LUT School of Business and Management
Strategic Finance and Business Analytics

Volatility Analysis of the Green Bond Market: Clustering, Leverage Effects and Spillovers from Conventional Bond Markets

Master's Thesis

21.12.2020

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Abstract

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Title	Volatility Analysis of the Green Bond Market: Clustering, Leverage Effects and Spillovers from Conventional Bond Markets
Faculty	LUT School of Business and Management
Degree Program	Strategic Finance and Business Analytics
Degree	Master of Science in Economics and Business Administration
Year	2020
Details	Master’s thesis 82 Pages, 13 Figures, 18 Tables, 6 Appendices
1st Examiner	Azzurra Morreale
2nd Examiner	Mikael Collan
Keywords	Volatility analysis, Green Bonds, Volatility Clustering, Leverage effect, Volatility Spillovers

The objective of this thesis is to examine the volatility behavior of the green bond market. The analysis is focused on volatility clustering, leverage effects and volatility spillovers from conventional bond markets since these volatility features are typical in financial time series. The presence of these volatility features is observed from three different econometric model modifications belonging to the Generalized Autoregressive conditional heteroscedasticity (GARCH) - family: GARCH -, GJR-GARCH and DCC-GARCH models.

The analysis is conducted to two different green bond market indices, S&P Green Bond Index and S&P Green Bond Select Index. The first one represents more general and inclusive green bond market whereas the latter represent a more exclusive and selective green bond market. The conventional bond markets used for reference and in the volatility spillover analysis are from the S&P US Aggregated Bond Index representing conventional bond markets in the United States and S&P China Bond Index representing conventional bond markets in China. The time period covers an entire decade from 1.1.2010 to 31.12.2019.

This study found evidence that the green bond markets experienced higher levels of volatility clustering and persistence of shocks compared to the conventional bond markets. Although the significance of these features lowered towards the end of the decade. There was some evidence of leverage effect in the green bond markets in the first half the decade but no longer in the second half. These volatility features were more persistent in the more inclusive market than the more exclusive. The green bond markets have been correlated with both conventional bond markets, in the US and in China throughout the decade since there is evidence of volatility spillovers between these markets. However, the green bond market has become more independent throughout the decade since the effect of volatility shocks in the conventional bond markets decreased towards the end of decade.

Tiivistelmä

Tekijä	Roosa Karesjoki
Tutkielman nimi	Vihreiden joukkuvelkakirjalaimarkkinoiden volatiliteettianalyysi: klusteroituminen, asymmetrisyys ja tavanomaisten joukkovelkakirjamarkkinoiden volatiliteetin vaikutus
Tiedekunta	LUT School of Business and Management
Maisteriohjelma	Strategic Finance and Business Analytics
Tutkinto	Kauppatieteiden maisteri (KTM)
Vuosi	2020
Tiedot	Pro gradu -tutkielma 82 sivua, 13 kuviota, 18 taulukkoa, 6 liitettä
Tarkastajat	Azzurra Morreale Mikael Collan
Hakusanat	Volatiliteettianalyysi, Vihreät joukkovelkakirjamarkkinat, Volatiliteetin klusteroituminen, Volatiliteetin asymmetrisyys

Tämän tutkimuksen tarkoituksena on tutkia vihreiden joukkovelkakirjalainojen volatiliteettia ja sen käyttäytymistä. Analyysi keskittyy kolmeen rahoitusmarkkinoille tyypilliseen ilmiöön: volatiliteetin clusteroimiseen, asymmetrisyyteen sekä muiden markkinoiden volatiliteetin vaikutukseen. Näiden ilmiöiden suuruutta ja esiintymistä tutkitaan kolmella erilaisella ekonometrisella mallilla, jotka kuuluvat GARCH – mallien kategoriaan.

Analyysi toteutetaan kahdelle erilaiselle vihreiden joukkovelkalainakirjojen markkinoita seuraavalla indeksille: S&P Green Bond ja S&P Green Bond Select indeksille. Näistä ensimmäinen kuvaa vihreiden joukkovelkakirjalainojen markkinoita kattavammin kun taas jälkimmäinen kuvaa eksklusiivisempia markkinoita, joihin sisältyy vain tarkemmin sertifioituja ja seurattuja joukkovelkakirjalainoja. Vertailuimarkkinoina käytetään "tavanomaisia" joukkovelkakirjalainojamarkkinoita kuvaavia indeksejä Yhdysvalloista ja Kiinasta: S&P US Aggregated Bond ja S&P China Bond indeksejä. Aineisto kattaa indeksien tuotot koko 2010-luvulta 1.1.2010 alkaen ja päättyen 31.12.2019.

Tutkimuksen tulosten perusteella vihreiden joukkovelkakirjamarkkinoiden tuottojen volatiliteetti klusteroituu vahvemmin kuin tavanomaisten joukkovelkakirjamarkkinoiden, vaikka taipumus klusteroitumiseen väheni vuosikymmenen loppupuolella. Lisäksi vuosikymmenen alkupuolella volatiliteetti käyttäytyi epäsymmetrisesti. Nämä ilmiöt olivat voimakkaampia yleisillä vihreiden joukkovelkakirjojen markkinoilla kuin ekslusiivisemmilla markkinoilla. Vihreät joukkovelkakirjamarkkinat ovat olleet myös hyvin linkittyneitä sekä Yhdysvaltojen että Kiinan joukkovelkakirjamarkkinoihin sillä tutkimuksessä löytyi vahvaa näyttöä volatiliteetin korreloimisesta vihreiden joukkovelkakirjamarkkinoiden ja vertailumarkkinoiden välillä. Volatiliteettien korrelaatio kuitenkin pieneni vuosikymmenen loppua kohden, mikä voi indikoida, että vihreät joukkovelkakirjamarkkinat ovat itsenäistyneet tavanomaisista markkinoista.

Acknowledgements

I wish to thank all friends and professors I have met during my studies in LUT. I am not exaggerating at all if I say that I could not have done this without you all. With your help and presence, I have not only survived but also enjoyed all lectures, assignments and long days in the library. A special thanks to my thesis supervisor, Azzurra Morreale for the help and patience. My thesis topic changed quite a few times and the project took longer than expected but now I can finally close the work.

Lastly, I wish to encourage the reader who is currently working on their own thesis. Whether it is trying to figure out the topic or just struggling with a detail, I'm sure you'll master it soon enough. You have already made it this far which itself is already a proof of your capabilities. In addition to that, you have also found your way to read this small attempt of mine to save the world. Also do take breaks since sometimes the struggles solve themselves while we rest.

Helsinki, December 2020

Roosa Karesjoki

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Abbreviations

ADF	Augmented Dickey Fuller
ARCH	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving Average
CCC	Constant Conditional Correlation
DCC	Dynamic Conditional correlation
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GBP	Green Bond Principles
GJR	Glosten-Jagannathan-Runkle
ICMA	International Capital Market Association
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroscedasticity
TGARCH	Threshold Generalized Autoregressive Conditional Heteroscedastic

1 INTRODUCTION

As estimated by the Stern review (2007), the climate change can eventually cost globally from five to 20 % of the yearly gross domestic product. Despite the uncertainty associated with the current climate crisis, it is evident that mitigation and prevention of the effects will require a significant amount funding and it is still unclear where and how required funding can be obtained. One solution to the allocation of funds are the green bonds: bonds that are specifically issued to fund projects with a positive impact to the environment. This new market was created when the European Investment bank (2020) issued the very first green bond in 2007. The very next year it was followed the by the World Bank (2019) and in the following 12 years, the green bond market has experienced significant growth. In 2019, the total amount of green bond issuances reached their all-time high of 257.7 billion US dollars and the yearly growth of the market was 51%. The market is dominated by the US and China but the growth in 2019 was mainly driven by the European Markets. (Climate Bonds Initiative 2020)

As this fairly new fixed-income financial instrument is growing and becoming an important member in the financial asset family, there is a need to understand the behavior of the market better. How does this asset class differ from more conventional bonds in terms of risk and return? Can green bonds be used as a substitute for conventional bonds or do they offer risk diversification benefits? Essentially green bonds are just conventional bonds that differ in the destination of the proceeds. According to the green bond definition made by International Capital Market Association (2018) and the Green Bond Principles, a green bond is any type of bond instrument where the proceeds will be exclusively used to finance a project which provides clear environmental benefits. However, there is evidence that the behavior of the green bond market does vary from the behavior of the conventional bond markets (Pham 2016, Febi et al. 2018, Reboredo 2018).

Volatility of the returns is an essential risk (or uncertainty) metric used in the financial decision making. Volatility and its dynamics are important in various finance applications such as asset allocation, risk management and derivative pricing. Therefore, understanding of the volatility behavior and dynamics of the green bond market is essential for participants in this new market. This study attempts to uncover the volatility behavior of the green bond market during the decade of 2010. Emphasis is put on the comparison between more conventional fixed-income markets and the green bond markets since this tells us how the bond markets differ in terms of volatility. We can also answer the question whether green bonds can be used as a substitute of other bonds or if they can be used for risk diversification.

This study continues the work of Pham (2016) who examined the volatility behavior and dynamics of the green bond market during the first half of 2010. According to the findings, the labeled green bond markets exhibit significant volatility clustering compared to conventional bond markets and the volatility tends to spill over from conventional bond markets to the green bond market. This study extends the knowledge by including the second half of the decade under examination. Since the market has developed significantly, it can be expected that the volatility dynamics of this market have possibly changed. This study also examines leverage effect for which Pham found no evidence.

1.1 Motivation

This study connects three different strands within Finance which are combined in Figure 1. First of all, this study continues the work of many other in the field of volatility in the financial markets. However, although volatility has been in great interest in the academic literature, most volatility studies have focused on equity markets. Thereby the second important contribution of this study is to increase the understanding of volatility dynamics in the fixed-income markets. However, the most unique contribution of this paper comes from the analysis of a fairly new type of market, the green market which consists of green investments. This type of investing usually refers to investment activities that have some sort of positive impact on the environment. Since this market has grown and developed tremendously in the past decade, the academic literature has not yet been able to keep up with explaining this market and its characteristics.

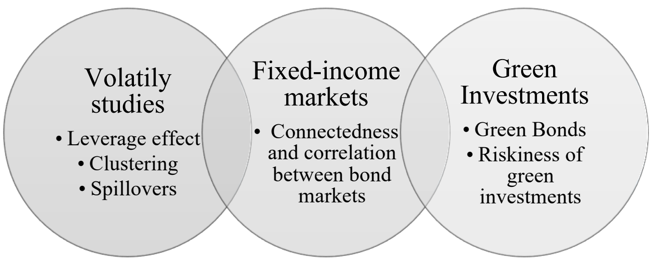

Figure 1. Three disciplines within Finance included in this study

As with volatility studies, the majority of green investing studies have been equity-related and the academic interest towards fixed-income markets has been lower. As the green fixed income markets are growing exponentially, there is a clear need to extend the objectives of the green investing studies into fixed income markets. So far, the green bond market studies have been focusing on describing and explaining the factors behind the development of the market. The previous literature has also examined the green bond premium and the pricing of green bonds. According to previous literature, Green bonds seem to exhibit a negative premium compared to conventional bonds (Zerbib 2019, Preclaw & Bakshi 2015, Baker et al. 2018). There are also studies examining the connectedness and correlation of the green bond market with other financial markets (Broadstock & Cheng 2019, Reboredo, Ugolini & Aiube 2020). However, the empirical and quantitative research on the differences between green bond markets and conventional bond markets in terms of risk and volatility is still insufficient since the focus has been mostly on the connectedness of returns and performance.

1.2 Objectives of the research

The objective of this research is to analyze the volatility and the behavior of the green bond markets and compare this behavior to conventional bond markets. To be able to properly assess the volatility of this market, the green bond market behavior is compared with conventional fixed-income markets. The main research question of this study can be stated as following

How does the behavior of green bond market differ from conventional bond markets in terms of volatility?

This study especially focuses on three volatility features that are common to financial data: volatility clustering, leverage effect and volatility spillovers. Thereby the sub research questions can be stated as following

Does the Green Bond market exhibit volatility clustering and/or leverage effects?

How do the volatility clustering and leverage effects compare between the Green Bond market and the conventional bond markets?

Do volatility spillovers occur between conventional bond market and green bond market?

Volatility clustering is a phenomenon very typical to financial time series where changes in prices cluster together. As defined by Mandelbrot (1963, p. 418) large changes follow large changes despite their sign and vice versa for small changes. This can obviously make the time series more challenging to predict which then increases the uncertainty and thereby riskiness. To make the series even more complicated and challenging to predict, the response to positive and negative shocks is often asymmetric. This phenomenon is referred to as the leverage effect. It can be expected that there is both volatility clustering and leverage effects present in the green bond market since they are very common to the financial time series. There is no reason to expect that these features would differ significantly from the conventional bond markets.

The second hypothesis is that the green bond market is dependent on the conventional bond markets and thereby there is volatility spillovers from the conventional markets. The volatility spillovers refer to a causal relation between previously occurred volatility on the other market and the current volatility on another market. Essentially as for volatility clustering, the past volatility in one market is correlated with the current volatility on the same market, in volatility spillover the past volatility in one market is correlated with the current volatility in another market. As the name suggest, volatility in one market spills over to another. It can be used to measure market co-movements and interdependence.

The results to these questions will help to answer the underlying question that motivates this study: Is the green bond market riskier than more conventional bond markets? This question is not involved in the official research questions since the concept of 'riskiness' is more extensive than the scope of this study. The scope and limitations of this study are explained in more details in the next chapter.

1.3 Scope and Limitations

This study is emerging from the willingness to understand the risks and risk behavior of the green bond market. As volatility is commonly used risk metric in the finance discipline, it is a good place to begin. However, volatility can be interpreted as the uncertainty or the variance riskiness of the market, but it does not independently state where the riskiness emerges from. To answer the question of why the green bond market riskiness differs from conventional bond market riskiness (if it does in the first place), the individual risk aspects and their effect on the overall riskiness of the market should be studied. The interest rate risk and the inflation risk are somewhat common to all bond markets so it is highly unlikely that they could explain the differences between bond markets. However, the green bond market might experience different levels of call, default, credit and liquidity risk than other bond markets. The effect of these risks cannot be captured by examining the volatility of the market so additional risk studies should be conducted to fully evaluate and understand the risks in the market. Understanding how the risks in green bond markets differ from conventional bond markets is essential in asset allocation and risk management for investors but also for issuers contemplating whether to issue a conventional or a green bond.

This study examines two slightly different green bond markets, the more inclusive and the more exclusive green bond market. The more inclusive green bond market consists of any bonds that have been labeled green whereas the more exclusive market consists of bonds that are more accountable and transparent about the actual greenness and impact of the bond. Since currently there are no binding standards or definition of green in the market, the green market is exposed to a risk of greenwashing where the non-green products are labeled as green in order to access the benefits associated with green label. This issue will be further discussed in Chapter 2 but it is important to investigate whether the exclusive market differs from the inclusive to determine if stricter rules have an effect on the volatility. Most likely these two markets also overlap since the underlying bonds in the more exclusive market also most likely belong to the more inclusive market but not necessarily the other way around.

These two green bond markets are then compared to conventional bond markets. Since the United States (US) and China are dominating the green bond market in amounts of bond issuances, this study is geographically focused on these two areas (Climate Bonds Initiative

2020, p. 2). Thereby this study is geographically limited to these two countries and all other conventional bond markets in other countries are excluded. The result of this study cannot thereby be directly applied to for example European bond markets.

What comes to the limitations of the data used in this study, according to Burn and Engle (1998, p. 7) daily closing prices of different markets might be too asynchronous for examining the volatility spillover effects properly. Daily returns tend to underestimate correlations, so it is possible that the hypothesis of no spillover effect is accepted falsely. However, if volatility is observed from a daily or weekly frequency, it leaves out the intraday volatility. If calculated from intraday data, volatility metrics get higher values. Thereby daily and weekly data can give too moderate values compared to intraday data.

However, according to Dany (2008, p. 2379) it needs to be noted that any choice of frequency can be equally valid. The outcome is that the results from different frequencies can be explained by different underlying reasons. The main reason for market volatility is that the arrival of new information usually appears quite randomly. Thus low-frequency volatility can be associated with the macroeconomical and institutional changes and high-frequency volatility can most likely be explained by the pressure and turbulence related to the trading such as trading volume. To get a profound understanding on the volatility of the market, the volatility should be observed over several frequencies.

This study is conducted on a daily data since it is a compromise between intraday and more scarce weekly data. Since this study examines volatility over a longer period, daily observations also create enough data to conduct the study statistically accurately. The trading volumes in the fixed income markets are also usually lower than in the equity markets so daily frequency should also be sufficient in that sense. However, it still needs to be taken into account when interpreting the results that the volatility metrics can get too moderate values and that there might exist spillover effects that the study is not able to notice.

1.4 Structure of the thesis

In addition to the objectives of the research, the introduction section of this thesis covers the motivations and limitations of this study. The literature review covers an overview of the previous research on green bond market. Since this study examines financial data, it is relevant to address volatility as a concept and the volatility features that are typical to financial time series such as volatility clustering and leverage effects. There will be a chapter about these characteristics in the methodology section since those are important for the choice of a volatility modelling method. This will be followed by a presentation of the generalized autoregressive conditional heteroskedasticity (GARCH) -framework and the adapted models chosen to be used in this thesis.

After the methodologies have been introduced, the data used in the study is described using both visual and statistical measures. This will be followed by the results of the GARCH models built for this study. The results consist of the models built to examine the volatility clustering, leverage effects and the volatility spillovers. The results will be discussed and summarized in the Discussion and Conclusions section.

2 LITERATURE REVIEW

This literature review focuses on the previous academic literature on green bond market. Chapter begins by covering the definition of a ‘green bond’ since there exists some variety in the previous literature. In addition to the definitions, the previous academic literature on green bond market can be divided into three categories: studies on the development of the market, green bond pricing and lastly comparison and connectedness to other markets. The first two categories have been widely studied but the third category, to which this study belongs, is clearly the less studied. This chapter has been divided according to these categories, each of which is are addressed in respective sub chapters.

2.1 Defining Green Bond

The World Bank (2015, p. 23) defines green bond as a “debt security that is issued to raise capital specifically to support climate related or environmental projects”. However, the definition of a ‘green’ in a financial framework varies across the industry significantly. There does not exist any commonly agreed binding standards or definition of a green bond. According to Inderst at al. (2012, 9) the only commonly used feature of green investments is the usage of proceeds to fund Climate Change adaptation or mitigation. Otherwise, there is variation on whether the definitions are implicit or explicit, are they based on specific indicators or ex ante arguments and is the greenness defined in absolute or relative terms. The monitoring and measurement of the success of the project is also inconsistent.

