The Dynamic Conditional Correlation and Volatility Linkages between Green and Conventional Bonds: Empirical Evidence on a Global level

الارتباط الديناميكي الشرطي ومدى رابطة التقلب بين السندات الخضراء والتقليدية: دليل تجريبي على المستوى العالمي

by

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Abstract

This study aims at examining the dynamic conditional correlations and the volatility linkages between the green bonds and the conventional bonds market on a global level. The paper chooses the Bloomberg Barclays MSCI Global Green Bond Index (GB) and the Bloomberg Barclays Global Aggregate Total Return Index (CB) to represent the green and conventional bonds markets on a global level, respectively. The paper gathers their weekly data over a period of six years from 17th October 2014 to 18th September 2020 from Bloomberg. It adopts Engle (2002) two-steps DCC multivariate GARCH model to carry out the analysis. In the first step, this paper finds the best fitting univariate GARCH model is ARMA (8,8)-GARCH (1,2) and finds evidence that GB is more sensitive and has higher reaction to market events than CB does. In addition, GB exhibit less persistency in its conditional volatility than CB does. In the second step, using the DCC-MGARCH (1,2), this paper finds short-term volatility spillover between GB and CB but the persistency of a shock in both markets relative to the other is low and fades away quickly. This paper concludes that a time-varying, positive, and strong conditional correlation exists between GB and CB. Also, it finds evidence of strong positive volatility linkages between GB and CB. Lastly, the paper identifies a structural break in March 2020 caused by the COVID-19 pandemic. The implications of this paper are important to investors, portfolio managers, and policymakers as they aid in making educated decisions related to portfolio diversification. Based on the results, this paper does not find evidence of gaining diversification benefits and, hence, does not recommend placing both types of bonds in the same portfolio.

Keywords: Dynamic conditional correlation (DCC), multivariate GARCH (MGARCH), GARCH, green bonds, green finance.

ملخص

تهدف هذه الدراسة إلى فحص الارتباطات الشرطية الديناميكية وروابط التقلب بين سوق السندات الخضراء و السندات التقليدية على المستوى العالمي. اختارت الورقة مؤشر بلومبرج باركليز مورجان ستانلي كابيتال انترناشونال (MSCI) لتمثيل أسواق السندات الخضراء على المستوى العالمي. واختارت هذه الدراسة مؤشر بلومبرج باركليز العالمي لإجمالي العائد الإجمالي لتمثيل أسواق السندات التقليدية على المستوى العالمي. قامت الدراسة بجمع أسعار المؤشرات من بلومبرج على مدى ست سنوات من 17 أكتوبر 2014 إلى 18 سبتمبر 2020.

تتبنى هذه الدراسة نموذج (2002) Engle المعروف بالإرتباط الديناميكي الشرطي متعدد المتغيرات المعمم الانحدار الذاتي الشرطي غير متجانس التباين (DCC MGARCH) المكون من خطوتين لإجراء التحليل. في الخطوة الاولى, وجدت هذه الورقة بأن أفضل نموذج المعمم الانحدار الذاتي الشرطي غير متجانس التباين الاحادي (GARCH) هو المتوسط المتحرك الانحدار التلقائي (ARMA) (8,8) - المعمم الانحدار الذاتي الشرطي غير متجانس التباين (GARCH)(1,2). وهذا النموذج يجد دليلا على ان مؤشر المستندات الخضراء اكثر حساسية ولديه رد فعل اقوى لأحداث السوق المالي من مؤشر المستندات التقليدية. بالإضافة إلى ذلك، يظهر مؤشر المستندات الخضراء أقل ثباتا في تقلبها الشرطي من مؤشر المستندات التقليدية. في الخطوة الثانية، بإستخدام بالإرتباط الديناميكي الشرطي متعدد المتغيرات المعمم الانحدار الذاتي الشرطي غير متجانس التباين (DCC MGARCH) (1,2) وجدت هذه الورقة امتداداً للتقلبات قصيرة المدى بين مؤشر المستندات الخضراء ومؤشر المستندات التقليدية. ولكن عند حدوث صدمة في كلا المؤشرين نسبة للآخر فإنه يكون منخفض ويتلاشى بسرعة. بالإضافة الى ذلك، تستنتج هذه الدراسة الى وجود ارتباط شرطي ايجابي قوي وعلى أن هناك روابط تقلب إيجابية بشكل قوي بين المؤشرين. أخيراً، قامت هذه الدراسة بتحديد وجود كسر هيكلي في مؤشر المستندات الخضراء والتقليدية في مارس من عام 2020 الذي تسببته جائحة كورونا. تعتبر الآثار المترتبة على هذه الورقة مهمة للمستثمرين ومديري المحافظ المالية وصناع السياسات لأنها تساعد في اتخاذ قرارات مدروسة متعلقة بتنويع المحفظات المالية. بناءً على النتائج، لا تجد هذه الورقة دليلا على اكتساب فوائد التنويع، وبالتالي لا توصي بوضع كلا النوعين من السندات في نفس المحفظة.

