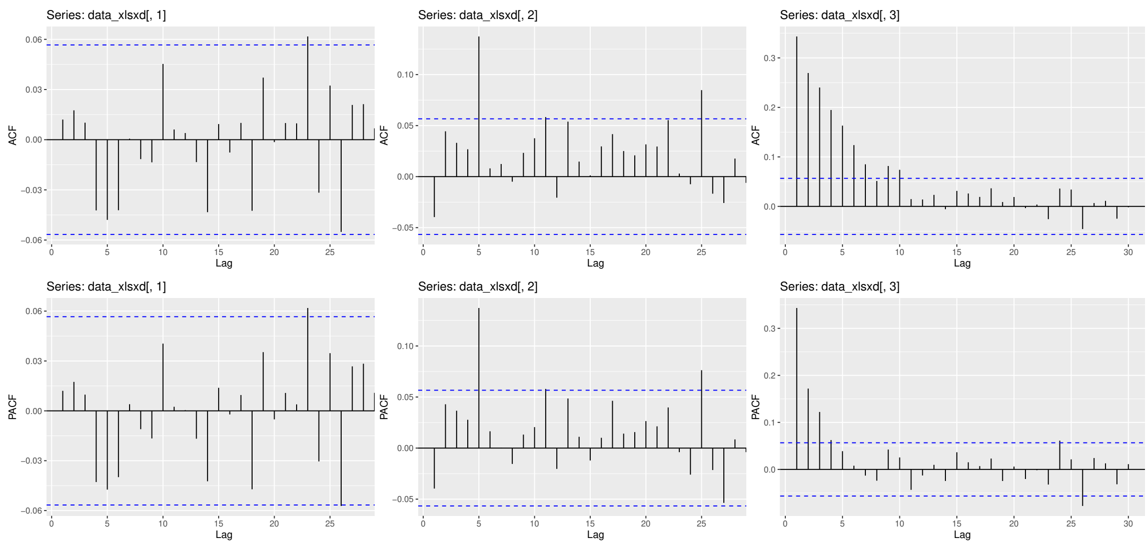
Function (6) denotes the conditional covariance matrix showing the concern of volatility spillover effect between two markets, and this matrix could be estimated by using functions (7) to (12). In the first step, since the conditional variance h_{it} and residual ε_{it} can be estimated using the univariate GARCH, and the standardized residual can be computed as z_t. Using z_t, the conditional covariance matrix of z_t could be estimated by using the function (12), which is denoted as $\mathbf{Q_T}$. After obtaining $\mathbf{Q_T}$, the conditional correlation matrix of two series $\mathbf{R_t}$ can be estimated and finally, the conditional covariance matrix of two series $\mathbf{\Sigma_t}$ can be calculated. In the variance equation (9) and (10), the interpretation of parameter a_1 and b_1 in economic sense is the same as that in function (2). However, following Engle (2002) and Chernov (2022), the parameters α and β can be interpreted as the level of volatility transformation between two markets in the short- & long-term respectively.

5 Empirical Results

5.1 Baseline Results Analysis

After the mean equation model identification (the model identification results are given in the Fig. 2 and Table 3), the univariate GARCH model estimation results can be represented in Table 4. From the estimation results, it's observed that the return of 3 markets' volatility is mainly driven by their own past volatility, which is consistent with the results provided by Pham (2016) and Park (2020). The persistence of three series are all smaller than 1 and volatility clustering is somehow observed.

Figure 2: **ACF & PACF Pattern of 3 series with Mean Equation Specification**



(a) Equity (b) Bond (c) Greenbond

Note: the upper panel shows the ACF patterns and the lower panel shows the PACF patterns. From left to right, column (a), (b) and (c) represent the autocorrelation function and partial autocorrelation function of equity market, conventional bond market and green bond market. Based on the identification commend of "auto. arima" in the statistical software R, the mean equation specification results are presented below.

Specification Results

	Mean Equation Specification
Returns on GB	ARIMA(1,0,1)
Returns on CB	ARIMA(5,0,3)
Returns on A300	ARIMA(1,0,0)

Table 3: **Box-Ljung Test of Squared Residuals Generated by ARIMA Models**

	GB Returns	CB Returns	Equity Returns
Q-statistics	21.112***	30.616***	66.46***

[1] *GB = green bond market; CB = conventional bond market; Equity = equity market;*

[2] $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$.