Few definitions of the ‘green bond’ from the previous literature have been combined to Table 1. Based on this concise overview, climate change seems to be present in most definitions. As stated by Gianfrate and Peri (2019, 128) climate change mitigation and adaptation is the primary destination of green bond proceeds, but other environmentally friendly projects are included also such as preservation of biodiversity. However, these definitions do not provide enough coverage to efficiently define and label certain bonds as ‘green’. Karpf and Mandel (2018, 161) mention sustainable development standards as a way to specify the appropriate projects. Unfortunately, commonly agreed binding standards have not yet existed in the market.

Table 1. Definitions of Green Bond as found from literature

Author(s)	Year	Definition of green bond
*ICMA	2018	Any type of bond instrument where the proceeds will be exclusively applied to finance or re-finance, in part or in full, new or/and existing eligible green projects
World Bank	2015	Debt security that is issued to raise capital specifically to support climate related or environmental projects
Gianfrate, G. & Peri, M.	2019	Conventional Bond with a distinguishing feature: proceeds are used for environment-friendly projects, primarily related to climate change mitigation and adaptation
Reboredo, J. C., Ugolini, A. & Aiube, F. A. L.	2020	Distinctive sustainability-oriented fixed-income financial instrument that are intended to raise funds earmarked by the issuer for environmentally friendly projects consistent with a climate-resilient economy
Tang, D. Y. & Zhang, Y.	2020	Newly developed financial instruments with the specific goals of improving environmental impacts and social welfare
Barua, S. & Chiesa, M.	2019	Embodies the commitment to exclusively use the funds raised to finance or re-finance “green” projects, assets, or business activities
Karpf, A. & Mandel, A.	2018	Proceeds of the bonds are used for environmental or climate-focused activities in accordance with sustainable development standards

*Notes: ICMA = International Capital Market Association

The Green Bond Principles (GBP) issued by the International Capital Market Association (2018) may have increased the coherence in the market in terms of definitions. The GBPs provide voluntary guidelines on four aspects of a green bond: use of proceeds, process for project evaluation and selection, management of proceeds and reporting. In addition to the climate change mitigation and adaptation, the GBPs also state that the proceeds could be used to natural resource conservation, biodiversity conservation as well as pollution prevention and control. There is even a list of project categories that are or should be covered by the green bond market. This list includes among other things renewable energy, pollution prevention, clean transportation and green buildings.

2.2 Green Bond Market development

There are contradictory opinions and evidence on whether the growth in the green bond market has been driven by supply or demand. According to Barua and Chiesa (2019, p. 1131) the market is supply-driven whereas both Febi at al. (2018, p. 53) and Deschryver and de Mariz (2020) state that the rapid growth in the demand for green bonds surpasses the supply. Pielichata (2019, p. 1) on the other hand states that the demand in the green bond market actually limits the supply. The demanding side has so many quality requirements that the issuers are not able to respond to the requirements. The issuers also have a perception that the costs of issuing a green bond are higher than a comparable conventional bond due to the additional monitoring and certifications needed to acquire the 'green' label (Deschryver and de Mariz 2020). This is related to the absence of standards and verifications in the market.

The absence of commonly agreed standards and their monitoring leads to the risk of greenwashing. As long as this information asymmetry risk of greenwashing is present in the market, it might prevent some entities to participate in the market and thereby act as a barrier for scalability in the market (Deschryver and de Mariz 2020). For example, it is challenging for pension funds and institutional investors to enter the market in full since there are no binding standards for issuers or verification of products (Pielichata 2019, p 2). Unfortunately, according to Tolliver et al. (2019) the current level of reporting of the green bond proceed allocations is not sufficient to monitor the environmental outcomes. Thereby the evaluation of true environmental benefits of the green bond market is challenging. Deschryver and de Mariz (2020) support that the overall infancy of the green bond market is a barrier for growth.

The growth drivers in the national green bond markets can also be found from macroeconomical and institutional factors. Tolliver, Keeley and Managi (2020) found that the macroeconomic factors such as the size of the economy, stock market capitalization and trade openness that traditionally drive the growth in the conventional bond markets, have a growing effect on the green bond issuance volumes as well. Institutional factors such as rule of law and regulatory quality drive the growth as well but indirectly through influencing the macroeconomic factors. Banga (2019) confirms that the lack of appropriate institutional factors acts as a barrier for green bond market growth in the developed countries.

The market could improve with more diversification into different credit ratings or industries (Pielichata 2019, p 2). As stated by Pham (2016, p.3), the Green Bond market consist of bonds of similar credit ratings whereas the aggregated bond markets are more dispersed. The green bond market is also not very dispersed geographically. According to the Climate Bonds Initiative (2020, p. 2) three countries, US, China and France accounted for 44% of all green bond issuances in 2019. The lack of green bond issuances in developed countries can be explained with the high transaction costs and the minimum size of issuance (Banga 2019). A combination of previous studies on the Green Bond market development can be found from Appendix 1.

2.3 Green Bond pricing

There is broad evidence that green bonds are priced differently than more conventional bonds but there is no coherence on whether green bonds exhibit a negative or a positive premium. Zerbib (2019) analyzed the pricing differences between green bonds and conventional bonds by examining whether the pro-environmental preferences have an effect on the bond prices. Based on the evidence, there seems to be a small negative green bond premium meaning that there is a yield differential between a green bond and a conventional bond. The findings of Nanayakkara and Colombage (2019) do support the yield differential but on the contrary find that green bonds are traded at positive premium of 63 basis points. Based on the evidence by Hyun, Park & Tian (2020) there exists neither a yield premium nor discount for green bonds on average. However green bonds certified by an external reviewer seem to exhibit a discount of about 6 bps and green bonds that obtain a Climate Bonds Initiative certificate exhibit a discount of around 15 bps.

Hachenberg and Schiereck (2018) found that especially well rated green bonds trade economically tighter than comparable conventional bonds. Generally, this can indicate good liquidity in the market. The findings of Febi et al. (2018) support the evidence of good liquidity circumstances in the green bond market. They found that on average green bonds were more liquid than the conventional bonds. However, the liquidity risk still has an effect on the green bond yield spread.

According to a study conducted by Lewis and Mackenzie (2000, 183) investors' perception of risk on ethical investments on average is about the same as in ordinary investments but they expect lower returns on ethical investments. This means that investors do not view ethical investments riskier but that they underperform compared to ordinary investments. However, many investors are actually willing to give up returns for ethical investing. For bond issuers this can mean more convenient terms. According to Gianfrate and Peri (2019) on average the green bond issuers' financial savings from lower interest rates exceed the additional costs related to green bonds making green bonds very attractive to organizations with green-like projects. In fact, in real estate investments, simply acquiring a green certification increases the rent premium by 4 % compared to corresponding non-certified properties according to Bond and Devine (2016). A combination of previous studies on the Green Bond pricing can be found from Appendix 2.

2.4 Green Bond market comparison and interdependence with other markets

The positive impact of a green bond issuance to the equity market and investors' positive attitude towards green bonds is supported by the findings of Vishaal (2019), Baulkaran (2019) and Mohd Roslen et al. (2017). This broad evidence suggest that the stock market generally reacts positively to a green bond issuance. Tang and Zhang (2020) state that this does not derive from cheaper debt financing but from the broadened investor base partly due to the media coverage of a green bond issuance. The green bond issuance also increases stock liquidity and institutional ownership.

Broadstock and Cheng (2019) studied if the volatility spillovers and thereby a connection between green and black bond market is systematically affected by macroeconomic factors such as financial market and economic activity, policy uncertainty and the price of oil. According to their evidence, the macroeconomic conditions are increasingly affecting the connection between these two markets. Reboredo (2018) compared the green bond market to other fixed-income markets and found out that the two markets are strongly dependent and experience large volatility spillovers. However, there was no evidence on significant volatility spillovers from the stock or the energy market. Thereby the participation in the green bond market offers diversification benefits for investors in the stock and energy market. Pham (2016) analyzing the volatility behavior of S&P Green Bond indices between

2010 and 2015 and found that there are volatility spillovers from the conventional bond market to the green bond market.

Pham (2016) also found that there is volatility clustering in the green bond market, but the ‘labeled’ segment of the market experienced larger volatility clustering as the ‘unlabeled’ segment. As stated in the introduction, this study is an expansion to her research by also taking into consideration the second half of the 2010’s. The green bond market has grown, developed and matured during this time and thereby she suggested that the results of her study should be updated after more observations would be available to examine a full business cycle. This study also expands the study geographically since in addition to the conventional bond markets in the US, this study also takes into consideration the conventional bond markets in China. This kind of geographical comparison has not yet been conducted.

3 METHODOLOGY

This Chapters explains the methodology used in this study. Since volatility is the main concept in this study and it's features highly affect the models chosen, it is essential to define and explain volatility as a concept in financial time series. In addition to defining volatility, this chapter includes a description of the volatility features analyzed in this study: volatility clustering, leverage effect and the volatility spillovers. After a comprehensive description of the volatility features in scope, the methodologies used to analyze the respective features are presented.

3.1 Volatility and related features

As defined by Daly (2008, p. 2378), volatility is the changeableness of a variable under consideration and the more the variable fluctuates over time, the more volatile the variable is. Hence volatility is often associated with unpredictability, uncertainty and especially in a financial context, risk. High volatility in the capital markets can also be interpreted as a symptom of market disruption or even partial malfunction.

Since volatility is very often used as a crude measure of the total risk of financial assets, it has become one of the most important concepts in finance. Thereby modelling volatility has been a subject of a vast amount of academic literature. However, the focus in volatility studies has traditionally been in the equity market and a smaller emphasis is put on the fixed-income markets. The volatility of stock market returns has been studied at least since the 1970's when Fisher and Lorie (1970) studied the variability of returns in common stocks listed in the New York stock exchange. On the contrary the bond market volatility studies have been concentrating on the interest rate volatility, which is partially justified since it is one of the main factors affecting bond return volatility (Kuberek 1992). But as stated in Chapter 1.3, there are various other risk factors that affect the bond return volatility as well.

Due to the broad academic interest towards volatility of the returns, there are various possible models developed to study this concept. The simplest ones are historical volatility, calculated as the standard deviation of the returns, implied volatility derived from option prices and the exponentially weighted moving average models, which is an extension of the historical volatility measure. However, these types of models or measures have proven to be limited and somewhat insufficient to fully capture the volatility behavior of financial markets. Standard deviation as such and other similar type of measures of volatility can be called time invariant since they are assumed to remain constant over time. It is highly unlikely that the variance of returns in financial time series remains constant over time so a more suitable approach to modelling and measuring volatility is to define volatility as time-variant and dependent on its own past values.

Financial time series usually exhibit some volatility related features that make linear modelling insufficient. These include for example leptokurtosis, volatility clustering and the leverage effect. Leptokurtosis can be defined as the returns having a distribution that exhibit fat tails and peakedness in the mean. Leptokurtosis will not be further addressed since it is out of scope of this study. Volatility clustering and the leverage effects are the main volatility features examined in this study hence they are explained below as well as the volatility spillovers between markets.

Volatility clustering occurs in a time series when large changes follow large changes despite their sign and vice versa for small changes (Mandelbrot 1963, p. 418). In other words, large changes in prices tend to cluster together as the name of the phenomenon implicates. This means that the current level of volatility is positively correlated with the previous periods' volatility. Leverage effect is present when the volatility rises more after a large price fall compared to a raise of the same magnitude. In other words, the response to positive and negative shocks is asymmetric.

As defined by Forbes and Rigobon (2002, 2228), the volatility spillover effect refers to a variance-covariance transmission mechanism across markets. Thereby it can be used to measures market comovements and interdependence. Volatility spillovers have been widely studied and confirmed for exchange rates (Engle et al. 1990, Mcmillan and Speight 2010) and equity markets (Wen-Ling et al. 1994) but less attention has been given to the bond markets. However, the existing literature does support the existence of volatility spillovers and interdependence between bond markets (Christiansen 2007, Skintzi and Refenes 2006).

3.2 Statistical methods

In addition to the volatility features presented above, the variance of errors also affects the model choice. In linear modelling, it is assumed that the variance of the errors is constant. This is called the assumption of homoscedasticity. If the variance of the errors is not constant, they are called heteroscedastic. It is very likely that in the case of financial time series the variance of errors varies over time so the models suitable for volatility modelling can be called Conditional Heteroscedastic models.

The statistical models in this study can be divided into three categories: one to examine volatility clustering, one to examine the leverage effect and the model to examine volatility spillovers. All of these models belong to the category of conditional heteroscedastic models. Since all the models used in this study evolve from the autoregressive conditional heteroscedastic (ARCH) – model, the first sub chapter is devoted to explaining the initial idea behind this model although it is not directly used in this study before explaining the models actually used in this study.

3.2.1 ARCH model

As stated in the previous chapter, linear modelling is often invalid to model financial time series since linear models are incapable to capture time-sensitive variance. The Autoregressive conditional heteroscedasticity (ARCH) – model lets the variance of the error term be dependent on the previous values of squared errors. Thereby making the variance conditional. When modelling the returns of the bond indices, we let the return r_t be determined as following

$$r_t = \mu + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_t^2) \tag{1}$$

Where μ stands for the unconditional mean of the returns and ε_t is the error term. Instead of letting the ε_t stand for a stochastic white noise process with constant variance, we denote σ_t^2 as following

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{2}$$

This means that the conditional variance of the error term, σ_t^2 is allowed to depend on the previous values of the squared error term. This is also known as the ARCH(q) model. (Engle 1982)

However, the conditional variance should always remain strictly positive. Thereby from above equation we can see that this non-negativity constraint requires that all coefficients in in the conditional variance need to be positive. Otherwise a sufficiently large lagged squared error could make the conditional variance negative. The value of q, which is the number of lags can also bring some difficulties. First of all, it might be challenging to choose the sufficient number of lags and/or that number might become very large. A Generalized autoregressive conditional heteroscedasticity (GARCH) -model, which is presented next, partially overcomes these problems.

3.2.2 GARCH -model

The Generalized autoregressive conditional heteroscedasticity (GARCH) - model is an extension to the ARCH- model. In GARCH- type models the current periods conditional variance depends on both the previous lags of conditional variance and the previous values of squared error term. GARCH(p,q) model developed by Bollerslev (1986) can be presented as following

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 , \tag{3}$$

where

$$\alpha_0 > 0, \qquad \alpha_i, \beta_j \geq 0, \qquad \sum_i \alpha_i + \sum_j \beta_j < 1 \tag{4}$$

As stated above volatility clustering occurs in a time series when large changes follow large changes despite their sign and vice versa for small changes (Mandelbrot 1963, p. 418). Hence empirically volatility clustering can be examined from a conditional volatility model, such as the GARCH- model presented above. If there is correlation between current period's conditional variance and previous periods' conditional variance, it can be stated that volatility clustering is present in the time series.

In this study the volatility clustering will mainly be studied using a simple GARCH(1,1) model which means that only one order is taken into account in the model. As noted by Bollerslev (1986, p. 309), the presence of lagged conditional variance seems to give the GARCH-type model some adaptive learning properties. Thereby the model can be accurate with fewer lags compared to a corresponding ARCH -model and information consisting in one lagged period should be sufficient in this context. The sufficiency of GARCH(1,1) model is also supported by previous academic literature since GARCH(1,1) model is found to outperform other more sophisticated models and is commonly used to study and investigate volatility clustering in financial time series (Hansen and Lunde 2005, Niu and Wang 2013, Khan et al. 2019, Zabiulla 2015).

Since the GARCH(1,1) model is found to be sufficient to examine volatility clustering behavior, the model used in this study can be stated as following

$$r_t = \mu + \varepsilon_t \, , \varepsilon_t \sim N(0, \sigma_t^2) \tag{5}$$

$$\sigma_t^2 = \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{6}$$

$$\alpha_0 > 0, \alpha \geq 0, \beta \geq 0, 0 < \alpha + \beta < 1 \tag{7}$$

The model leads to a positive autocorrelation in the volatility process σ_t. The short-run persistence of shocks is captured by the ARCH(α) effect and the long-run persistence is captured by the GARCH(β) effect. The rate of decay is determined by the sum of the coefficients $\alpha + \beta$. If the coefficients are statistically significant and the sum of the coefficients is close to 1, it indicates that the movements in the conditional variance are highly persistent, so the time series exhibits significant volatility clustering. In other words, the closer the sum of the coefficients is to 1, the slower the decay of the autocorrelation of σ_t is. If the result is exactly 1, the process is said to be integrated. (Sudha 2015, p. 1336)

The GARCH model presented above is very sufficient to examine the volatility clustering in the time series. However, it does experience some limitations, one of which is that it does not take into account the leverage effect. The GARCH model enforces a symmetric response of volatility to positive and negative shocks but as presented in previous chapters, it is often common in financial time series that a negative shock causes the volatility to rise more than a positive shock of the same magnitude. To examine this asymmetry, a GJR model can be used. The Glosten-Jagannathan-Runkle (GJR) GARCH model, presented by Glosten et al. (1993) will be explained in the next sub chapter.

3.2.3 GJR- GARCH model

The GJR- GARCH model extends the GARCH model by adding a term to account for asymmetries. The model by Glosten et al. (1993) can be presented as following

$$\sigma_t^2 = \alpha_0 + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} \tag{8}$$

where

$$\alpha_0 > 0, \alpha > 0, \beta \geq 0, \alpha + \beta < 1, \alpha + \gamma \geq 0 \tag{9}$$

Where I_{t-1} = 1 if ε_t^2 < 0 and 0 otherwise. In case of a leverage effect, the γ coefficient would get a value higher than 0. The model is often also referred to as the Threshold GARCH (TGARCH) model since it uses zero as a threshold to separate positive shocks from negative shocks. In the ‘rugarch’ package for R studio, which is used to estimate the models in this study, the ARCH order defines the order of the leverage parameter (Ghalanos 2020, 8).

Both models presented above, GARCH and GJR model are called univariate models since they include only one variable, the returns of one specific index over time. Thereby they can be used to examine the clustering and leverage effects only on one specific return series independently. Since the spillover effect is essentially a correlation between two markets, the models presented above need to be modified into a multivariate GARCH (MGARCH) model. This type of models will be presented in the next chapter.

3.2.4 Multivariate GARCH models

The multivariate GARCH (MGARCH) models can be used to estimate and forecast correlations and covariances among assets. They extend the univariate GARCH model by letting also the covariances to be time varying in addition to the conditional variances.