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List of Abbreviations

ARCH – Autoregressive Conditional Heteroskedasticity.

ARMA – Autoregressive moving average.

CAB – Climate Awareness Bonds.

CB – Bloomberg Barclays Global Aggregate Total Return Index (LEGATRUU)

CBI – Climate Bonds Initiative

CCC – Constant Conditional Correlation.

CICERO - Centre for International Climate and Environmental Research

DCC-MGARCH – Dynamic Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroskedasticity.

EIB – European Investment Bonds

ESG – Environmental, Social, and Governance

GARCH – Generalized Autoregressive Conditional Heteroskedasticity.

GB – Bloomberg Barclays MSCI Global Green Bond Index (GBGLTRUU)

GBP – Green Bonds Principles

ICMA – International Capital Market Association

IFC - International Finance Corporation

MGARCH – Multivariate Generalized Autoregressive Conditional Heteroskedasticity.

OLS – Ordinary Least Square

SRI – Socially Responsible Investments

UNFCC – Nations Framework Convention on Climate Change

Chapter 1: Introduction

1.1 Background

Over the past two decades, more specifically the last one, climate change became a matter concerning all countries around the world. NASA (2020) reported that the global warming increase trend is attributed to the human anti-environmental actions that began in the 1950s and is continuing to rise at an extraordinary rate. As a matter of fact, climate change is increasing the frequencies at which catastrophes such as floods, wildfires, storms, and droughts are occurring. Therefore, in an attempt to combat climate change and reduce the financial risks it imposes; governments and global organizations are taking numerous measures and serious initiatives towards having a greener and more environment friendly world. These measures include agreements, implementation of rules and regulations to ensure compliance by the capital market, and introducing new financial assets.

One of the most remarkable initiative is the Paris Agreement. On 12th December 2015, the United Nations Framework Convention on Climate Change (UNFCC) issued the COP 21 Paris Agreement bringing all nations to fight climate change and limit the increase of the global temperature beyond 2 degrees Celsius by increasing green and sustainable projects and investments. This agreement also aims to support developing countries to work towards this goal (United Nations Climate Change 2020).

But how is climate change affecting the financial market? Catastrophes are substantially impacting our economies posing numerous challenges to the financial sector around the world. It is creating systematic risks that are threatening our financial markets' stability (Gelzinis & Steele 2019; Herz 2020). These risks are categorized as either physical or transitional. Physical risks come in perceptible forms such as increase in temperature, floods,

droughts, increase in sea level while transitional risks are the ones that rise from the required changes in policies and technologies to have a green economy (Gelzinis & Steele 2019). As a matter of fact, Kompas, Ha & Che (2018) conducted a study analyzing the economic impact of the Paris Agreement. They found that if the global temperature increases by 4 degrees Celsius by the year 2100, the yearly global economy income will witness losses of more than USD $23 trillion – an amount that represent having the financial crisis of 2008 three or four times every year. On the other hand, the researchers stated that complying with the Paris Agreement and keeping the temperature rise within 2 degrees Celsius, the world would gain around USD $17 trillion per year by 2100.

Moreover, in 2004, climate change has called for Kofi Annan to invite the CEOs of the top fifty financial institutions to collaborate under the supervision of the UN Global Compact, the International Finance Corporation (IFC), and the Swiss Government to integrate the Environmental, Social, and Governance (ESG) criteria to the capital markets (Kell 2018). Responsible investors are now using these criteria to assess whether the activities of a certain company are being socially responsible in order to avoid investing in ones that are not becoming "green" and, ultimately, contributing to the risks associated with climate change. Such action was the reason behind the development of Socially Responsible Investments (SRI). SRIs now include several financial markets such as stocks, bonds, private equity and venture capital, mutual funds, exchange-traded funds (ETFs) (Maretich n.d.). The introduction of these financial instruments allowed many responsible investors to consider investment choices that best serves, specifically, the environment, and, generally, the economy.