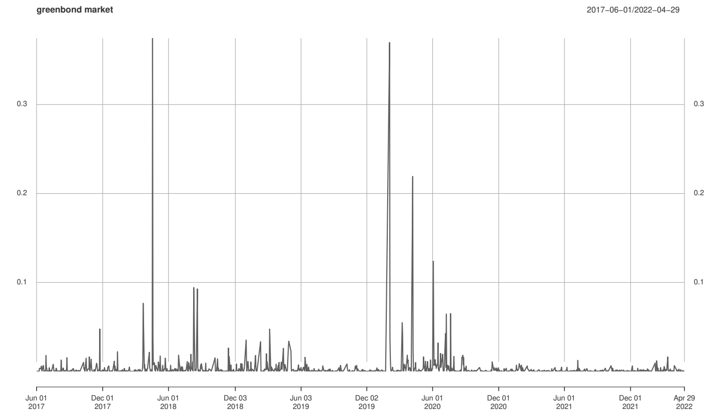
Table 4: **Univariate GARCH model estimation results**

	GB Returns	CB Returns	Equity Returns
a_0	0.000115***	0.005721**	34.60248*
a_1	0.062198***	0.147723**	0.12849***
b_1	0.924123***	0.597723***	0.86842***
Persistence: $a_1 + b_1$	0.986321	0.745446	0.99691
Half-life (Days)	50.325	2.360	223.973

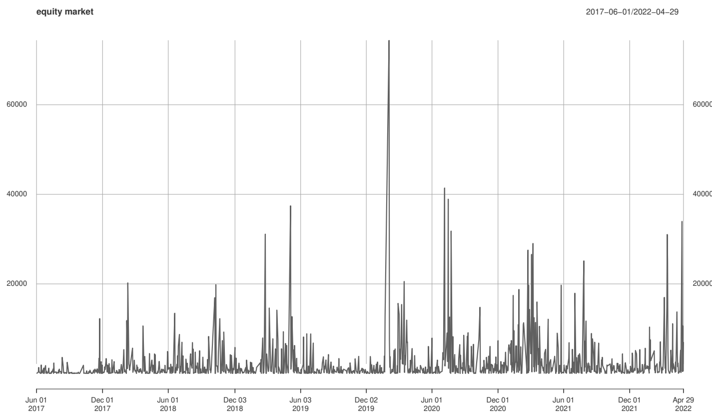
[1] *GB = green bond market; CB = conventional bond market; Equity = equity market;*
[2] **p < 10%, **p < 5%, ***p < 1%.*
[3] *The regression results are based on the GARCH (1,1) model, a_0 panel shows the constant in 3 regressions, a_1 shows the contribution of shock (measured as residual) at time t-1 to aggregate volatility (measured as conditional variance of series) at time t. b_1 represents the contribution of past volatility (also denoted as 'experience') at time t-1 to the aggregate volatility at time t.*

For baseline model extension results, according to Table 5, it's observed that the Half-life of the equity market is relatively higher than that of the other two markets, which indicates that the equity market needs more time to "cure" its pain after suffering from a shock. What's more, when estimating the existence of threshold effect, it's also observed that the equity market's volatility responds more rapidly to the negative shock, and the green bond market responds more rapidly during the period of positive shock, which is different from most of the financial markets with different financial instruments. What's more, the market for green bonds appears to have experienced reduced levels of volatility following the Covid-19 pandemic, which is consistent with the volatility pattern (measured using the square residuals estimated from ARIMA models) of green bond market provided in Fig. 3 (a) (note: all the volatility patterns are measured using the squared residuals generated from ARIMA models).