A general representation of a MGARCH model can be presented as following

$$r_t = \mu + \varepsilon_t \tag{10}$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t) \tag{11}$$

Where r_t stands for a *N* x 1 vector of returns at time t, μ stands again for the unconditional mean of the returns just as for the univariate GARCH models and ε_t is an *N* x 1 vector of random errors at time t with a corresponding *N* x *N* conditional variance-covariance matrix H_t. This variance-covariance matrix is defined for example in the BEKK-GARCH by Engle and Kroner (1995) model as following

$$H_t = W + A_1' \varepsilon_{t-1} \varepsilon_{t-1}' A_1 + B_1' H_{t-1} B_1 \tag{12}$$

Where W, A_1 and B_1 are (k x k) matrices, with W symmetric and positive definite. The A_1 matrix captures the ARCH effects and the B_1matrix captures the GARCH effects. The diagonal elements in these matrices capture the ARCH and GARCH effects of the "home" market whereas the off-diagonal elements capture the respective effects between the markets.

These types of models have been widely used to model volatility linkages between assets and markets but they have proven to be quite complex. Another approach is based on the Constant Conditional Correlation (CCC) model presented by Bollerslev (1990) where the conditional variance-covariance matrix at time t H_t is presented as following

$$H_t = D_t R D_t \tag{13}$$

$$D_t = diag\{\sqrt{h_{i,t}}\} \tag{14}$$

Where R is a correlation matrix containing the conditional correlations and $h_{i,t}$ stands for the conditional variance of each series *i* estimated from a respective univariate GARCH model.

In this study a generalization of this, a Dynamic Conditional Correlation (DCC) MGARCH model by Engle (2002) is used to estimate the spillover effects. It modifies the CCC model by letting also R be time varying as following

$$H_t = D_t R_t D_t \tag{15}$$

where

$$R_t = \begin{bmatrix} 1 & \rho_{ijt} \\ \rho_{jit} & 1 \end{bmatrix};\ D_t = \begin{bmatrix} \sigma_{it} & 0 \\ 0 & \sigma_{jt} \end{bmatrix} \tag{16}$$

Where ρ_{ijt} and ρ_{jit} stand for the correlation estimates between markets *i* and *j*. This model has the flexibility of a univariate GARCH without the complexity of the conventional multivariate GARCH since these models parametrize the conditional correlations directly. Thereby the DCC models are estimated in two steps as following

1. Series of univariate GARCH estimates for the variance equation using the mean equation
2. Correlation estimates among the series

Since this study examines volatility linkages between two markets, the green bond market and the conventional bond market, the mean equations of the bivariate model can be presented with the following set of equations

$$r_{it} = \mu_i + \varepsilon_{it} \tag{17}$$

$$r_{jt} = \mu_j + \varepsilon_{jt} \tag{18}$$

$$\varepsilon_t\ |\Omega_{t-1} = \begin{bmatrix} \varepsilon_{it} \\ \varepsilon_{jt} \end{bmatrix} |\Omega_{t-1} \sim WN(0, H_t), \tag{19}$$

$$H_t = D_t R_t D_t;\ R_t = \begin{bmatrix} 1 & \rho_{ijt} \\ \rho_{jit} & 1 \end{bmatrix};\ D_t = \begin{bmatrix} \sigma_{it} & 0 \\ 0 & \sigma_{jt} \end{bmatrix} \tag{20}$$

where *i* presents the green bond market and *j* presents the conventional bond markets in this study as will be explained in the next chapter. The univariate GARCH(1,1) variance estimates of the first step of DCC modelling can be presented as following

$$\sigma_{it}^2 = \alpha_{0i} + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2 \tag{21}$$

$$\sigma_{jt}^2 = \alpha_{0j} + \alpha_j \varepsilon_{jt-1}^2 + \beta_j \sigma_{jt-1}^2 \tag{22}$$

The conditional correlation estimates of the second step can be presented with following equations.

$$\hat{\rho}_{ijt} = {}^{\hat{q}_{ijt}}\Big/_{\sqrt{\hat{q}_{iit}, \hat{q}_{jjt}}} \tag{23}$$

$$\hat{q}_{ijt} = Cov\left(\hat{z}_{it}, \hat{z}_{jt} | \Omega_{t-1}\right) \tag{24}$$

$$= \hat{E}\left[\hat{z}_{it}, \hat{z}_{jt}\right](1 - a - b) + a(\hat{z}_{it-1}\hat{z}_{jt-1}) + b\hat{z}_{ijt-1}$$

Where the standardized residuals $\hat{z}_{it}, \hat{z}_{jt}$ are calculated from the above GARCH models as following

$$\hat{z}_{it} = {}^{\hat{\varepsilon}_{it}}\big/_{\hat{\sigma}_{it}}\ , \hat{z}_{jt} = {}^{\hat{\varepsilon}_{jt}}\big/_{\hat{\sigma}_{jt}} \tag{25}$$

With the univariate volatility estimates from the first step and the bivariate conditional correlation estimates from the second step, the conditional variance-covariance matrix H_t can be calculated according to equation 20. The parameters a and b present the conditional correlation and thereby volatility spillovers from one market to another.

4 DATA

This study uses daily returns of two green bond market indices and two benchmark indices, one from the United States and one from China. Since the United States and China are geographically dominating the green bond market in amounts of bond issuances, they were the logical choice for the benchmarks (Climate Bonds Initiative 2020, p. 2). The time period covers the entire decade from 1.1.2010 to 31.12.2019. The returns have been calculated using the arithmetic return formula from the denoted end of day prices of all indices. In order to clearly capture the development in the green bond market, the data is divided into two periods for the volatility analysis. The first dataset includes the first half of the decade (1.1.2010-31.12.2014) and the second dataset includes the second half (1.1.2015-31.12.2019). The first half of the decade can be considered as the growth period of the market whereas during the last half the market can be considered more stable and mature. This division is also supported by visual evidence as will be explained later in this chapter.

The used indices are explained and described in detail in this chapter. The first sub chapter describes the two green bond indices used in this study, S&P Green Bond index and S&P Green Bond Select index. The second sub chapter describes the two benchmark indices used, S&P US Aggregated bond index and S&P China Bond Index. The chapter will be concluded with descriptive statistics of the indices and their returns and with some preliminary test results.

4.1 Green Bond indices

The first green bond index included in this study is the S&P Green Bond index which represents the inclusive green bond market mentioned in the introduction. The index measures the performance of green-labeled bonds issued globally from any country or in any currency. It includes green bonds issued by multilateral, government and corporate issuers that have clearly indicated the rationale behind the green label. The bonds must be flagged green by the Climate Bonds Initiative. In April 2020, the outstanding market value of the index was 602 136,32 USD and it included 6 378 constituents. (S&P Dow Jones Indices 2020b.)

The second green bond index included is the S&P Green Bond Select index which represents the exclusive green bond market. This index requires a higher standard of transparency, disclosure and accountability than the S&P Green Bond index. Thereby it is more likely that the so called ‘green-washed’ bonds are excluded from this index. The returns of this index are calculated by aggregating the interest return, reflecting the return due to paid and accrued interest, and price return, reflecting the gains or losses due to changes in the end-of-day price and principal repayments. (S&P Dow Jones Indices 2020c.)

The daily returns of S&P Green Bond and S&P Green Bond Select indices for the entire sample period can be seen in Figure 2. The returns are presented as the daily returns of the index, the squared daily returns and the absolute daily returns. As can be seen from Figure 2, the returns of both indices seem to have followed a similar pattern however the fluctuation has been slightly more significant in the returns of the S&P Green Bond Select index compared to the S&P Green Bond index returns. It can also be noted that both indices have fluctuated more during the first half of the decade whereas the returns seem to have slightly stabilized in the second half. This visual evidence supports the division of the dataset to half from the beginning of 2015. Based on this visualization we can expect that both the volatility and the volatility clustering are more significant during the first half of the decade for both green bond indices. Based on the squared returns in the middle figures it seems that at least in the beginning of the decade, large changes tend to follow large changes and vice versa for small changes. The stabilization in the second half could be explained by the maturation of the market.

The next subchapter presents the benchmark indices used in this study in a similar manner than the green bond indices in this chapter. More statistics and visualizations of the indices and a comparison between all of the indices used and their returns will be conducted in the end of this chapter.

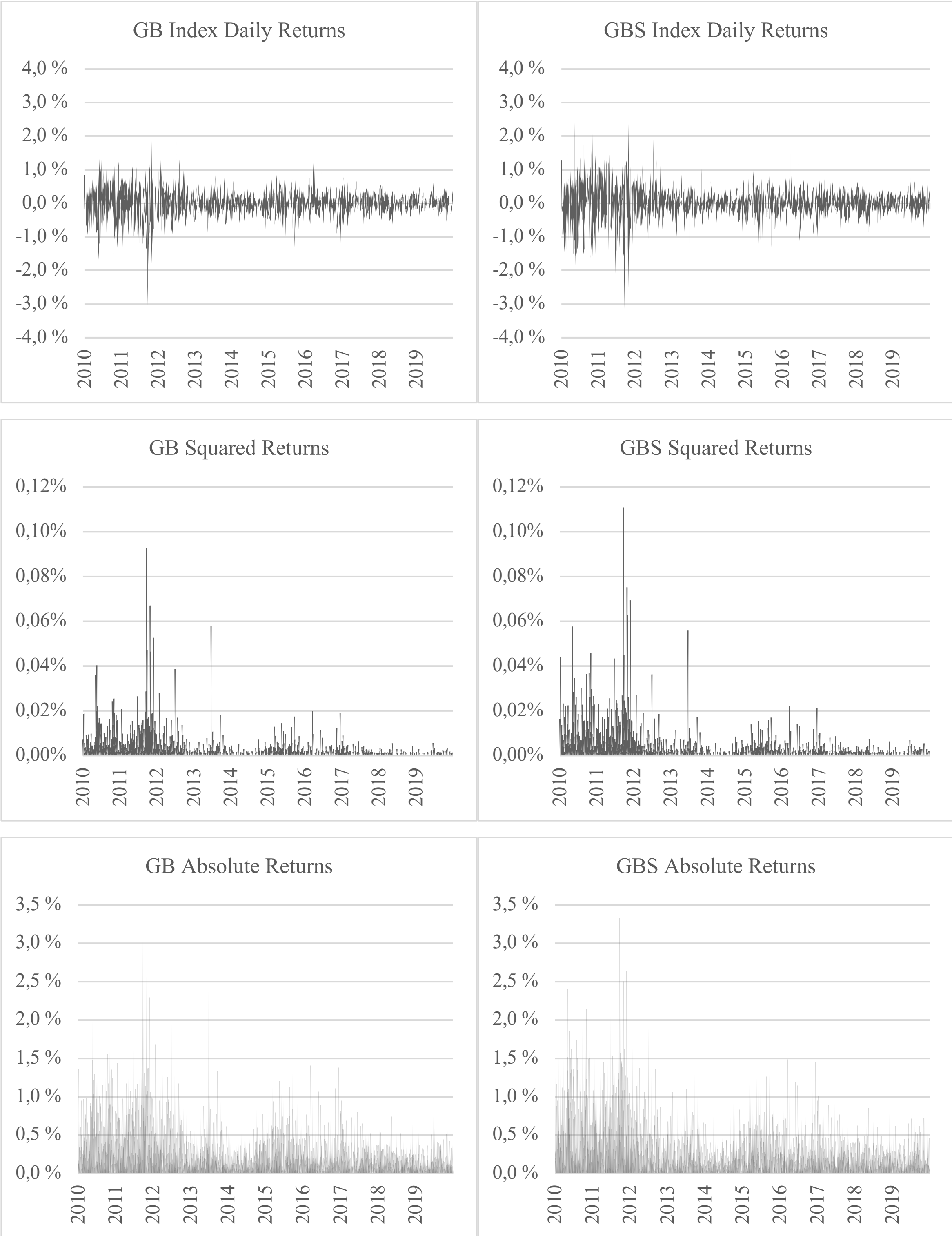

Figure 2. Daily Returns of S&P Green Bond Index and S&P Green Bond Select Index

Note: GB = S&P Green Bond Index and GBS = S&P Green Bond Select Index

4.2 Benchmark indices

Two aggregated bond indices were chosen to act as benchmarks and thereby present the conventional bond markets: S&P US Aggregated Bond and S&P China Bond index. The first one presents the conventional bond markets in the United States and the second in China. The geographical choice in the indices is purely based on the current situation in the green bond market. The market is dominated by bonds issued in the United States and China and therefore the comparison to the bond markets of the above-mentioned countries is logical in this case (Climate Bonds Initiative 2020, p. 2).

S&P US Aggregated bond index was chosen for the benchmark index because it covers broadly the investment-grade US fixed income market by measuring the performance of publicly issued US dollar denominated investment-grade debt. It consists of seven fixed income asset classes and thereby provides a good benchmark for the fixed income market comparison in the United States. The index includes US treasuries, quasi- governments, corporates, taxable municipal bonds, foreign agency, supranational, federal agency and non-US debentures, covered bonds and residential mortgage pass-throughs. (S&P Dow Jones Indices 2020b.)

S&P China Bond index was chosen as the second benchmark index since it is approximately an equivalent of the first benchmark index but for the Chinese Bond market. It tracks the performance of local-currency denominated government and corporate bonds from China and thereby provides a proper benchmark for the conventional bond markets in China. It is a subindex of the S&P Pan Asia Bond index which includes bonds with fixed, zero, step-up and fixed-to-float coupon types. In April 2020, the outstanding market value of the index was 81 035 275,15 CNY Million and it consisted of 12 989 constituents. (S&P Dow Jones Indices 2020a.)

The daily returns of the S&P US Aggregated bond index and the S&P China Bond index for the entire sample period can be seen in Figure 3. The returns are presented the same way as for the green bond indices: the daily returns, the squared daily returns and the absolute daily returns. As can be seen from Figure 3, the returns of the US aggregated bond index do not seem to exhibit the same kind of development as the green bond index, but the returns of the

Chinese bond index seem to experience higher fluctuation in the first half of the decade. The magnitude of the daily returns, either positive or negative, of the China bond index is also higher than of the US Bond index. For the returns of the US bond index, there could be slightly more fluctuation during the first years but the difference between first and second half of the decade does not seem to be significant. Yet overall, the aggregated indices seem to be more stable than the green bond indices based on this visual evidence. However, there seems to be volatility clustering present during the entire sample period.

The comparison of the green bond indices and the chosen benchmark indices continues in the next chapter. There are also some preliminary tests conducted to the indices to describe the characteristics of the returns and to validate the models chosen for this study.

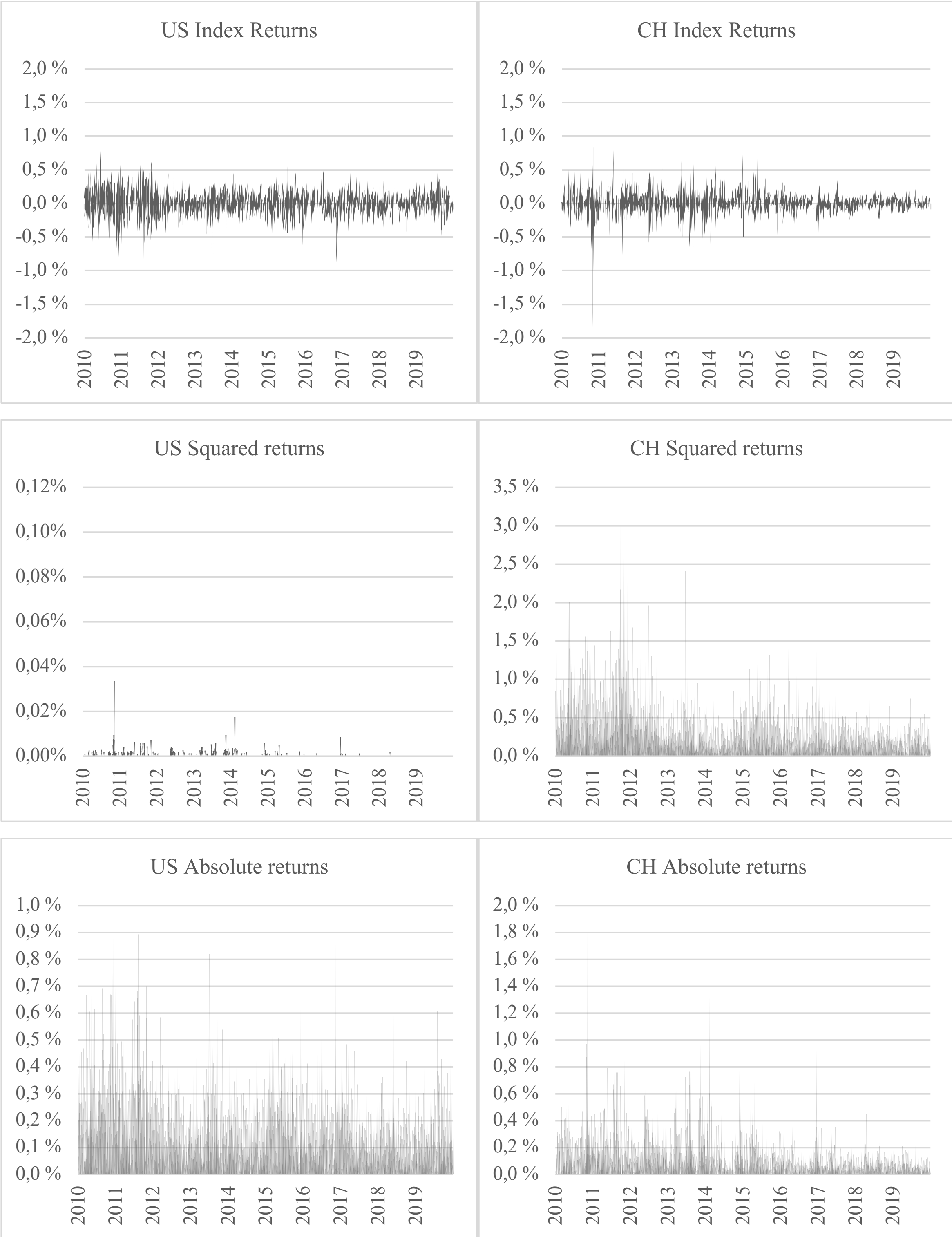

Figure 3. Daily Returns of the S&P US Aggregated Bond Index and S&P China Bond index

Note: US = S&P US Aggregated Bond Index and CH = S&P China Bond index

4.3 Descriptive statistics and preliminary tests

The price development of the absolute prices of all indices are combined in Figure 4 below for comparison. Based on this figure, the green bond indices seem to fluctuate more than the benchmark indices. During the first half the green bond indices also perform significantly better than the benchmarks, but this development seems to become more uncertain during 2015-2019. This again supports the division of the dataset into two parts from the beginning of 2015.

Figure 4. Price development of all indices between 1.1.2010 and 31.12.2019

Some descriptive statistics of the arithmetic returns of all indices and for the entire sample period can be found from Table 2 below. During the entire period both indices seem to have performed almost similarly in terms of average daily returns. The first rows include statistics from the entire period 2010-2019. As stated previously, the dataset was split half to two time periods: 1.1.2010-31.12.2014 and 1.1.2015-31.12.2019. However, there are significant differences between the two periods. During the first half the green bond index had a significantly larger average daily return than the aggregated index whereas during the second half the average return was in fact negative and a lot smaller than of the aggregated.