The availability of such financial markets encouraged investors who are concerned about climate change to take actions adhering to the Paris Agreement. For instance, in January 2020, BlackRock, the world's leading asset management company, became part of the Climate Action 100+ organization (Herz 2020). This organization started in 2017 with 225 investors managing USD $26 trillion worth of assets while, as of 2019, it now has 373 investors managing more than USD $35 trillion (Ceres 2018; Climate Change 100+ 2019). It aims at pressuring companies To reduce their CO2 emissions in a tangible effort to achieve the Paris Agreement goals. (Ceres 2018).

The goal of achieving greener economies and developing green projects and infrastructure to reduce carbon dioxide emissions requires large amount of funding over a long period (Park, Park & Ryu 2020). Hence, special attention from the bonds market was required to finance these ecofriendly projects which led to the inception of the green bonds market.

Just like the name suggests, the green bonds market is a sub-market of the broader bonds market that specializes in financing or raising capital for green projects. Similar to the conventional bond market, the green one acts as a platform where bond issuers (borrowers) and bondholders (lenders) meet. Bonds, referred to as conventional or non-green bonds in this paper, are financial instruments issued by borrowers and sold to investors for the mere purpose of raising capital. Straight bonds, also known as plain vanilla, are the simplest and the most standard forms (Chen 2020). Green bonds, also known as climate bonds, are like plain vanilla traditional bonds in terms of mechanism and structure. However, they are issued by governments and entities to raise funds purely for environmental projects and investments (The World Bank 2015; CBI 2020). Both types of bonds have present value, interest rate, coupon payments, time to maturity, and face value. Both are traded in the primary and

secondary markets. Both are treated as debt instruments which does not translate to considering an investor as a shareholder.

The two bonds, green and conventional, belong to the same family of financial instruments and have similar characteristics and features but are they experiencing co-movements? In other words, if investors are to consider investing in both types of bonds, are they better-off or worse-off having both in their portfolios, are they reducing or adding risks to their portfolios, are they going to yield diversification benefits from investing in both or not?

1.2 Significance of the Study

The motive behind this paper is to understand the conditional correlation, volatility linkages, and spillover effects between green and conventional bonds markets. With the increasing awareness to have a greener and more sustainable economies, market participants such as issuers, investors, rating agencies, and regulators are now tapping into the green bonds market more than ever before. In fact, by the end of 2019, the issuance of green bonds globally has reached to USD $257.7 billion representing a growth of 51% from 2018 (CBI 2020). The shift in the mindset of many investors from being purely all about the returns to being more involved in SRIs combined with the exponential growth witnessed in the green bonds market makes this research paper is of a high importance in portfolio management sector.

In addition, understanding the conditional correlation and volatilities of these two financial instruments is of high importance as they both belong to the same broader market and, hence, have similar characteristics. So this paper is important in providing guidance to investors who might be interested in the different segments of the broader bond market. As a matter of fact, according to the U.S. Securities and Exchange Commission (n.d.), investors choose to

participate in the bond market for multiple reasons. Firstly, bonds' returns and period payments are predictable and steady. Secondly, investors save their capital when they hold the bond till maturity, the bond issuers have the obligation to pay back the principle amount. Thirdly, investors consider bonds in order to balance some of the risks associated with holding stocks.

Moreover, this study is important because it provides an understanding of the green bonds' volatility characteristics which is vital for interested investors. Furthermore, this paper contributes to the existing literature of examining the conditional correlation between green and the broader non-green bonds markets and modeling their volatilities side by side as there is a lack of academic research that addresses this topic.

1.3 Aims and Objectives

The aim of this paper is to examine the conditional correlation between the green and the conventional bonds market. It also aims at analyzing the volatility characteristics of both bond markets.

The objectives of this research paper are the following:

- ➢ To investigate the conditional volatilities of the conventional bonds market on a global level.
- ➢ To investigate the conditional volatilities of the green bonds market on a global level.
- ➢ To examine the spillover effect between the green bonds market and the conventional bonds market on a global level.
- ➢ To measure the shock persistency response between the green bonds market and the conventional bonds market on a global level.