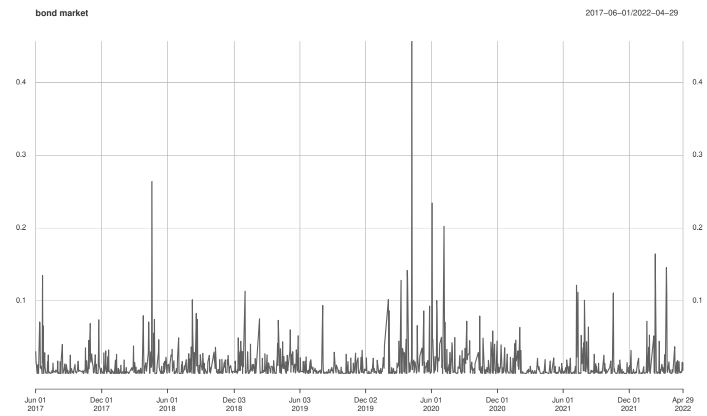
Figure 3: **Volatility Pattern of 3 Series**



(a) Green Bond Market's Volatility



(b) Equity Market's Volatility



(c) Conventional Bond Market's Volatility

Table 5: **Univariate GARCH Model Regression Extension**

	GB Returns	CB Returns	Equity Returns
Threshold Effect (When it's negative shock, the dummy variable = 1)	-0.028337^{**}	-0.017194	0.058595^{***}
Covid-19 Impact (After Covid =1, Before Covid = 0)	-0.000330^{*}	-0.000643	0.000207^{**}

[1] *GB = green bond market; CB = conventional bond market; Equity = equity market;*
[2] $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$.
[3] *The upper panel shows the threshold effect that whether each series responds to negative or positive news more rapidly; the lower panel shows whether the return of three series becomes more volatile during the pandemic.*

5.2 Bivariate DCC-GARCH results analysis

Although the univariate GARCH analysis could encapsulate the mode of volatility clustering of one specific market, it's unable to identify and apprehend the potential fluctuation transmission between two markets. The DCC-GARCH estimation results are shown in Table 6. Specifically, the column GB & CB presents the estimation results of the bivariate model for the returns of the GB market and the CB market. Column GB & Equity displays the outcomes of the identical bivariate model for the returns of the Chinese GB market and equity market. From the parameter of the first and second columns, it's observed that the GB market exhibits more volatility clustering than the CB market, and the equity market has a greater volatility clustering phenomenon than the GB market, which is in accord with the results estimated under the univariate GARCH framework. The estimations of conditional covariance parameters show whether there exists short-term or long-term volatility transformation between two markets. From the bottom panel, it's observed that the parameter α is insignificant in both relationship of GB & CB and GB & Equity.

The parameter β is significant in two relationships. This estimation results indicate that there only exists long-term volatility spillover effect among green bond market and other two benchmark markets.

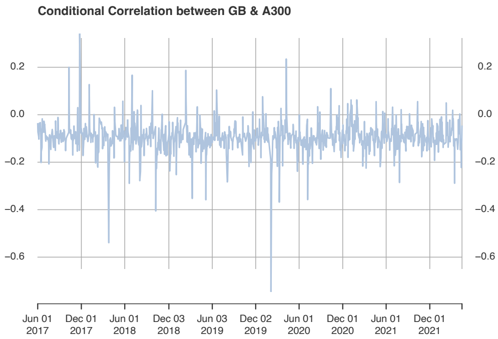
Table 6: **Bivariate DCC-GARCH Model Estimation Results**

	GB & CB		GB & Equity
Parameter Estimation: GB		Parameter Estimation: GB	
a_{0g}	0.000273	a_{0g}	0.000273
a_{1g}	0.141202*	a_{1g}	0.141202*
b_{1g}	0.8274412***	b_{1g}	0.827441***
Parameter Estimation: CB		Parameter Estimation: Equity	
a_{0b}	0.000691**	a_{0e}	37.962883*
a_{1b}	0.092199*	a_{1e}	0.130569***
b_{1b}	0.855476***	b_{1e}	0.863876***
Estimations for the conditional covariance parameters		Estimations for the conditional covariance parameters	
α	0.011759	α	0.054674
β	0.959064***	β	0.384216***