Table 2. Descriptive Statistics

	S&P GREEN BOND INDEX	S&P GREEN BOND SELECT INDEX	S&P US AGGREGATE BOND INDEX	S&P CHINA BOND INDEX
Observations	2607	2607	2607	2607
Average	-0,0009 %	0,0036 %	0,0025 %	0,0010 %
Median	0,0035 %	0,0053 %	0,0009 %	0,0000 %
Min	-3,044 %	-3,330 %	-0,894 %	-1,833 %
Max	2,590 %	2,742 %	0,796 %	1,326 %
Std.Dev	0,0041	0,0047	0,0019	0,0017
Skewness	0,000017	0,000022	0,000004	0,000003
Kurtosis	-0,171454	-0,067534	-0,175177	-0,378054

As can be seen from both the Figures 1, 2, 3 and the Table 1 above, the green bond index seems to be experiencing higher return volatility (standard deviation) in all time periods. Both markets seem to be more stable during the second half of the decade since the standard deviation is lower for both indices. Both datasets seem to be fairly symmetrical and experience some leptokurtosis which is very common to financial returns.

Based on Figures 2 and 3, the daily returns of all indices seem to revert to the mean which could indicate stationarity. The stationarity assumption of all bond index returns is supported by results from a unit root test that can be seen from Table 3. The unit root was tested using the Augmented Dickey Fuller (ADF) test. Since the test statistics for all indices are more negative than the critical value of -3.96, the null hypothesis of non-stationarity is rejected (Fuller 1976, p.373). Thereby both the green bond indices and the benchmark indices are stationary.

In order to validate the models chosen in this study, the autocorrelation of the squared returns is tested using a Ljung-Box test and supported by plotting the autocorrelation functions. The results of the Ljung-Box autocorrelation test can also be found from Table 3. The results show that the null hypothesis of no serial correlation is rejected for all indices. These results are supported by the plotted autocorrelation and partial autocorrelation functions in Figure 5.

Based on this visual evidence there seems to be correlation between present returns and lagged returns. This could also be interpreted as a preliminary support for the existence of volatility clustering in the returns of all indices. The plotted autocorrelation and partial autocorrelation functions for returns of both indices can be found from Figure 5. The existence of autocorrelation validates that the GARCH framework is a suitable approach for modelling the volatility of returns for the respective indices.

Table 3. Unit root and autocorrelation test statistics of the daily index returns

	ADF test statistics	Box-Ljung test statistics
S&P Green Bond index	-29,924***	38,33***
S&P Green Bond Select Index	-30,611***	53,591***
S&P US Aggregated Bond Index	-30,628 ***	65,158 ***
S&P China Bond Index	-32,224 ***	189,31 ***

**p < 10 %, **p < 5 %, ***p < 1 %*
Note: Box-Ljung test on squared returns

As explained in Chapter 3.2.2, the GARCH(1,1) model has proven to be sufficient to model volatility for financial data. The sufficiency of GARCH(1,1) was also confirmed comparing the Akaike and Bayes information criteria of different GARCH(p,q) modifications for all indices for the entire sample period. The mean equation was also validated using the Bayes information criteria and comparing different Autoregressive moving average ARMA(p,q) modifications. The information criteria values for different modifications can be found from Appendix 4 for the GARCH(p,q) modifications and from Appendix 5 for the ARMA(p,q) modifications for the mean equation. The ARMA(0,0)-GARCH(1,1) was found to be sufficient for all indices with the exception of the China Bond index. Based on the information criteria values, it would be optimal to add lags to the China Bond index mean equation and the GARCH model. However, to keep the analysis between indices more consistent and to formalize the comparison, the model chosen for the China bond index was also of form ARMA(0,0)-GARCH(1,1). However, in addition to the ARMA(0,0)-GARCH(1,1) model estimations and comparison with other indices, there is a parallel analysis conducted for the Chinese Bond index with the optimal mean and GARCH model modification in the end of each sub chapter. Since the ARMA(0,0) was found to be sufficient for the other indices, no further examination on the mean equation was done for the other indices. The next chapter presents and describes the results of the GARCH models built for this study.

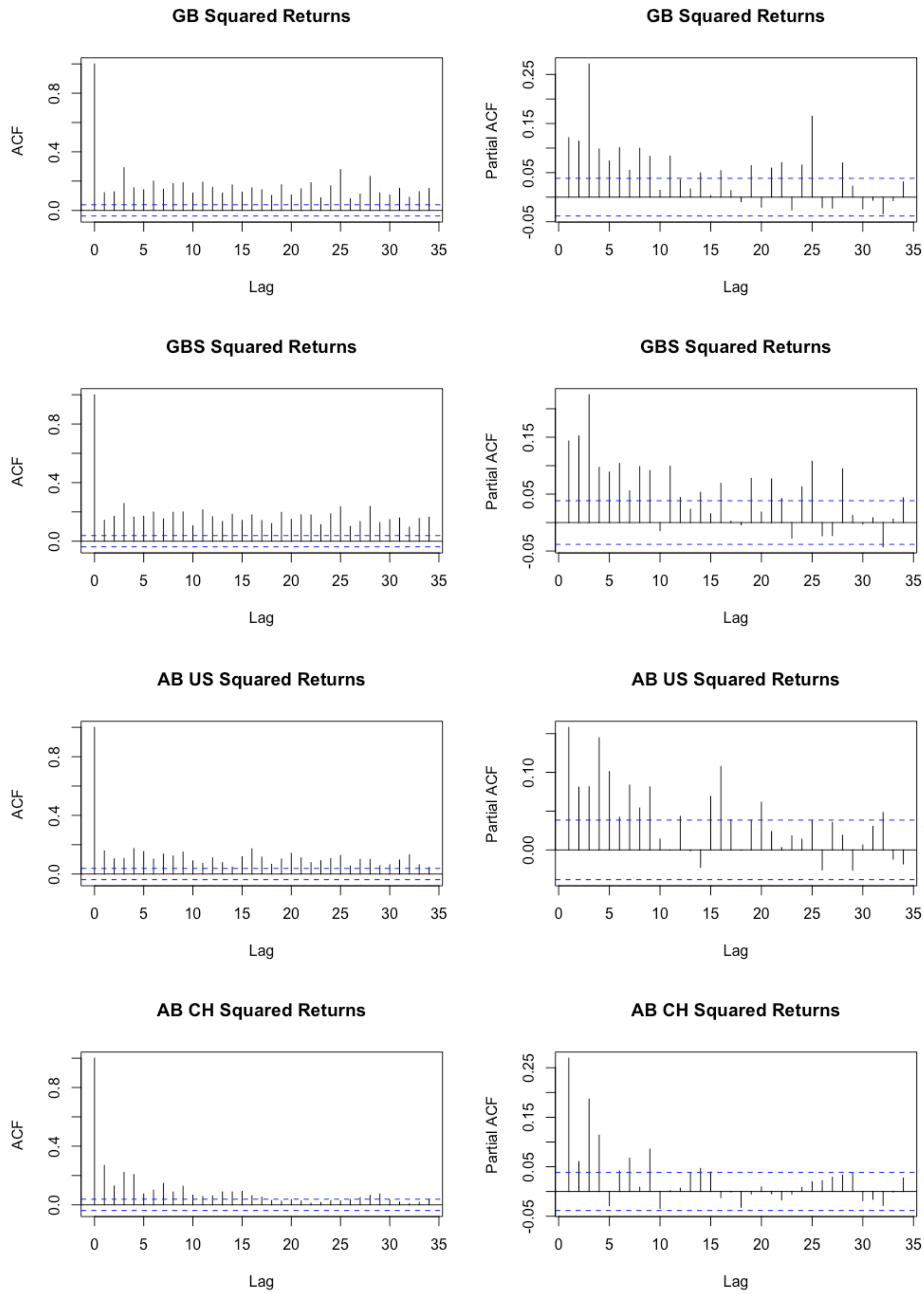

Figure 5. Autocorrelation and partial autocorrelation functions of the Green Bond index and Aggregated Bond index squared returns

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

5 RESULTS

The results of the GARCH models are presented in this chapter. As explained in Chapter 3, each observed feature, clustering, leverage effect and spillovers, can be observed from different models of the GARCH framework. Thereby this chapter is divided into three sub chapters each of which present the results of a model for the respective feature.

5.1 Volatility clustering

Volatility clustering is observed from an univariate GARCH(1,1) model. The estimated parameters of the model for all indices' return series for the entire sample period 2010-2019 can be found from Table 4. As in equations 5 and 6, μ stands for the unconditional mean in the mean equation and α_0 stands for the intercept in the conditional volatility equation. These are both insignificant for all indices. However, the main interest in this study, the ARCH(α) and GARCH(β) effects are both statistically significant for all indices. The sum of these effects, Rate of Decay is close to 1 for all indices as well. This means that the movements in conditional variance are highly persistent and all indices experience significant volatility clustering.

Table 4. Univariate volatility model for the entire sample period 2010-2019

GARCH(1,1) 2010-2019	GB Returns	GBS Returns	US Returns	CH Returns
μ	-0,000006 (0,000059)	-0,000008 (0,000067)	0,000020 (0,000034)	0,000053 (0,000022)
α_0	0,000000034 (0,000000)	0,000000047 (0,000000)	0,000000012 (0,000000)	0,000000011 (0,000000)
α	0,039215*** (0,003586)	0,033138*** (0,002814)	0,030469*** (0,002754)	0,086989*** (0,011590)
β	0,958318*** (0,003215)	0,963637*** (0,002539)	0,966567*** (0,002428)	0,909689*** (0,010366)
Rate of Decay	0,997533	0,996775	0,997036	0,996678
Unconditional variance	0,000000034	0,000000047	0,000000012	0,000000011
Half-life (days)	281	215	234	208

Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

The unconditional variance is calculated as the intercept divided by the Rate of Decay. The formula can be expressed as following

$$\frac{\alpha_0}{\alpha + \beta} \tag{26}$$

The half-life indicates how long does it take for a shocks' impact to be reduced by 50%. It is calculated as following

$$\ln(0{,}5)/\ln(\alpha + \beta) \tag{27}$$

As explained in Chapter 3, the short-run persistence of shocks is captured by the ARCH(α) effect and the long-run persistence is captured by the GARCH(β) effect. For all indices the GARCH effect seems to have more explanatory power over the overall persistence since the parameter estimates for all indices are significantly higher than for the ARCH effect. This result is expected. When the effects are compared between the indices, it seems that the short-run persistence is significantly lower for the Chinese bond index returns than the returns of the other indices. Conversely, the long-run persistence is the highest for the Chinese Bond index returns. Thereby it seems that the Chinese Bond market returns differ more in terms of shock persistence from the Green Bond market than the US Bond Market returns. However, the estimates do differ between the US Bond index returns and both green bond index returns: return volatility of both green bond indices seem the be more effected by the short run persistence than the return volatility of US bond index and vice versa by the long run persistence. Overall, the differences in persistence and half-lives between the indices is fairly minor but it can still be stated that the volatility clustering effect is more present for the Green Bond index and the US Bond index.

The conditional standard deviations for all indices and time periods are plotted in Figures 6 based on the respective GARCH(1,1) model estimated. Again it seems that the conditional standard deviation follows a similar pattern for the Green bond indices and the US Bond index whereas the pattern in the Chinese bond index is seems to be slightly different from the rest. However, for all indices the conditional standard deviation is higher during the first half of the decade than the second half. For the US Bond index this is not as clear as for the other indices. The volatility peaks do seem to occur in similar manner which could indicate correlation between the return series. This spillover effect is tested statistically later on. As the green bond market seems to have developed and shows some signs of stabilization based on this visual evidence, there will be additional analysis conducted.

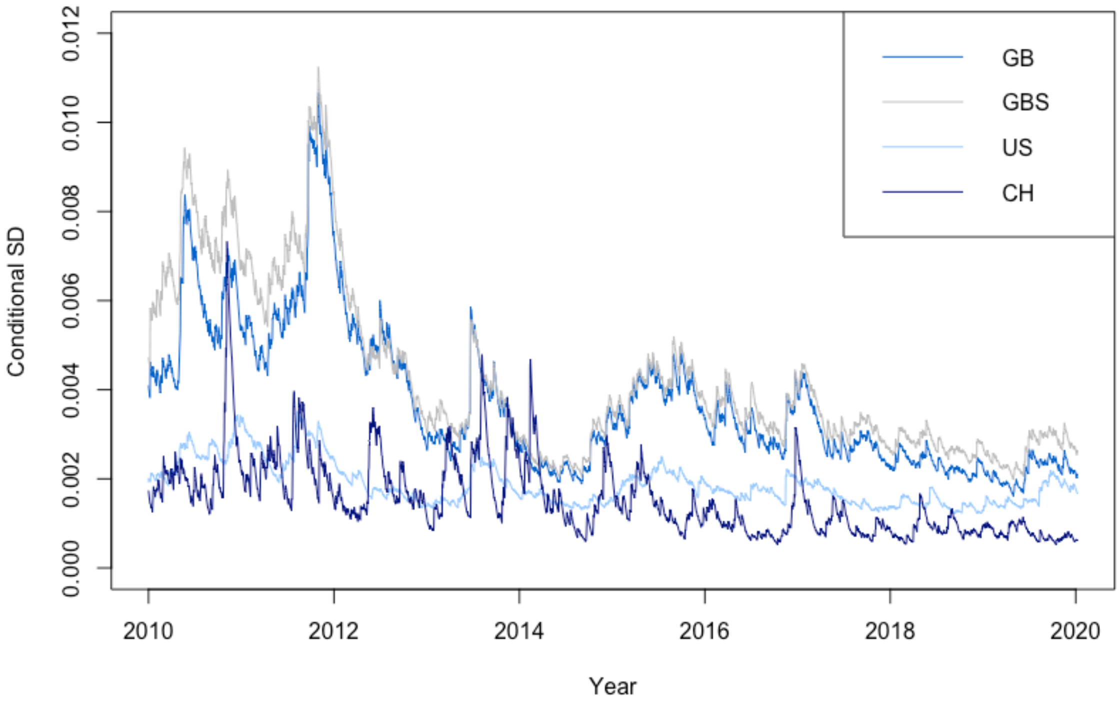

Figure 6. Conditional standard deviation of all index return series for entire sample period based on the estimated GARCH(1,1) model

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

In order to examine the development of the volatility clustering throughout the entire sample period, the sample period was split and two additional GARCH(1,1) models were created. The differences between the first half and the second half of the entire sample can be observed from these models. The estimated parameters for the first half of the sample period can be found from Table 5 and for the second half from table 6. Again the unconditional mean μ and the intercept α_0 are not statistically significant for both periods but the ARCH(α) and GARCH(β) effects are.

The Rate of Decay is higher for both indices during the first half of the sample period compared to the second half of the sample period. Thereby, the volatility clustering has been more present during the first half for both indices. For both indices, the half-life decreased more than 100 days for the second half of the sample period. In addition to the decrease in clustering behavior, there is clear development for the short-run ARCH(α) and long-run GARCH(β) persistence of shocks. The significance of short-run persistence seems to lower for the second half whereas the significance of long-run persistence increases.

Table 5. Univariate volatility model for the first half of the sample period 2010-2014

GARCH(1,1) 2010-2014	GB Return	GBS Return	US Return	CH Return
μ	-0,000033	-0,000003	0,000013	0,000028
	(0,000100)	(0,000110)	(0,000051)	(0,000046)
α_0	0,000000069	0,000000061	0,000000017	0,000000629**
	(0,000001)	(0,000001)	(0,000001)	(0,000000)
α	0,052505***	0,041097***	0,043074**	0,256355***
	(0,019348)	(0,010349)	(0,019606)	(0,034378)
β	0,945809***	0,956695***	0,953950***	0,627214***
	(0,017736)	(0,009531)	(0,017857)	(0,016804)
Persistence	0,998314	0,997792	0,997024	0,883569
Unconditional variance	0,000000069	0,000000061	0,000000017	0,000000712
Half-life (days)	411	314	233	6

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

As can be seen from all models, the volatility clustering is more present for the green bond indices returns than for the conventional bond index returns. The rate of decay which indicates the persistence of shocks is higher for the green bond index returns for all time periods. The significance of short-run ARCH(α) and long-run GARCH(β) persistence of shocks varies across the time periods. However, presence of volatility clustering behavior seems to lower for the second half of the decade.

Table 6. Univariate volatility model for the second half of the sample period 2015-2019

GARCH(1,1) 2015-2019

	GB Return	GBS Return	US Return	CH Return
μ	0,000010	0,000027	0,000009	0,000040*
	(0,000072)	(0,000084)	(0,000045)	(0,000024)
α_0	0,000000017	0,000000031	0,000000018	0,000000015
	(0,000000)	(0,000000)	(0,000000)	(0,000000)
α	0,020546***	0,018264***	0,017220***	0,077092***
	(0,001027)	(0,000801)	(0,001271)	(0,012220)
β	0,976619***	0,978203***	0,976192***	0,905451***
	(0,001335)	(0,001150)	(0,001618)	(0,011579)
Persistence	0,997164	0,996467	0,993412	0,982544
Unconditional variance	0,000000018	0,000000031	0,000000018	0,000000016
Half-life (days)	244	196	105	39

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

The conditional standard deviations for all indices and both time periods are plotted in Figure 7 based on the respective GARCH(1,1) models estimated. This visual evidence supports the findings that the presence of volatility clustering lowers towards the end of the decade in both indices. Pairwise comparison between the indices shows that generally the conditional standard deviation remains higher for the green bond indices than for the conventional bond indices. However, there are significant volatility peaks in the Chinese bond index which do not seem to occur in other indices.

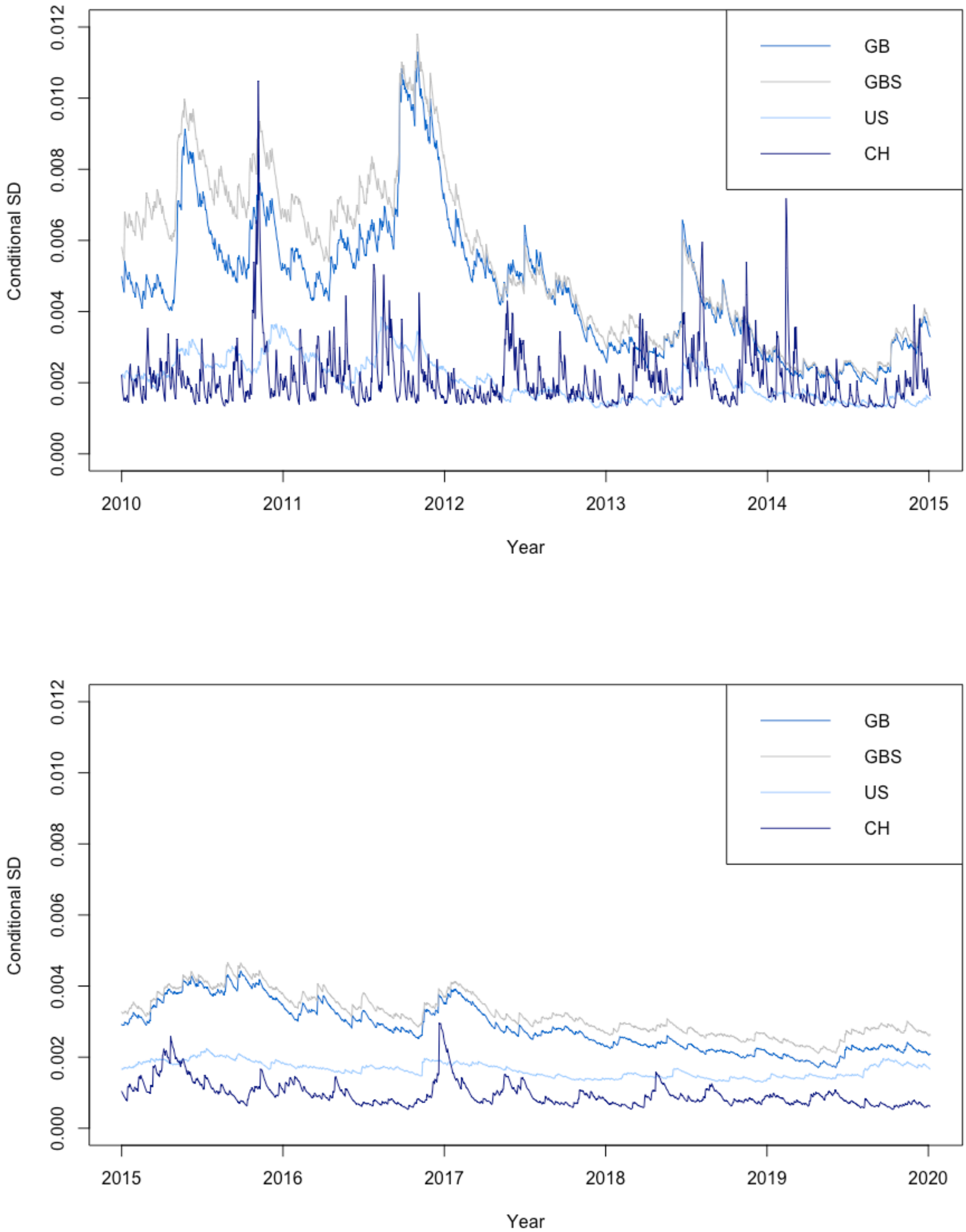

Figure 7. Conditional standard deviation of all index return series for both sample periods based on the estimated GARCH(1,1) model

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

As mentioned in the previous chapter, the robustness tests showed that for the Chinese Bond index the most optimal model would be of form ARMA(0,1)- GARCH(1,2). To keep the volatility clustering analysis between indices consistent, the same model, ARMA(0,0)-GARCH(1,1) was implemented for all indices including the Chinese index. However, the results from ARMA(0,1)- GARCH(1,2) model for the Chinese index for the entire sample period can still be found from Table 7.

Table 7. Additional Univariate volatility models for the Chinese Bond Index for all three sample periods

ARMA(0,1) - GARCH(1,2) for CH Return			
	2010-2019	2010-2014	2015-2019
μ	0,000045967**	0,000022212	0,000051618**
	(0,000018)	(0,000028)	(0,0000239)
ma_1	-0,180258***	-0,4047535***	0,0225200
	(0,022701)	(0,029046)	(0,0309213)
α_0	0,000000036	0,00000065390***	0,000000021
	(0,000000)	(0,000000)	(0,0000001)
α	0,1691115***	0,2801032***	0,1295716***
	(0,031105)	(0,039854)	(0,0273670)
β_1	0,3776402***	0,3550666***	0,4323045
	(0,115481)	(0,090246)	(0,2736743)
β_2	0,4482688***	0,2262432***	0,4234057**
	(0,098986)	(0,070481)	(0,2403827)
Persistence	0,995021	0,861413	0,985282
Unconditional variance	0,0000000362	0,0000007591	0,0000000210
Half-life (days)	139	5	47

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses, CH = S&P CHINA BOND INDEX

The main improvements in this model are that the parameters in the mean equation, constant and the moving average (MA), are both statistically significant. However, the mean equation is not of significant interest, since the focus in this study is in the ARCH and GARCH effects. The main findings from this model are that first of all, adding another lag to the long-run persistence (the GARCH effect) increases the significance of short-run persistence in and decreases the significance of long-run persistence explaining the return volatility. The parameter estimate for the ARCH effect is higher and the sum of the two GARCH effects is lower than in the first model presented. When this is compared against the other indices in scope, this model makes the volatility behavior of the Chinese bond index returns stand out even more from the other indices. Since the information criteria suggests that this model is more suitable for the Chinese bond index, it will be implemented also in the following analysis for the leverage effect and the spillover analysis.

The models presented above prove the presence of volatility clustering for all sample periods and for all indices. However, these models assumed asymmetry between negative and positive shocks which might not always be the case for financial return series. The next chapter examines whether there is a difference in the volatility behavior if the sign of the shock changes. This is called the leverage effect.

5.2 Leverage effects

As stated in Chapter 3, leverage effect is present when the volatility rises more after a large price fall compared to a raise of the same magnitude. The leverage effect is examined from GJR-GARCH(1,1) model presented in Chapter 3. The parameter estimates for all indices and for the entire sample period can be found from Table 8. The unconditional mean μ and the intercept α_0 are not statistically significant for any indices but the ARCH(α) and GARCH(β) effects are. The leverage effect coefficient γ does get a value higher than zero for both green bond indices but the coefficient is statistically significant only for the S&P Green Bond index and insignificant for the S&P Green Bond Select index. Thereby, leverage effect is present for the Green Bond index but not the Green Bond Select index when examined the entire sample period.

What comes to the benchmark indices, the ARCH(α) and GARCH(β) effects are again statistically significant as expected and they further confirm the results from previous sections that volatility clustering is present. The leverage effect coefficient γ for the US bond index gets a negative value which would indicate that there is an opposite leverage effect present: the volatility rises less after a price fall compared to a raise of the same magnitude. However, since the coefficient is not statistically significant, it cannot be confirmed that the US bond index would exhibit any leverage effect. On the contrary, for the Chinese bond index the leverage effect coefficient is not only statistically significant, but the magnitude of the leverage effect is highest among the examined indices.

Table 8. Univariate volatility model with leverage effects for entire sample period 2010-2019

GJR-GARCH(1,1) 2010-2019	GB Return	GBS Return	US Return	CH Return
μ	-0,000004	0,000024	0,000030	0,000035
	(0,000056)	(0,000064)	(0,000033)	(0,000019)
α_0	0,000000031	0,000000045	0,000000021	0,000000031
	(0,000000)	(0,000000)	(0,000000)	(0,000001)
α	0,0244682***	0,02944939***	0,0351829***	0,1110663**
	(0,006012)	(0,006422)	(0,006069)	(0,035052)
β	0,9637364***	0,963283***	0,9607913***	0,8502141***
	(0,003047)	(0,003111)	(0,002899)	(0,039620)
γ	0,01731417*	0,008526	-0,004471	0,06513118***
	(0,009129)	(0,009797)	(0,009100)	(0,013201)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

These models thereby confirm that volatility clustering is present for all indices during the entire sample period. What comes to the real interest of these models, the leverage effect, evidence can only be found for the S&P Green Bond and for the S&P China Bond index. Introducing the leverage effect into the models didn't change the ARCH and GARCH estimates much. The Chinese Bond index is again an exception where the introduction of the leverage effect increased the significance of ARCH effect and decreased the of GARCH effect.

Interestingly the results change slightly when the sub sample periods, 2010-2014 and 2015-2019 are examined the same way. The results for the first sample period can be found from Table 9 and for the second from Table 10. For the first sample period the ARCH and GARCH effects are again present and statistically significant. However, the leverage effect is only statistically significant for the S&P Green Bond index but not the S&P China Bond index unlike during the entire sample period 2010-2019. Again, for all other indices except the Chinese Bond index, where the ARCH and GARCH estimates remained fairly constant, the introduction of the leverage effect shifted explanatory power from the ARCH effect to the GARCH effect. However, since the statistical insignificance results in having no evidence of leverage effect for most of the indices, the models presented in Chapter 5.1 are more valid for the Green Bond Select, US Bond and Chinese Bond index.

Table 9. Univariate volatility models with leverage effects for 2010-2014

GJR-GARCH(1,1) 2010-2014	GB Return	GBS Return	US Return	CH Return
μ	-0,000014	0,000042	0,000063	-0,000001
	(0,000093)	(0,000100)	(0,000051)	(0,000041)
α_0	0,000000025	0,000000024	0,000000013	0,000000369
	(0,000001)	(0,000001)	(0,000001)	(0,000001)
α	0,02079181***	0,02546895***	0,03443145*	0,2581852***
	(0,005620)	(0,007367)	(0,020271)	(0,078304)
β	0,9588487***	0,9613863***	0,9572232***	0,6749046***
	(0,008686)	(0,009388)	(0,017768)	(0,054346)
γ	0,03854951**	0,023474	0,009451	0,131808
	(0,015379)	(0,014829)	(0,014711)	(8,918853)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

For the second sample period, there seems to be no evidence of the leverage effect for any of the indices since the parameter estimate is statistically insignificant for all indices. The ARCH and GARCH effects are significant with the exception of the ARCH effect of the Chinese Bond index. Therefore with the models presented in Chapter 5.1 it can be conducted that during the second half of the decade, the indices experience volatility clustering but no leverage effect.

Table 10. Univariate volatility models with leverage effects for 2015-2019

GJR-GARCH(1,1) 2015-2020	GB Return	GBS Return	US Return	CH Return
μ	0,000016	-0,000001	0,000020	0,000013
	(0,000070)	(0,000081)	(0,000043)	(0,000022)
α_0	0,000000024	0,000000035	0,000000006	0,000000013
	(0,000000)	(0,000000)	(0,000000)	(0,000001)
α	0,0179516***	0,02115097***	0,02467785***	0,064661
	(0,004162)	(0,004447)	(0,003962)	(0,040765)
β	0,9759454***	0,9753048***	0,9754403***	0,9155217***
	(0,001396)	(0,001542)	(0,001637)	(0,039411)
γ	0,003861	-0,000582	-0,006757	0,013251
	(0,008897)	(0,009664)	(0,008045)	(0,020122)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

As stated in previous chapters, the optimal mean equation and GARCH model for the Chinese Bond index is of form ARMA(0,1)- GARCH(1,2). However, it also needs to be examined whether the leverage effect is present in this modification during all sample periods. The results can be found from table 11. For the entire sample period all ARCH and GARCH estimated are statistically significant but there is no evidence of leverage effect since the leverage effect coefficient is not statistically significant. Thereby the optimal model for the entire sample period is of form ARMA(0,1)-GARCH(1,2). For the second sample period the leverage effect seems to be present but the ARCH estimate however is not statistically significant. Both GARCH estimates are statistically significant and thereby it seems that the long run persistence is more prominent in defining the conditional volatility. For the second sample period the results are similar than for the entire sample period so there is no evidence of leverage effect.

Table 11. Additional Univariate volatility model stating the leverage effects for the Chinese Bond Index for all three sample periods

ARMA(0,1)-GJR-GARCH(1,2) AB CH Return			
	2010-2019	2010-2014	2015-2019
μ	0,000027*	0,000014	0,000028
	(0,000016)	(0,000024)	(0,000021)
ma	-0,189477***	-0,387851***	-0,020298
	(0,020906)	(0,025394)	(0,029159)
α_0	0,000000047	0,000000542	0,000000016
	(0,000000)	(0,0000021)	(0,0000002)
α	0,1764325***	0,3572601	0,1116184***
	(0,027869)	(0,2381505)	(0,0166735)
β_1	0,3927387***	0,2890383**	0,6091756***
	(0,068714)	(0,0965988)	(0,0579777)
β_2	0,4031464***	0,2721193**	0,2599939***
	(0,088881)	(0,085623)	(0,098702)
γ	0,053204	0,1413179**	0,0195187
	(0,032578)	(0,0628212)	(0,0292773)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
AB CH = S&P CHINA BOND INDEX

The models presented above have examined the indices individually and have shown some differences in terms of mean equation, volatility clustering and the leverage effect between the indices. During this process it was also investigated which model modification is the most suitable to present the volatility behavior of the indices during the sample periods. These model modifications are combined in table 12 below.

Table 12. Optimal ARMA-GARCH models for the indices and sample periods

	2010-2019	2010-2014	2015-2019
GB	ARMA(0,0)-GJR-GARCH(1,1)	ARMA(0,0)-GJR-GARCH(1,1)	ARMA(0,0)-GARCH(1,1)
GBS	ARMA(0,0)-GARCH(1,1)	ARMA(0,0)-GARCH(1,1)	ARMA(0,0)-GARCH(1,1)
US	ARMA(0,0)-GARCH(1,1)	ARMA(0,0)-GARCH(1,1)	ARMA(0,0)-GARCH(1,1)
CH	ARMA(0,1)-GARCH(1,2)	ARMA(0,1)-GJR-GARCH(1,2)	ARMA(0,1)-GARCH(1,2)

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, AB US = S&P US AGGREGATE BOND INDEX and AB CH = S&P CHINA BOND INDEX

Hereafter the analysis focuses on examining the dependence and connectedness between the indices by studying the volatility spillover effect. For this analysis it is also essential to have the individual volatility behavior modelled as properly as possible so the modifications from table 11 will be used in the spillover modelling.

5.3 Volatility Spillovers

The volatility spillovers between green bond and conventional bond markets are examined from the bivariate DCC-MGARCH(1,1) model presented in Chapter 3. The univariate ARMA-GARCH model modifications for each index are determined based on the analysis conducted in the first part of this study. Instead of forcing the univariate models to be consistent between indices and sample periods, it was prioritized to choose the most optimal models from the GARCH family for each analyzed dataset. The results for the entire sample period 2010-2019 can be found from tables 13 for US aggregated bond index and 14 for China aggregated bond index.

For the models with the US Aggregated bond index and the green bond indices the results for the univariate models are similar to the previously estimated in Chapters 5.1 and 5.2 as expected. The unconditional mean estimates μ_{GB} and μ_{AB} or the intercepts α_{0GB} and α_{0AB} are not statistically significant for any of the indices. However, the ARCH(α) and GARCH(β) effects for all indices and the conditional correlation parameters are statistically significant. Again, the persistence is more significant for the green bond indices than for the US aggregated bond index, so the volatility clustering effect is more profound for the green bond indices than for the US aggregated bond index. For the S&P Green Bond Index the leverage effect is also present as expected.

The conditional correlation parameter estimates a and b are positive and statistically significant for both models and thereby validate the existence of volatility spillovers between the green bond market and the conventional bond market in the US. The sum of a and b is also close to 1 for both models which indicates time varying conditional correlation and highly persistent behavior between the green bond markets and the US bond market. The visual representation of the development of the conditional correlation and conditional covariance between the indices can be found from Figure 8. During the first half of the sample period there seems to be a clear increasing correlation between the indices since it shifts from negative correlation to positive correlation. After the shift the correlation flees back towards zero twice but otherwise remains strongly positive around 0.4 and even 0.6. There does not seem to be a clear pattern for neither of the indices yet there are also no clear differences between the two green bond indices. The visualization of conditional covariance is in line with the conditional correlation: the covariance gets negative values during the first half of the decade but remains positive during the second half. Despite few peaks towards zero, the indices seem to have stabilized in terms of conditional covariance for the second half of the decade.

Table 13. Bivariate volatility model for entire sample period 2010-2019 Green Bond indices and the US Aggregated Bond index

DCC-MGARCH(1,1) 2010-2019		
	GB	GBS
Parameter estimates for the Green Bond Market index		
μ_{GB}	-0,0000041	-0,0000080
	(0,0000567)	(0,0000669)
α_{0GB}	0,000000031	0,000000047
	(0,0000004)	(0,0000002)
α_{GB}	0,0244682***	0,0331384***
	(0,0063944)	(0,0030120)
β_{GB}	0,9637364***	0,9636373***
	(0,0028279)	(0,0020907)
γ	0,01731417**	
	(0,00938176)	
Parameter estimates for the Conventional Bond Market index (US)		
μ_{AB}	0,0000198	0,0000198
	(0,0000335)	(0,0000335)
α_{0AB}	0,000000012	0,000000012
	(0,0000001)	(0,0000001)
α_{AB}	0,03046923***	0,03046923***
	(0,0022842)	(0,0022838)
β_{AB}	0,9665665***	0,9665665***
	(0,001755409)	(0,00175948)
Estimates for the conditional correlation parameters		
a	0,02040869***	0,02020054***
	(0,0049726)	(0,0049781)
b	0,9777056***	0,9779665***
	(0,005902)	(0,005858)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P US AGGREGATE BOND INDEX