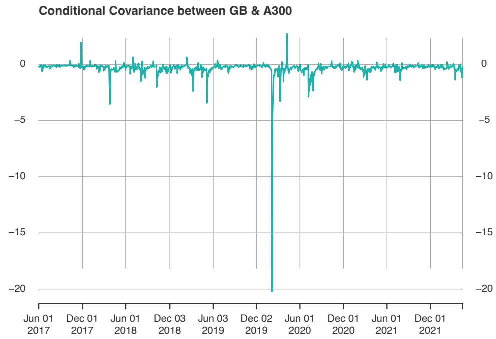
1 *GB = green bond market; CB = conventional bond market; Equity = equity market;*
2 *$^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$.*
3 *The interpretation of a_1, b_1 can be interpreted as that in the univariate GARCH section; the estimations for the conditional covariance parameters α can be interpreted as the existence of short-term volatility transformation between two markets in an economic sense, the β can be interpreted as the existence of long-term volatility transformation between two markets in an economic sense.*

What's more, the dynamic conditional correlation matrix can also be estimated from the DCC-GARCH model. Fig. 4 represents the conditional correlation series between GB market and the other two reference markets. It's observed that, from the dynamic perspective, the conditional correlation between the GB market and the equity market fluctuates from time to time and it's not always negative as the same as previously thought in a perspective of hedging. The dynamic conditional correlation between green bond and conventional bond market is consistently positive. The conditional covariance matrix can also be calculated under the DCC-GARCH framework. Fig. 5 shows how the conditional covariance alternation response to shocks in different markets. The Fig. 5 (a) and (b) all show that the conditional covariance between two markets increase as the shocks to the two indices are of the same sign and decrease when shocks of two markets are of opposite sign. What's more, if the magnitude of the green bond market's shock (shock[z_1]) is fixed, when the equity and conventional bond market's shock (denoted as shock[z_2] in Fig. 5 (a) and (b) respectively) increase or decrease by the same amount of value, the alternation of conditional covariance between the green bond market and equity market is significantly larger than that between green bond market and conventional bond market, which might not be counter-intuitive since the covariance is composed by the correlation and standard deviation of two series. Although the conditional correlation might be very close under the DCC-GARCH framework, the standard deviation of equity market is definitely larger than that of conventional bond market for burdening more risk and uncertainty, thus generating a greater alternation of conditional covariance.

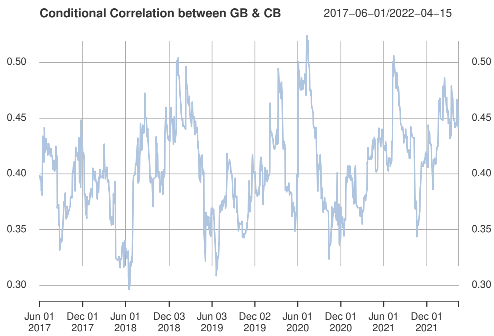
Figure 4: **Conditional Correlation&Covariance between green bond and two benchmark markets**