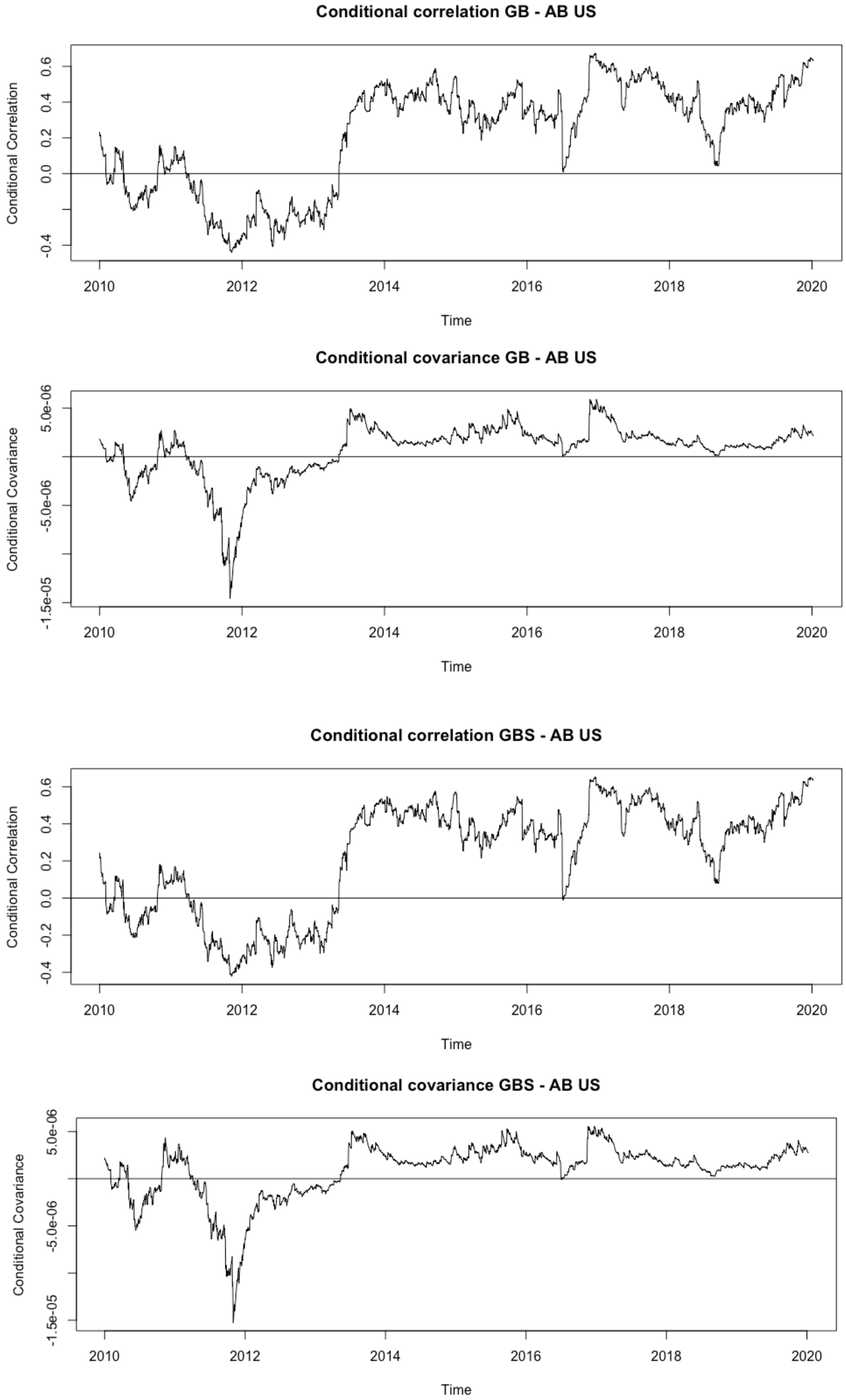

Figure 8. Conditional correlation and conditional covariance between the green bond indices and the US Aggregated bond index for the entire sample period 2010-2019

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P US AGGREGATE BOND INDEX

As for the models with US Aggregated bond index, the results for the univariate model for the China Aggregated Bond index are similar to the previously estimated in Chapters 5.1 and 5.2. For the green bond indices the parameter estimates for the mean equation are the same as for the previous models presented in Table 7 with the US Aggregated Bond index. Unconditional mean estimates μ_{GB} or the intercepts α_{0GB}, which are not of interest in this study are not statistically significant for neither of the green bond indices but the parameter estimates for ARCH(α) and GARCH(β) effects are. Leverage effect is again present for the Green Bond index and for the China Aggregated bond index there is statistical significance for all parameters of the ARMA(0,1)-GARCH(1,2) model except the intercept α_{0AB} of the volatily model. What comes to the ARCH(α) and GARCH(β) effects, the short run persistence ARCH(α) is significantly higher for the China Aggregated bond index than for both of the green bond market indices but the opposite stands for the long run persistence GARCH(β) effect. Overall the persistence is more significant for the China Aggregated Bond index than for the Green Bond index but slightly less significant than for the Green Bond Select index Thereby the volatility clustering is the most profound for the S&P Green Bond Select index and the least for the S&P Green Bond index.

What comes to the result with the China bond index, the conditional correlation parameter estimates a and b between the green bond markets and the China bond market are positive and statistically significant for both models and thereby validate the existence of volatility spillovers between the green bond market and the conventional bond market in China. The sum of a and b is also close to 1 for both models which indicates time varying conditional correlation and highly persistent behavior between the green bond markets and the China bond market.

Table 14. Bivariate volatility model for entire sample period 2010-2019 Green Bond indices and China Aggregated Bond index

DCC-MGARCH(1,1) 2010-2019		
	GB	GBS
Parameter estimates for the Green Bond Market index		
μ_{GB}	-0,0000041 (0,0000567)	-0,0000080 (0,0000669)
α_{0GB}	0,000000031 (0,0000004)	0,000000047 (0,0000002)
α_{GB}	0,0244682*** (0,0063944)	0,03313839*** (0,0030120)
β_{GB}	0,9637364*** (0,0028279)	0,9636373*** (0,0020907)
γ	0,01731417** (0,00938176)	
Parameter estimates for the Conventional Bond Market index (CH)		
μ_{AB}	0,000046** (0,000018)	0,000046* (0,000018)
ma	-0,180258*** (0,028428)	-0,180258*** (0,028427)
α_{0AB}	0,000000036 (0,000001)	0,000000036 (0,000001)
α_{AB}	0,1691115** (0,094531)	0,1691115** (0,094552)
β_{1AB}	0,3776402* (0,251879)	0,3776402* (0,251927)
β_{2AB}	0,4482688** (0,191569)	0,4482688* (0,191595)
Estimates for the conditional correlation parameters		
a	0,006549* (0,004340)	0,006375* (0,004361)
b	0,970432*** (0,009035)	0,971663*** (0,009324)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P CHINA BOND INDEX

The visual representation of the development of the conditional correlation and conditional covariance between the indices can be found from Figure 9. There does not seem to be clear development or trend through time in the conditional correlation between the indices. The conditional correlation fluctuates around zero for both green bond indices and there can be found few peaks, for example a highly negative peak in 2013 when the conditional correlation between green bond indices and the US bond index was also low. After that there has been quite a few positive peaks and the conditional correlation has mainly remained positive. There are no significant differences found between the green bond indices so they seem to develop similarly compared with the China Bond index. The visualization of conditional covariance shows that it has stabilized towards the end of the dataset. There can be found strong fluctuation in the beginning of the decade which slowly quiets down and has stayed fairly constant after around 2017. Overall the conditional covariance has also stayed either positive or close to 0. To put it shortly, in terms of conditional correlation, the indices still experience large fluctuation but in terms of conditional covariance, the indices have stabilized throughout the observed decade.

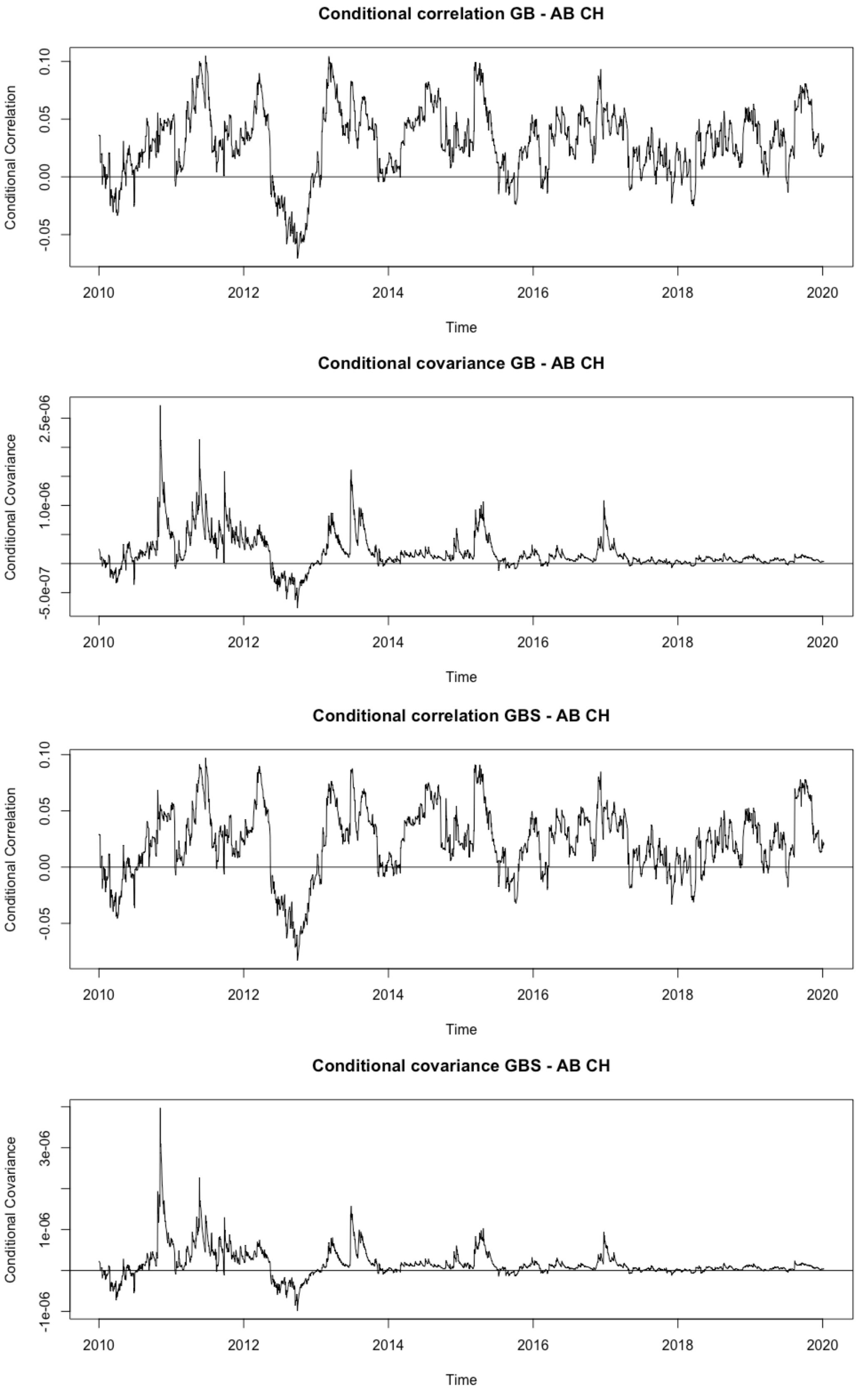

Figure 9. Conditional correlation and conditional covariance between the green bond indices and the China Aggregated bond index for the entire sample period 2010-2019

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P CHINA BOND INDEX

To further analyze and demonstrate the development of the indices through the decade, two additional models are built to examine the differences between the first and second half of the decade similarly as for the volatility clustering in Chapters 5.1 and 5.2. The results of bivariate DCC-MGARCH(1,1) model with the US aggregated bond index and the green bond indices for the first sample period from the beginning of 2010 to the end of 2014 can be found from Table 15 and for the second sample from the beginning of 2015 to the end of 2019 period from Table 16. The results of the univariate models for the US Aggregated bond index and the green bond indices are similar to the results estimated in Chapters 5.1 and 5.2 as expected for both sample periods. The unconditional mean estimates μ_{GB} and μ_{AB} or the intercepts α_{0GB} and α_{0AB} are not statistically significant for any of the indices. Surprisingly, the ARCH(α) effect is not statistically significant for the green bond or the US bond index but the GARCH(β) effects and the conditional correlation parameters are for all indices and both models. Leverage effect is also present for the S&P Green Bond index during the first half of the decade.

The conditional correlation parameter estimates a and b are positive and statistically significant for both indices during the first sub-sample period. This result validates the existence of volatility spillovers between the green bond market and the conventional bond market in the US during the first half of the decade. The sum of a and b is also close to 1 for both models which indicates time varying conditional correlation and highly persistent behavior between the green bond markets and the US bond market.

The visual representation of the development of the conditional correlation and conditional covariance between the indices can be found from Figure 10. The figures are very similar for both green bond indices and no clear differences cannot be found between the S&P Green bond index and the S&P Green bond Select index. However, these figures seem to validate the initial assessment from the model for the entire sample period that during the first half of the decade there is overall an increasing trend in the correlation between the indices starting from 2012. Before that the correlation had remained negative with few expectations. The visualization of conditional covariance is in line with the conditional correlation: the covariance gets negative values similarly as the correlation but exhibits an increasing trend from 2012. One major takeaway from this visualization is that the conditional correlation and covariance developed significantly during the first half of the decade. By no means it can be stated that the market would have been stable during this time in terms of conditional correlation and covariance which can be expected from a newly founded market. Thereby it could be expected that the result for the second sub- sample period are more mature.

Table 15. Bivariate volatility model for the first sub-sample period 2010-2014 Green Bond indices and US Aggregated Bond index

DCC-MGARCH(1,1) 2010-2014		
	GB	GBS
Parameter estimates for the Green Bond Market index		
μ_{GB}	-0,000014	-0,000003
	(0,000097)	(0,000110)
α_{0GB}	0,000000025	0,000000061
	(0,000001)	(0,000001)
α_{GB}	0,020792	0,041097**
	(0,020009)	(0,023388)
β_{GB}	0,958849***	0,956695***
	(0,016756)	(0,0205324)
γ	0,038550*	
	(0,015385)	
Parameter estimates for the Conventional Bond Market index (US)		
μ_{AB}	0,000013	0,000013
	(0,000051)	(0,000051)
α_{0AB}	0,000000017	0,000000017
	(0,000002)	(0,000002)
α_{AB}	0,043074	0,043074
	(0,054157)	(0,054157)
β_{AB}	0,953950***	0,953950***
	(0,048815)	(0,048815)
Estimates for the conditional correlation parameters		
a	0,023361***	0,0234828***
	(0,005535)	(0,005408)
b	0,976138***	0,9763948***
	(0,006267)	(0,005851)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P US AGGREGATE BOND INDEX

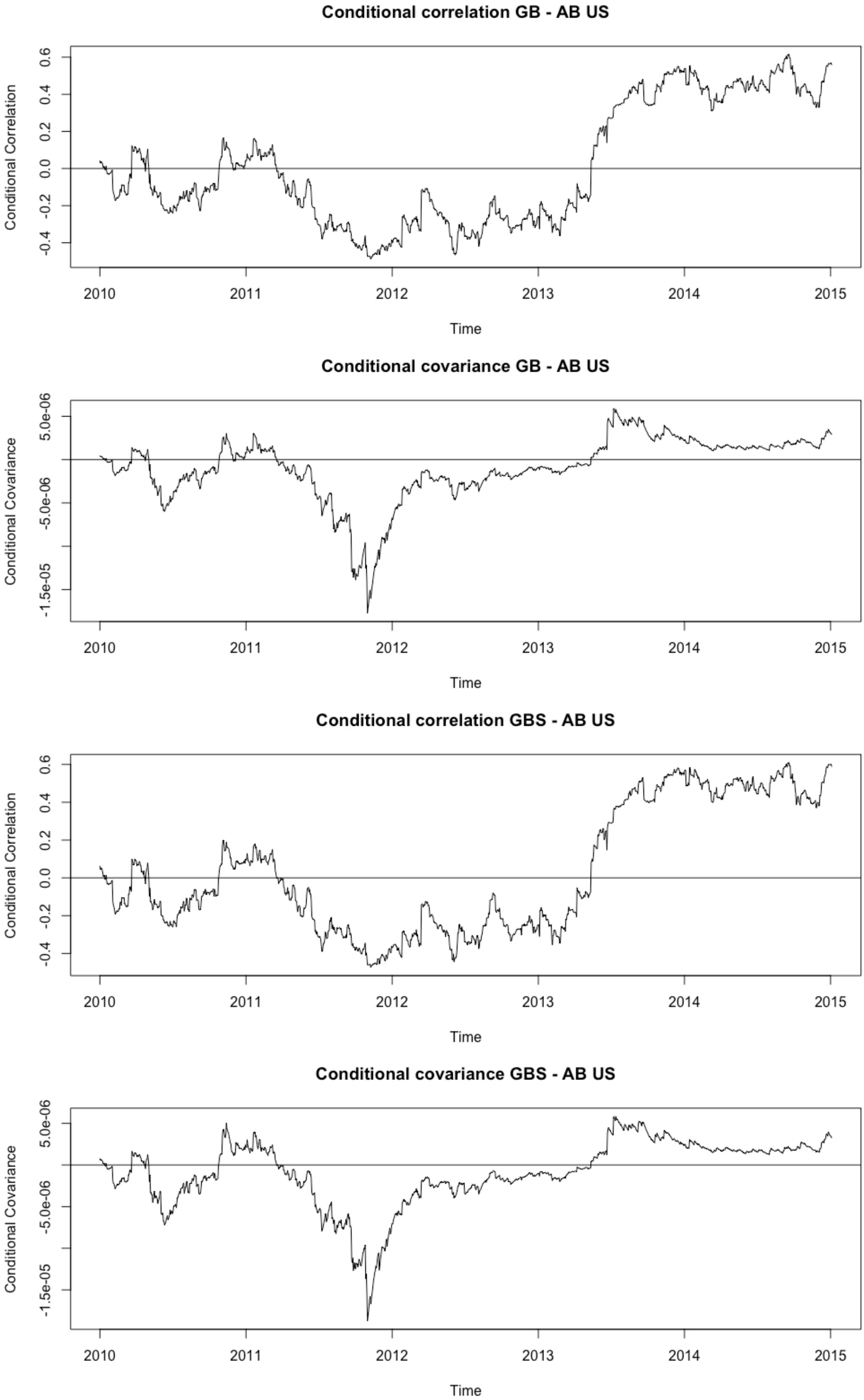

Figure 10. Conditional correlation and conditional covariance between the green bond indices and the US Aggregated bond index for the first sub-sample period 2010-2014

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P US BOND INDEX

As already mentioned, the results of the univariate models for the US Aggregated bond index and the green bond indices are similar to the results estimated in Chapters 5.1 and 5.2 for the second sub-sample as well. The conditional correlation parameter estimates a and b are positive and statistically significant for both indices during the second sub-sample period. This result validates the existence of volatility spillovers between the green bond market and the conventional bond market in the US during the second half of the decade as well. However, estimates for both a and b are significantly lower than for the first sub-sample period and the sum of a and b is only around 0,8 for both models. This still indicates time varying conditional correlation and persistent behavior between the green bond markets and the US bond market, but it is less significant this time.

The visual representation of the development of the conditional correlation and conditional covariance between the indices for the second sample period can be found from Figure 11. The findings from the figures further validate the initial assessment from the first model for the entire sample period. For both models the term of the correlation has remained positive during the sample period with one exception around mid 2016. This can be interpreted as a stabilization of the relationship between the two markets, green bond market and the US Bond market. Compared to the first sample period which exhibits a clear increasing trend, the conditional correlation during the second sample period does not exhibit much trend at all. Most of the values land somewhat randomly between 0.2 and 0.6. The conditional correlation seems to move again very similarly for both, the green bond index and the green bond select index so no clear differences between these two indices can be found in terms of conditional correlation with the US bond index. For conditional covariance there can be found a slightly decreasing trend for both models. However mostly it seems that the conditional covariance has fluctuated more in the beginning of the sample period than in the end. It could be stated that whereas the conditional correlation has not developed much during this sample period, the conditional covariance has stabilized since the changes are less significant in the end than in the beginning. This development is clearer for the green bond index than for the green bond select index.

Table 16. Bivariate volatility model for the second sub-sample period 2015-2019 Green Bond indices and US Aggregated Bond index

DCC-MGARCH(1,1) 2015-2019	GB	GBS
Parameter estimates for the Green Bond Market index		
μ_{GB}	0,000006	0,000025
	(0,000073)	(0,000085)
α_{0GB}	0,000000016	0,000000030
	(0,000000)	(0,000000)
α_{GB}	0,019987***	0,0179707***
	(0,000956)	(0,000872)
β_{GB}	0,977330***	0,978448***
	(0,000444)	(0,000354)
Parameter estimates for the Conventional Bond Market index (US)		
μ_{AB}	0,000014	0,000011
	(0,000045)	(0,000045)
α_{0AB}	0,000000018	0,000000018
	(0,000000)	(0,000000)
α_{AB}	0,017326***	0,01757488***
	(0,001494)	(0,001566)
β_{AB}	0,9759395***	0,9755992***
	(0,000719)	(0,000802)
Estimates for the conditional correlation parameters		
a	0,062929***	0,062990***
	(0,021845)	(0,022371)
b	0,788908***	0,772232***
	(0,063843)	(0,057043)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P US AGGREGATE BOND INDEX

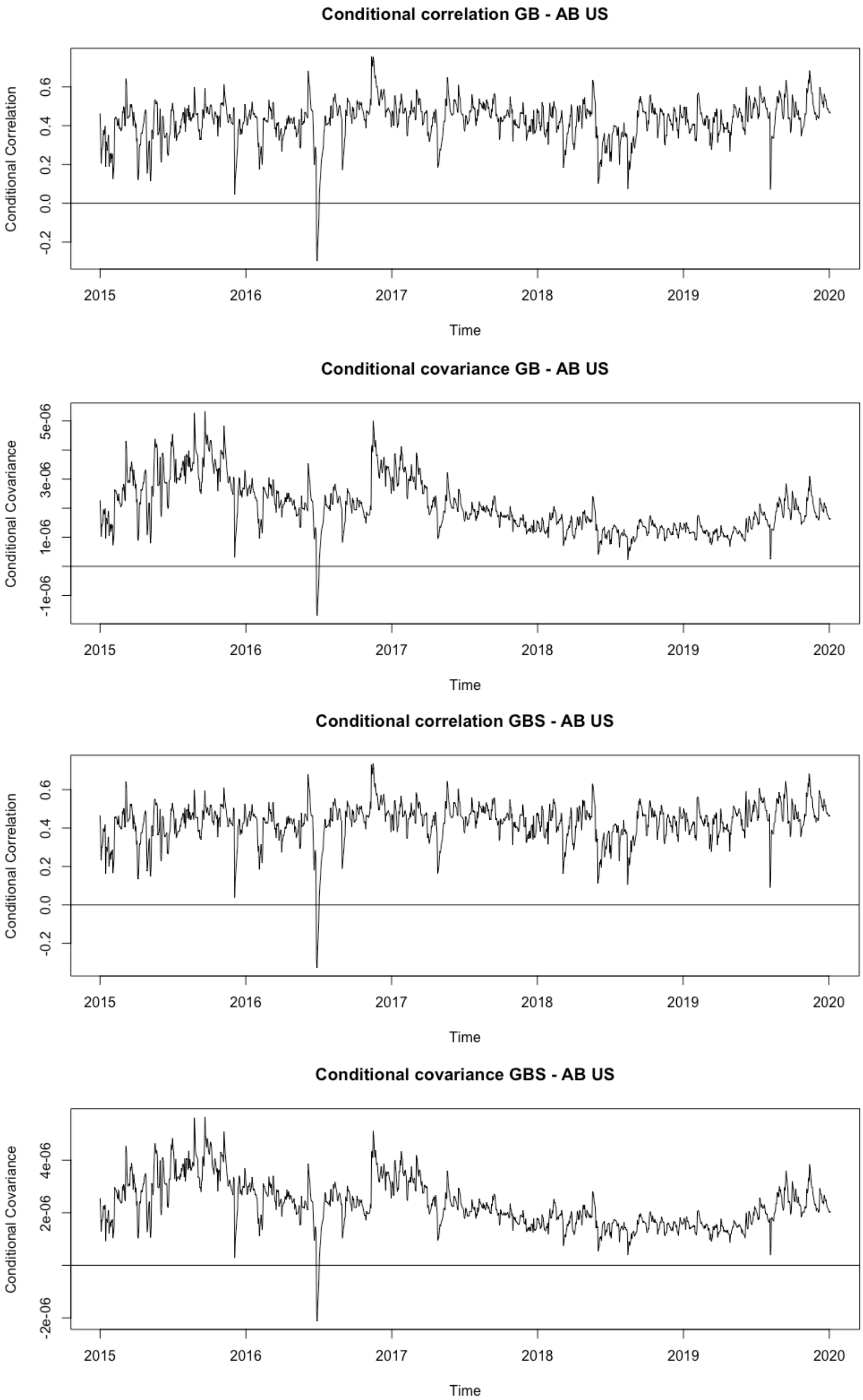

Figure 11. Conditional correlation and conditional covariance between the green bond indices and the US Aggregated bond index for the second sub-sample period 2015-2019

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P US BOND INDEX

According to all the models for different periods for the US Bond index, there is a trend of stabilization and normalization in the conditional correlation and the conditional covariance between the indices. Based on the first multivariate model with the China bond index for the entire sample period, it seems that not quite similar findings can be found for the correlation and covariance between Chinese bond markets and the green bond markets. This initial hypothesis is further examined with two following models for the two sub sample periods and a similar analysis is conducted for the Chinese bond index as was for the US bond index. The results of bivariate DCC-MGARCH(1,1) model with the China aggregated bond index and the green bond indices for the first sample period from the beginning of 2010 to the end of 2014 can be found from Table 17 and for the second sample from the beginning of 2015 to the end of 2019 period from Table 18.

For both green bond indices the results of the univariate models are similar to the previously estimated as expected. For the China bond index from the univariate model only the moving average parameter is statistically significant. However both conditional correlation parameters a and b are statistically significant and those are the interest of this analysis. Both a and b are positive, and the sum is close to 1. This result again validates the existence of volatility spillovers between the green bond market and the conventional bond market in the China during the first half of the decade. It also indicates time varying conditional correlation and highly persistent behavior between the green bond markets and the China bond market.

The visual representation of the development of the conditional correlation and conditional covariance between the indices can be found from Figure 12. What comes to the similarities in conditional correlation with the green bond indices among the US and China bond indices, the sum of conditional correlation parameters is very similar. But as can be seen from figures 10 and 12, the development and trend during the period is very different. As with the US bond index there was a clear increasing trend in the conditional correlation, with the China bond index it’s more challenging to find any trend at all. Conditional correlation constantly shifts between positive and negative and there are peaks on both sides. However, based on the figure and the estimates for a and b, on average the correlation is more positive than negative. The most significant period of negative correlation lands to the second half of 2012. The development is similar for both green bond indices and also for the covariance except that for the covariance the peaks and changes are more precise.

Table 17. Bivariate volatility model for the first sub-sample period 2010-2014 Green Bond indices and China Aggregated Bond index

DCC-MGARCH(1,1) 2010-2014	GB	GBS
Parameter estimates for the Green Bond Market index		
μ_{GB}	-0,000014	-0,000003
	(0,000097)	(0,000110)
α_{0GB}	0,000000025	0,000000061
	(0,000001)	(0,000001)
α_{GB}	0,020792	0,04109691**
	(0,020021)	(0,023403)
β_{GB}	0,9588487***	0,9566947***
	(0,016702)	(0,020525)
γ	0,03854951*	
	(0,015410)	
Parameter estimates for the Conventional Bond Market index (CH)		
μ_{AB}	0,000014	0,000014
	(0,000026)	(0,000026)
ma	-0,387851***	-0,387851***
	(0,052832)	(0,052837)
α_{0AB}	0,0000001	0,000001
	(0,000009)	(0,000009)
α_{AB}	0,357260	0,357260
	(1,046648)	(1,046484)
β_{2AB}	0,289038	0,289038
	(0,393691)	(0,393609)
β_{2AB}	0,272119	0,272119
	(0,324778)	
		(0,324743)
γ	0,141318	0,141318
	(0,380039)	(0,380060)
Estimates for the conditional correlation parameters		
a	0,016316*	0,015696**
	(0,006420)	(0,006829)
b	0,9735873**	0,9740494***
	(0,006428)	(0,007055)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P CHINA BOND INDEX

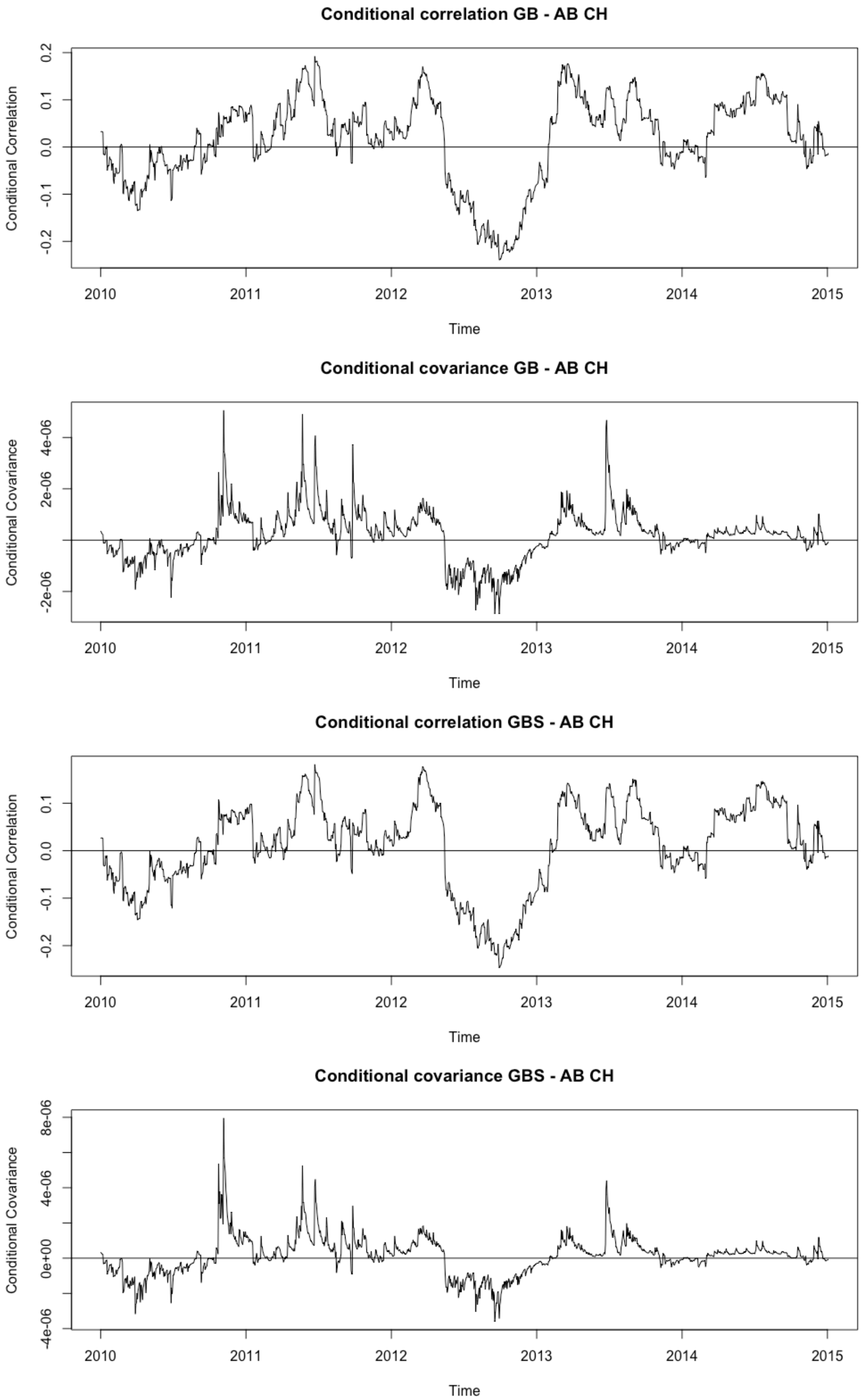

Figure 12. Conditional correlation and conditional covariance between the green bond indices and the China Aggregated bond index for the first sub-sample period 2010-2014

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P CHINA BOND INDEX

When moving to the second sample period there is again nothing outstanding with the univariate models and their results. For green bond indices the result are similar to previously estimated and for the China bond index only the mean estimate and the ARCH estimate are statistically significant. Interestingly the conditional correlation parameter a gets a value of 0 and is not statistically significant. However since the conditional correlation parameter b is positive and statistically significant, it can still be stated that there is time varying conditional correlation and highly persistent behavior between the green bond markets and the China bond market during the second sample period as well. The estimates are lower than for the first sample period so it seems that the conditional correlation is not as high as during the first half of the sample period. The same development was found for the US bond index as well.

The visual representation of the development of the conditional correlation and covariance between the green bond markets and the China bond market can be found form Figure 13. Interestingly both the correlation and covariance have remained positive during the entire sample period but still fluctuated quite constantly experiencing both upward and downward peaks. However compared to the first sub sample period there can be some stabilization found since the estimates remain positive throughout.

Table 18. Bivariate volatility model for the second sub-sample period 2015-2019 Green Bond indices and China Aggregated Bond index

DCC-MGARCH(1,1) 2015-2019	GB	GBS
Parameter estimates for the Green Bond Market index		
μ_{GB}	0,000010	0,000025
	(0,000072)	(0,000085)
α_{0GB}	0,000000018	0,000000030
	(0,000000)	(0,000000)
α_{GB}	0,020750***	0,017971***
	(0,001018)	(0,000879)
β_{GB}	0,976371***	0,978448***
	(0,000527)	(0,000353)
Parameter estimates for the Conventional Bond Market index (CH)		
μ_{AB}	0,000052**	0,000052**
	(0,000024)	(0,000024)
ma	0,020828	0,020827
	(0,032557)	(0,032560)
α_{0AB}	0,000000021	0,000000021
	(0,000001)	(0,000001)
α_{AB}	0,131150**	0,131150**
	(0,078717)	(0,078700)
β_{1AB}	0,432882	0,432882
	(0,859052)	(0,858850)
β_{2AB}	0,421288	0,421288
	(0,788002)	(0,787821)
Estimates for the conditional correlation parameters		
a	0,000000	0,000000
	(0,000239)	(0,000000)
b	0,905123***	0,904189***
	(0,143514)	(0,176085)

**p < 10 %, **p < 5 %, ***p < 1 %*
Notes: Standard errors in parentheses
GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P CHINA BOND INDEX

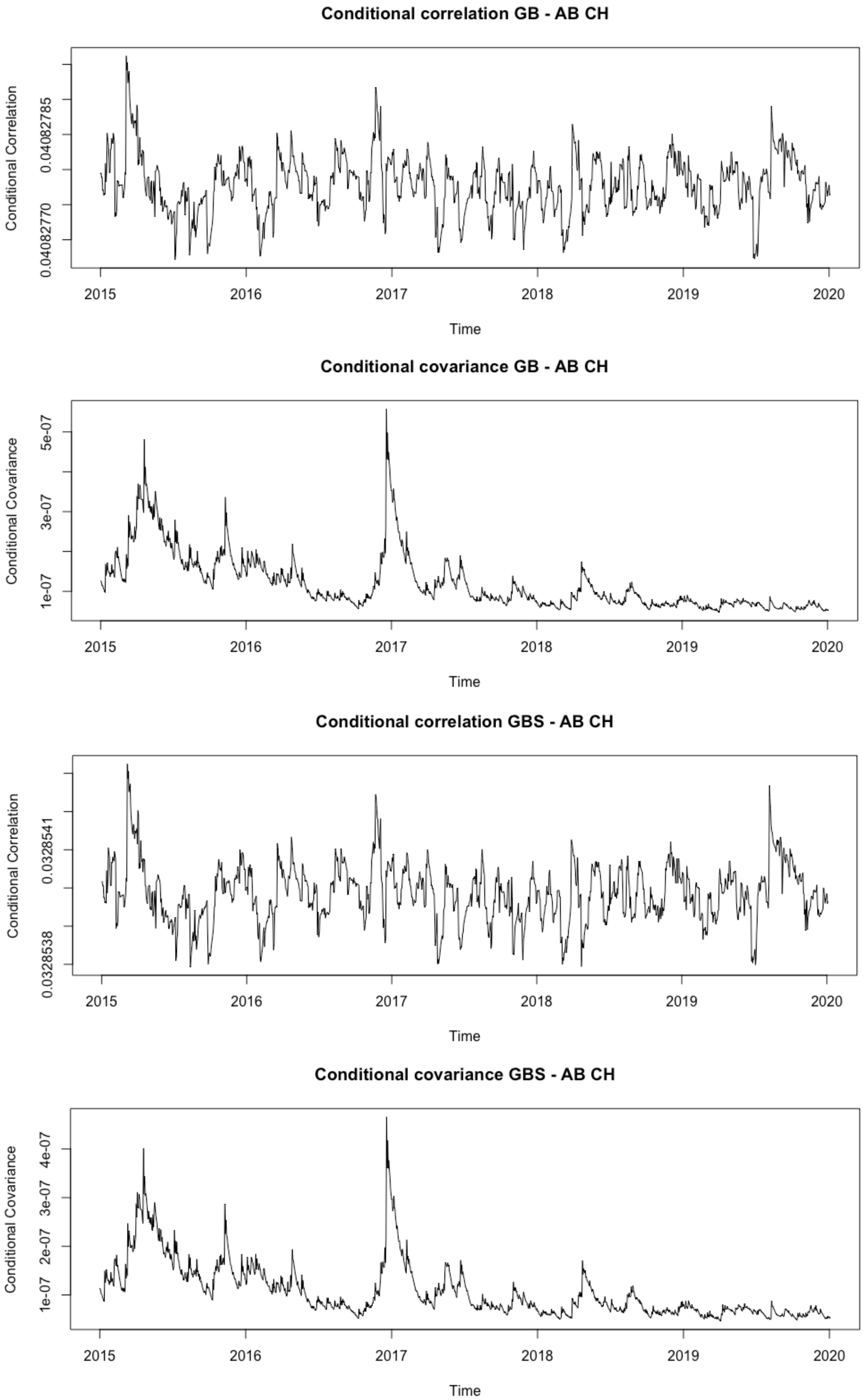

Figure 13. Conditional correlation and conditional covariance between the green bond indices and the China Aggregated bond index for the second sub-sample period 2015-2019

Notes: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX and AB = S&P CHINA BOND INDEX

The results presented in this chapter will be further discussed in the next chapter. It is also concluded how these results can be implemented into real life applications and how they can affect the decisions of the participants in the green bond markets.