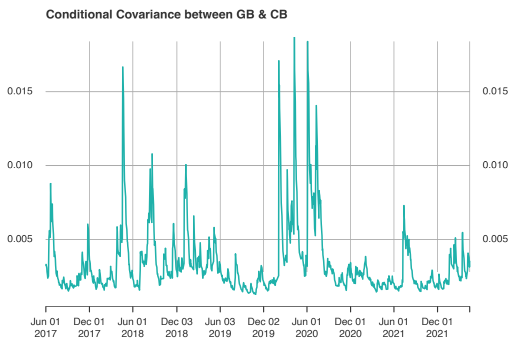
(a) Conditional Correlation: GB & A300



(b) Conditional Covariance: GB & A300

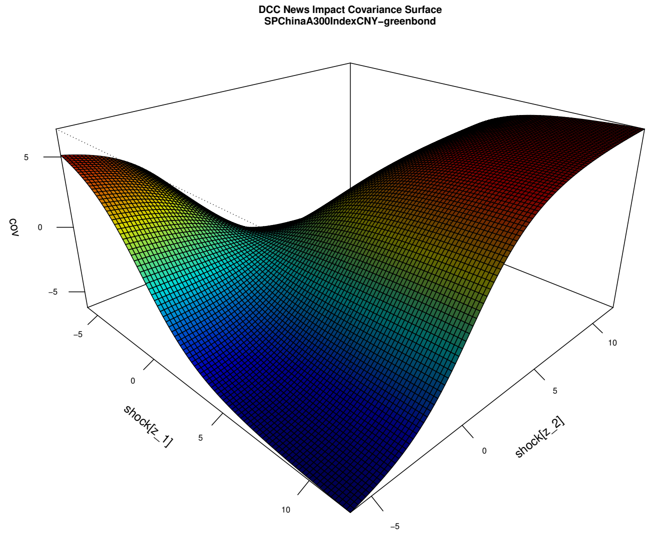


(c) Conditional Correlation: GB & CB

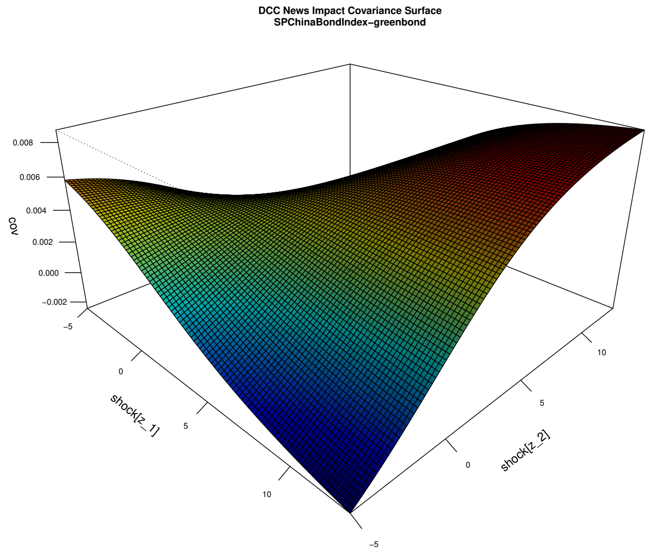


(d) Conditional Covariance: GB & CB

Figure 5: **Conditional Covariance between GB and Two Benchmark Markets Responding to Shocks**



(a) Conditional Covariance between GB & Equity Market



(b) Conditional Covariance between GB & CB Market

Note: The subscript shock[z_1] of two 3-dimension graphs refers to the shock of green bond and shock[z_2] in figure (a) refers to the shock of equity market, shock[z_2] in figure (b) refers to the shock of the conventional bond market.

5.3 Further Discussion

Within the DCC-GARCH estimation results, it has been noticed that there is a sole long-term fluctuation conversion between the green bond market and the other two benchmark markets. Before explaining why there only exists long-term volatility spillover, the problem that firstly needed to be addressed is the non-existence of short-term volatility spillover effect. One educated guess is that, from the perspective of asset quality, when the other two benchmark markets face innovation, the investors might not drop the green bond since most of the green bond has government funding support and are rated as triple A, which qualifies green bond as a high-quality asset. Companies issuing green bonds are basically large entities with stable revenue profiles and high creditworthiness levels. Considering the additional costs and issuance thresholds, the economic benefits of green bonds for issuers are not significant, and the main attraction is to enhance corporate reputation. In China, bonds issued in the market are generally highly rated, and this is also true for green bonds. Most publicly traded bonds are rated above A-, and some companies are required to apply for external guarantees for credit enhancement based on their financial condition. Although it suggests that as many low-rated investors are rejected by the capital market and lower the credit risk of the bond, it may lead to the inefficient allocation of monetary resources in the Chinese bond market.

What's more, the low sensitivity of green bond market's response to other two benchmark markets' shock might be linked to the "isolation" of the Chinese GB market. Since the development of the green bond market started late, and the current role of green bond is similar to a goal-oriented fund pool that can bring extremely stable return, which makes it relatively "isolated" from other markets with different financial instruments for its low marketization degree. Similar to methods used by Kroner and Sultan (1993), the GB and the other two benchmark markets' hedge ratios could be calculated by employing the equation:

$$Optimal\ \ Hedge\ \ Ratio = \frac{\sigma_{ikt}}{\sigma_{kt}^2} \tag{13}$$

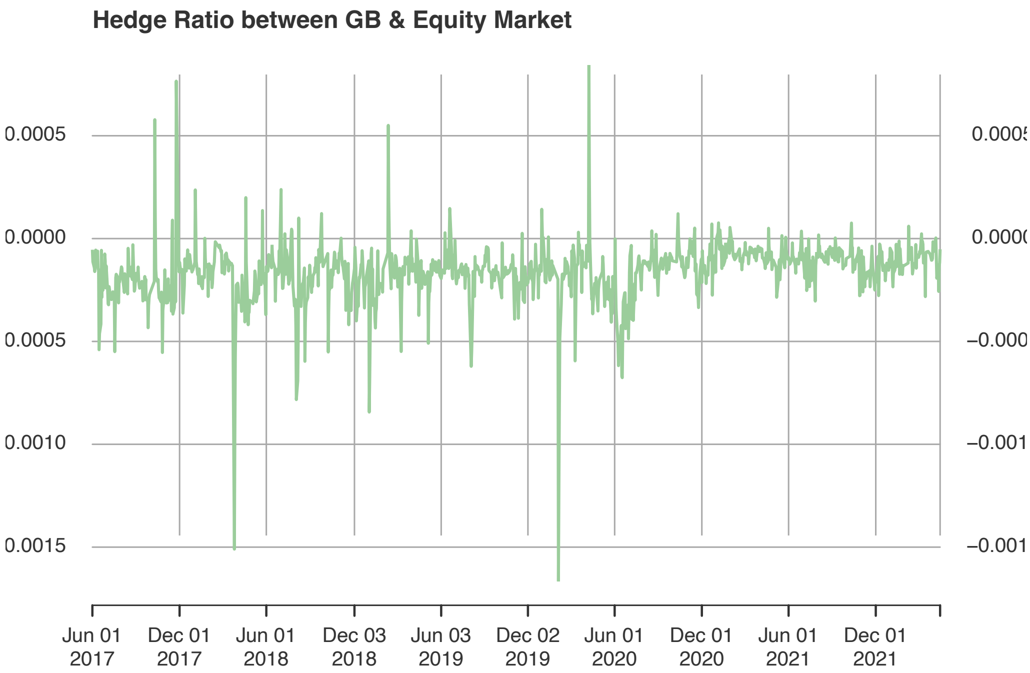
Where σ_{ikt} implies the conditional covariance between the GB market and one specific benchmark market and σ_{kt}^2 denotes the variance of one specific benchmark market. If the hedge ratio calculated is positive, it indicates how much a long position in the green bond market can be offset by taking a short position in a different market. On the other hand, a hedge ratio that is negative would reveal the degree to which a short position in the GB market can hedge by taking a long position in another benchmark market. The hedge ratio calculation results can be shown in Fig. 6. From figures (a) and (b) in 6.5, there is a significant amount of variabilities observed in the hedge ratios, and this indicates that the volatility interaction between the GB market and the other two benchmark markets is inconsistent. The hedge ratio between the equity market and GB market fluctuates between -1.5 per thousand and 0.5 per thousand. Such a small hedging ratio indicates that green bonds cannot provide sufficient hedging protection for stock investment. To some extent, this also confirms the previous hypothesis that green bonds are not so sensitive to the shock of the equity market. And it can be observed that the CB & GB hedge ratio fluctuates between 0.1 and 0.7, and the mean is around 0.25. This indicates that there is an asymmetry in the returns of the green bond market and the traditional bond market. (detailed information of the hedge ratio is provided in Table 7).