6 DISCUSSION AND CONCLUSIONS

The results of this study show that the green bond market has developed and matured during the decade of 2010 in terms of conditional volatility. First of all, there is evidence that both examined green bond markets, the inclusive and the exclusive experienced volatility clustering throughout the entire decade. However, the volatility clustering behavior was more present during the first half of the decade for both examined green bond markets compared to the second half of the decade. The persistence of shocks also lowered significantly towards the end of the decade which essentially means that a shock in conditional volatility will have an effect on the return volatility for a shorter period of time. The development was similar for both examined green bond indices although the more inclusive green bond market experienced more significant volatility clustering and higher persistence of shocks compared to the more exclusive green bond market. This could be explained by the wider range of underlying bonds that the more inclusive market holds. The bonds included in the more inclusive market most likely vary a lot more in terms of credit ratings, currencies, background of the issuers and the destination of the proceeds compared to the more inclusive market where more strict rules apply. Since the more exclusive market requires higher standards of transparency, disclosure and accountability, the underlying bonds also most likely hold higher credit ratings and are more focused towards higher quality issuers.

Another difference between these two indices is that during the first half of the decade the more inclusive market experienced some leverage effect whereas for the more exclusive market no evidence of the leverage effect was found. For fixed-income market returns this result is slightly surprising. As the name suggest, leverage effect has been explained in the equity markets by the change in the degree of leverage in the capital structure of the company caused purely by the decrease in the equity valuation. Obviously in the fixed income markets this explanation no longer stands. Although it needs to be noted that during the first half of the decade leverage effect was present for the Chinese bond markets as well so experiencing leverage effect is nothing unprecedented for fixed income market returns. When moving towards the end of the decade, the market no longer seems to experience the leverage effect which is more expected for a fixed income market.

When the development in volatility behavior of the green bond markets is compared to the conventional bond markets, it seems that the development of the conventional bond markets in the US was similar to the of green bond indices. The conventional bond markets in the US also experienced lowering persistence of shocks towards the end of the decade so it seems that the green bond market follows a more general trend of the western bond markets. The conventional bond markets in China on the other hand developed the exact opposite way where the persistence of shocks actually increased towards the end of the decade. Although it needs to be noted that the persistence of shocks and the volatility clustering behavior in the conventional bond markets in China was significantly lower throughout the decade compared to all other examined bond markets even after the increase in persistence towards the end of the decade. Taken all this into account, this could indicate that the green bond market is more connected to the western bond markets. The question of correlation and connectedness between the green bond markets and the conventional bond markets has been addressed with the volatility spillover analysis.

The results of the volatility spillover analysis show that there have been volatility spillovers between the green bond markets and both examined conventional bond markets in the US and China throughout the observed decade. As mentioned in the introduction, essentially green bonds are just conventional bonds that differ in the destination of the proceeds so it can be expected that some correlation between the green bond markets and the conventional bond market is exists. Interestingly the conditional correlation with conventional bond markets was not inherently different for the more exclusive green bond market than the more inclusive green bond market. The conditional correlation between the green bond market and both conventional bond markets, the US and China, decreased throughout the decade. During the first half of the decade the green bond markets and the US bond market were highly correlated, but the conditional correlation was often negative. When moving towards the end of the decade, the conditional correlation maintained mainly positive, but the significance of the correlation was much lower. Both green bond markets have been less correlated with the China bond markets than with the US bond markets as anticipated. However, with the China bond market no clear development in the conditional correlation with the green bond market was found otherwise. Taken that the green bond market has grown during the decade significantly in terms of size and diversity, the decreased positive correlation could indicate that the green bond market has become more independent of the overall bond markets.

The findings of this study can be beneficial for both the investors and green bond issuers. Investors willing to participate in the green bond market can use the results in asset allocation and risk optimization. For portfolios consisting of US bonds, participation in the green bond market would not offer that much diversification benefits. Instead, green bonds could be used as a substitute for more general bonds within this market. For portfolios consisting of Chinese bonds, green bonds could still offer some diversification benefits since the conditional correlation levels are much lower compared to the US bond markets. Although the green bond markets still experience slightly higher conditional volatility levels compared to the conventional bond markets, meaning that the uncertainty in the green market returns is higher, the conditional volatility levels have moved significantly closer to the of conventional bond markets throughout the decade. Thereby in terms of conditional volatility, the green bond market is now almost similar to the conventional bond markets.

Another implication of the results of this study concerns all participants in the market: investors, green bond issuers and even policymakers. Since there was evidence that the returns in the more exclusive green bond market include less uncertainty compared to the returns of the more inclusive green bond market, focusing on binding standards and accountability would benefit all participants. For more risk-averse investors, certifications can provide security of a kind and for green bond issuers it can attract a wider range of interest towards the issued bond. The results thereby provide motivation for bond issuers to invest and obtain a third-party certification when planning a green bond issuance. For policymakers and the society as a whole, increased transparency can help to allocate more funds to projects creating a positive impact on the environment. Thereby the results of this study indicate that higher standards of transparency, disclosure and accountability would support the growth of this market by making it more approachable and favorable for participants.

Both the conventional bond markets in the US and China and the green bond markets develop constantly and are affected by infinite number of factors such as politics, megatrends and global events. Thereby it is clear that the results from this study might no longer stand even in the nearest future. To keep the result valid and beneficial for the participants in these markets, this study should be continued by conducting a similar study in the future in quite a similar manner as this study has continued the work of Pham (2016). Since it is expected that the green bond market will continue expanding, it could be considered to introduce some more bond markets from other geographical areas such as Europe and Africa to this study. Europe was the home of the very first green bond and has been a growth area for green bonds in the recent years. Africa on the other hand is expected to be highly affected by the climate change which's prevention and mitigation is at the core of the green bond definition.

What comes to the more technical aspects of this study, it could be considered to conduct a similar study using different volatility models. Perhaps for some bond markets, it is not required to use a conditional volatility model but a constant would suit better. In this study the chosen volatility model for the China bond index was not perfect so more options could be examined. The frequency of the data is also worth considering and a similar study could also be conducted using multiple frequency data. In this study we used daily frequency, but also intraday or even weekly data could be used. High frequency data could capture the turbulence and pressure in the market better whereas low-frequency data can focus on the macroeconomical and institutional changes.

As mentioned in the introduction, the underlying interest of this study is to examine if the green bond market is riskier than conventional bond market. Although volatility is commonly used as a risk metric in the financial discipline, it still only describes the uncertainty in the market. What is left unanswered are the aspects that cause the riskiness and why the green bond market is riskier than the conventional bond markets. In order to determine this, it should be studied whether the green bond market carries different level of default, credit or liquidity risk to mention a few possible reasons.

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Appendices

Appendix 1. Previous Studies of Green Bond market development

Authors	Year	Topic	Methodology	Data	Findings
Tolliver, C., Keeley, A. R. & Managi, S.	2020	Drivers of green bond market growth: The importance of Nationally Determined Contributions to the Paris Agreement and implications for sustainability	Structural equation model	Green bonds issued in 49 countries between 2007 -2017.	Nationally Determined Contributions and other macroeconomic and institutional factors are driving growing green bond issuances
Dou, X. & Qi, S	2019	The choice of green bond financing instruments	Logit model	Public Bond issuances in China during 2016–2018 by non-financial companies	The type of bonds and the purpose of raising funds are the important factors affecting enterprises to issue labeled green bonds under policy difference caused by “multi-sector supervision” on China’s bond markets
Deschryver, P. & de Mariz, F.	2020	What Future for the Green Bond Market? How Can Policymakers, Companies, and Investors Unlock the Potential of the Green Bond Market?	Literature review, market data analysis, and interviews	Large spectrum of green bond market participants	The current barriers explaining the lack of scalability of the green bond market: a deficit of harmonized global standards; risks of greenwashing; the perception of higher costs for issuers; the lack of supply of green bonds for investors; and the overall infancy of the market
Banga, J.	2019	The green bond market: A potential source of climate finance for developing countries	Literature review, market data analysis, and interviews	Large spectrum of green bond market participants in developed countries	The key barriers to the development of green bonds in developing countries are the lack of appropriate institutional arrangements for green bond management, the issue of minimum size, and high transactions costs associated with green bond issuance.
Agliardi, E. & Agliardi, R.	2019	Financing environmentally-sustainable projects with green bonds	Structural model		An improvement in credit quality could ultimately lead to a lower cost of capital for green bond issuers. Governmental tax-based incentives and an increase in investors' green awareness play a significant role in scaling up the green bonds market.
Barua, S. & Chiesa, M.	2019	Sustainable financing practices through green bonds: What affects the funding size?	Cross Selection OLS Regression, Blinder–Oaxaca decomposition analysis	Global dataset of green bonds issued 2010-2017	From bond characteristics coupon rates and credit rating have an effect on the issue size. From Issuer related characteristics revenue growth and profitability affect the issue size.

Appendix 2. Previous Studies of Green Bond pricing

Authors	Year	Topic	Methodology	Data	Findings
Hyun, S., Park, D. & Tian, S	2020	The price of going green: the role of greenness in green bond markets	Matching method, two-step regression procedure	Green bond issuances that comply with the GBP and synthetic conventional bonds that have the same issuers, currency denomination, credit rating, maturity and bond structures during 2010-2017	On average, there is no robust and significant yield premium or discount on green bonds. Green bonds certified by an external reviewer enjoy a discount of about 6 bps and green bonds that obtain a Climate Bonds Initiative certificate show a discount of around 15 bps
Nanayakkara, M. & Colombage, S.	2019	Do investors in Green Bond market pay a premium? Global evidence	Panel data regression with hybrid model	Daily observations of Green Bonds and Conventional Bonds during 2016-2017	Green Bonds are traded at a premium of 63 basis points (BPS) compared to Conventional Corporate Bonds
Zerbib, O. D.	2019	The effect of pro-environmental preferences on bond prices: Evidence from green bonds	Matching method, two-step regression procedure	1065 green bonds complying with the Green Bond Principles indexed by 2018	On average, the green bond premium is -2 basis points for the entire sample and for euro and USD bonds separately
Wang, Q., Zhou, Y., Luo, L. & Ji, J.	2019	Research on the Factors Affecting the Risk Premium of China's Green Bond Issuance	Multivariate Regression	China's labeled green bonds from 2016 to 2018	The factors affecting green bond risk premium: The green attribute factor: third-party green assessment certification. The bond factors: debt credit rating, issue period, and issue size. The issuer factors: debt principal, nature of property rights, and return on net assets. The macro factor: the current market interest rate.
Febi, W., Schäfer, D., Stephan, A. & Sun, C.	2018	The impact of liquidity risk on the yield spread of green bonds.	Regression	64 labeled green bonds that are listed on the London Stock Exchange and on the Luxembourg Stock Exchange, and 56 conventional bonds traded on the Luxembourg Stock Exchange	On average green bonds are more liquid when compared to conventional bonds, over the years 2014–2016
Hachenberg, B. & Schiereck, D.	2018	Are green bonds priced differently from conventional bonds?	Panel regression	Labeled green bonds outstanding in August 2016.	Gren Bonds trade marginally tighter compared to non-green bonds of the same issuers.Financial and corporate green bonds trade tighter than their comparable non-green bonds, and government-related bonds on the other hand trade marginally wider.
Gianfrate, G. & Peri, M.	2019	The green advantage: Exploring the convenience of issuing green bonds	Propensity score matching and regression	All the bonds issued between 2007 and 2017 and listed in Bond Radar	Green bonds are more convenient than conventional bonds.

Karpf, A. & Mandel, A.	2018	The changing value of the 'green' label on the US municipal bond market.	Blinder–Oaxaca decomposition analysis, Regression	1,880 green bonds issued by 189 distinct issuers on the municipal market in the US	Returns on conventional bonds are on average higher than for green bonds, the differences can largely be explained by the fundamental properties of the bonds

Appendix 3. Previous studies on comparison and interdependence between the Green Bond market and other markets

Authors	Year	Topic	Methodology	Data	Findings
Mohd Roslen, S., Yee, L. & Binti Ibrahim, S.	2017	Green Bond and shareholders' wealth: A multi-country event study	Multi-Country Event Study	Green Bond issuances and country market indices between 2010 and 2015	Shareholders generally react positively a day after the Green Bond announcements were made by issuers
Baulkaran, V.	2019	Stock market reaction to green bond issuance	Event Study, Regression Analysis		Shareholders view green bond issuance as value-enhancing and funds from green bonds issuance are used to undertake profitable green projects or as a means of risk mitigation.
Tang, D. Y. & Zhang, Y.	2020	Do shareholders benefit from green bonds?	Event Study, Panel data Regression Analysis	Stock and market index prices and Green Bonds issued between 2007-2017 worldwide	Stock prices respond positively to green bond issuance
Pham, L.	2016	Is it risky to go green? A volatility analysis of the green bond market	Multivariate GARCH framework	S&P green bond and aggregated bond indices during 2010-2015	”The ‘labeled’ segment of the green bond market experiences large volatility clustering while the pattern of volatility clustering is weaker in the ‘unlabeled’ segment of the market. Shock in the overall conventional bond market tends to spill over into the green bond market.” (p.1)
Reboredo, J. C.	2018	Green bond and financial markets: Co-movement, diversification and price spillover effects	Copula Model	4 Global Green Bond market indices, Corporate, Treasury, Stock and Energy indices between 2014-2017	Green bond market couples with corporate and treasury bond markets and weakly co-moves with stock and energy commodity markets
Reboredo, J. C., Ugolini, A. & Aiube, F. A. L.	2020	Network connectedness of green bonds and asset classes	Wavelet-based methods and VAR models	Green Bond price indices for US and EU, 5 different financial market indices between 2014-2018	Green bonds strongly comove at different time scales with treasury and corporate bonds in EU and US markets. Co-movement of green bonds with other asset classes such as high yield corporate bonds, stocks and energy stocks is weak and varies in intensity over the sample period and over all time scales.

Appendix 4. Information criteria for different ARMA(0,0)-GARCH(p,q)- model modifications as calculated by 'rugarch' package in RStudio.

	GB		GBS		US		CH	
	Akaike (AIC)	Bayes (BIC)	Akaike (AIC)	Bayes (BIC)	Akaike (AIC)	Bayes (BIC)	Akaike (AIC)	Bayes (BIC)
GARCH(1,1)	**-8,4866**	**-8,4776**	**-8,2278**	**-8,2188**	**-9,7777**	**-9,7687**	-10,317	-10,308
GARCH(1,2)	-8,4855	-8,4742	-8,2255	-8,2142	-9,7771	-9,7658	-10,327	**-10,315**
GARCH(2,1)	-8,4865	-8,4752	-8,2268	-8,2155	-9,7767	-9,7654	-10,316	-10,305
GARCH(2,2)	-8,4854	-8,4719	-8,2261	-8,2126	-9,7766	-9,7631	-10,325	-10,311
GARCH(2,3)	-8,4849	-8,4692	-8,2244	-8,2087	-9,7763	-9,7605	**-10,328**	-10,313
GARCH(3,2)	-8,4852	-8,4694	-8,2249	-8,2092	-9,775	-9,7593	-10,326	-10,31
GARCH(3,3)	-8,4856	-8,4676	-8,2242	-8,2063	-9,7743	-9,7563	-10,327	-10,309

Note: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, US = S&P US AGGREGATE BOND INDEX and CH = S&P CHINA BOND INDEX

Appendix 5. Information criteria for different ARMA(p,q)-GARCH(1,1)- model modifications as calculated by 'rugarch' package in RStudio.

	GB		GBS		US		CH	
	Akaike (AIC)	Bayes (BIC)	Akaike (AIC)	Bayes (BIC)	Akaike (AIC)	Bayes (BIC)	Akaike (AIC)	Bayes (BIC)
ARMA(0,0)	**-8,4866**	**-8,4776**	-8,2278	**-8,2188**	-9,7777	**-9,7687**	-10,317	-10,308
ARMA(0,1)	-8,4865	-8,4752	-8,2289	-8,2177	**-9,7799**	-9,7686	-10,344	**-10,333**
ARMA(1,0)	-8,4864	-8,4752	**-8,229**	-8,2178	-9,7795	-9,7682	-10,343	-10,332
ARMA(1,1)	-8,4863	-8,4728	-8,2287	-8,2153	-9,7778	-9,7643	-10,344	-10,33
ARMA(1,2)	-8,4857	-8,4699	-8,2267	-8,211	-9,7788	-9,7631	-10,342	-10,326
ARMA(2,1)	-8,4856	-8,4698	-8,2267	-8,211	-9,7789	-9,7632	-10,342	-10,326
ARMA(2,2)	-8,486	-8,468	-8,2266	-8,2086	-9,7778	-9,7598	**-10,346**	-10,328

Note: GB = S&P GREEN BOND INDEX, GBS = S&P GREEN BOND SELECT INDEX, US = S&P US AGGREGATE BOND INDEX and CH = S&P CHINA BOND INDEX

Appendix 6. Alternative models for the S&P China Bond Index

ARMA(0,0) - GARCH(1,2) 2010-2019

	CH Return
μ	0,000044**
	(0,000021)
α_0	0,000000023
	(0,000000)
α	0,147554***
	(0,023782)
β_1	0,3636560***
	(0,106525)
β_2	0,484692***
	(0,094214)

Notes: Bayes (BIC) = **-10,315**

ARMA(0,1) - GARCH(1,1) 2010-2019

	CH Return
μ	0,000037**
	(0,000018)
ma_1	-0,165465***
	(0,021868)
α_0	0,000000019
	(0,000000)
α	0,104271***
	(0,016046)
β_1	0,893310***
	(0,013349)

Notes: Bayes (BIC) = **-10,333**

ARMA(0,1) - GARCH(1,2) 2010-2019

	CH Return
μ	0,000046**
	(0,000018)
ma_1	-0,180258***
	(0,022701)
α_0	0,000000036
	(0,000000)
α	0,169112***
	(0,031105)
β_1	0,377640***
	(0,115481)
β_2	0,448269***
	(0,098986)

Notes: Bayes (BIC) = **-10,337**

ARMA(0,1)-GJR-GARCH(1,2) 2010-2020

	CH Return
μ	0,000027*
	(0,000016)
ma	-0,189477***
	(0,020906)
α_0	0,000000047
	(0,000000)
α	0,176433***
	(0,027869)
β_1	0,392739***
	(0,068714)
β_2	0,403146***
	(0,088881)
γ	0,053204
	(0,032578)

Notes: Bayes (BIC) **= -10.437**