Table 7: **Summary of Hedge Ratios**

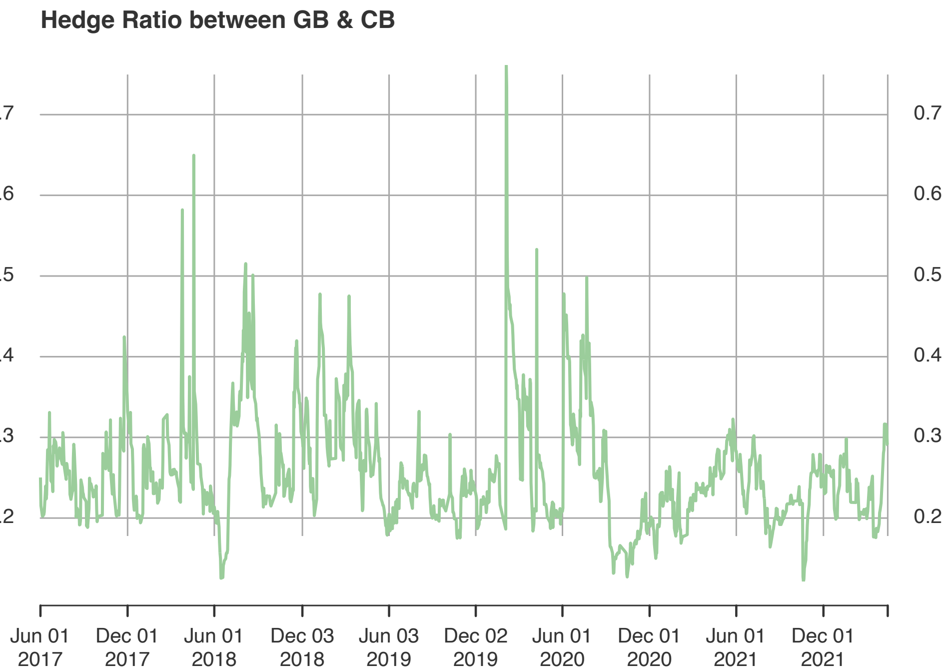
	Green Bond & Equity	Green Bond & Conventional Bond
Minimum.	$-1.666e-03$	0.1215
1^{st} Quartile	$-2.136e-04$	0.2125
Median	$-1.450e-04$	0.2432
Mean	$-1.626e-04$	0.2576
3^{rd} Quartile	$-9.319e-05$	0.2836
Maximum.	$8.436e-04$	0.7611

The existence of long-term volatility spillover effect between the green bond and the other two benchmark markets might be related to some "structural changes" that could last for a long period of time in the financial system and create pessimism among investors about the overall macro-financial market. For instance, from the view of the aggregate conventional bond market, the level of credit risk is greater compared to that of the green bond, and there still exists a lot of low-rated bond, which might contain default risk. A default in the bond market might generate an impact on the liquidity of the market and trigger liquidity risk. The outbreak of bond defaults will trigger the emergence of liquidity stratification in the money market. Bond defaults lead to market concerns about the creditworthiness of small and medium-sized financial institutions, resulting in increased difficulty in funding some of the less qualified financial institutions and a significant liquidity stratification phenomenon. The difficulty of financing companies in small and medium size might reduce investors' optimistic estimates for the overall financial market. From the equity market's perspective, the structural shock might manifest itself in the possibility that some companies in financial markets are overrated, and there might

Figure 6: **Hedge Ratio between GB and Two Benchmark Markets**



(a) Hedge Ratio between GB & Equity Market



(b) Hedge Ratio between GB & CB Market

exist inadequate financial regulation in the whole financial system, which might also lower investors' optimistic assessments of the financial markets as a whole and generate an impact on the green bond market.

6 Conclusion

With the rising concern of environmental issues, the green bond has become an important tool for financing environmental protection project. As the market for green bonds is consistently expanding., it's necessary for investors to gain a deeper comprehension of the volatility pattern of this market. This thesis examines the volatility patterns within the green bond market and investigates whether there is a spillover effect of volatility between the green bond market and either the equity market or the conventional bond market, using a dynamic approach. It's observed that the green bond market's volatility is mainly driven by its own "experience", and it responds more rapidly when receiving a positive shock, which is different from other financial markets. By the way, after Covid-19 pandemic, the volatility of green bond market become smaller. Under the DCC-GARCH analytical framework, a long-term volatility spillover effect is found between the green bond market and other two benchmark markets. The only existence of long-term volatility might be correlated with the structural change in financial markets that might make investors feel pessimistic about the whole financial system, and it somehow shows that the green bond market is still "isolated" relative to other mature financial markets since it is less volatile when exposed to larger volatility in other financial markets in the short run. From the perspective of hedging and portfolio optimization, the green bond market does not provide effective hedge protection against equity market. Hence, in the future, the policy makers are supposed to improve the policy support system, promote the implementation of green projects, guide the wide participation of social capital, and improve the marketization level of green bonds. Also, the authority should improve the rules of the green bond opening system, enhance financial infrastructure, and optimize the investment environment and further enrich the types of green bond investors to make the green bond more attractive in the aspect of investment and facilitate the green bond market's development.

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