➢ To analyze the dynamic conditional correlations between the green bonds market and the conventional bonds market on a global level.

➢ To examine the co-movements and volatility linkages between the green bonds market and the conventional bonds market on a global level. If so, to which extent?

➢ To examine the existence of any structural break in the conditional volatilities of the green bonds and conventional bonds during the selected period.

To achieve the above, this paper relies on the weekly returns of the global indices of the green and conventional bond. This paper uses the Bloomberg Barclays MSCI Global Green Bond Index (GBGLTRUU) to represent the global green bonds market and Bloomberg Barclays Global Aggregate Total Return Index (LEGATRUU) to represent the global conventional bonds market. The time frame of the data will be for six years from 17 October 2014 to 18 September 2020.

1.4 Research Questions

The enormous growth the green bonds market is witnessing calls for an immediate and extensive research on its comparability with its non-green counterpart. This is in order for investors and portfolio managers understand how the two financial instruments work together and, hence, make educated decisions when it comes to organizing portfolios. This research paper will address the following research questions:

➢ Is there a dynamic conditional correlation between the green and the conventional bonds markets?

➢ Is there a difference between the volatility behavior of the green and the conventional bonds markets?

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➢ Is there evidence of spillover effect between the green and the conventional bonds markets?

This paper aims at understanding the conditional volatility of the green and conventional bonds markets. In addition, it aims at analyzing whether the conditional correlation between the green and the broader non-green bonds market is time varying.

1.5 Thesis Structure

The remaining of this study is structured as per the following. Chapter 2 will focus on providing an overview of the green bonds market. It will discuss green bonds market's history, principles, SWOT analysis, and its current statistics. Then, chapter 3 provides literature review on the studies conducted comparing green to its non-green counterpart. It also provides the theory behind the development of the model used in this thesis, the DCC multivariate GARCH model, and the studies that applied it. Afterwards, chapter 4 provides detailed description of the methodology used to answer the research questions. Next, in chapter 5, a detailed presentation of findings and interpretation of the results is provided. Lastly, chapter 6 concludes this paper by providing an overall summary of the study and its findings, addresses the implications and limitations, and recommends topics for future research.

Chapter 2: Green Bonds Market Overview

2.1 Introduction

Governments, firms, and municipalities enter the bond market to raise long-term capital requirements and achieve their growth goals. The green bond market is not different but instead it allows issuers achieve their sustainability goals too. According to the International Capital Market Association (ICMA 2020), the global bond market size reached to USD $128.3 trillion as of August 2020. Green bonds' issuances around the world is now only at around 3% of the broader conventional global bond market (IFC 2020).

There are plenty of literature on the background and different aspects of the conventional bonds market. Hence, this chapter will focus on providing an overview and introduce the green bonds market. This chapter is segmented into four main categories. It will start by providing historical background on the green bonds market. Then, it will discuss the Green Bond Principles (GBP) that govern green bonds. Next, it describes the strengths, weaknesses, opportunities, and threats of the market. Lastly, it presents the current market statistics.

Figure 1. Developed and Emerging Markets Green Bonds Issuance
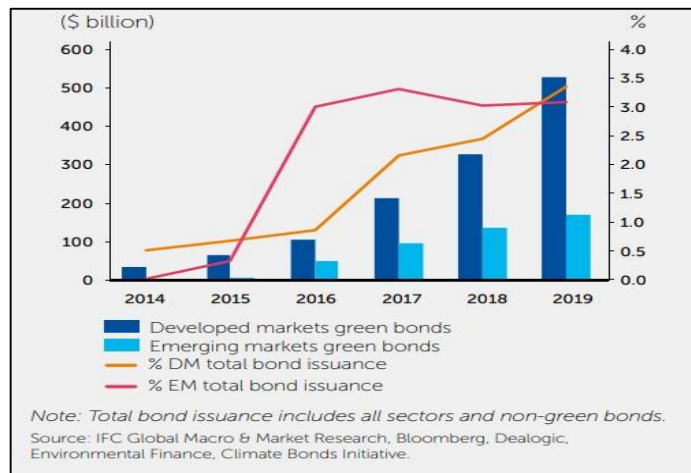
(IFC 2020, p. 12)

2.2 The Beginning of the Green Bonds Era

While conventional bonds were established hundreds of years ago, green bonds have not been around for a long time. As a matter of fact, it all started in 2007 when the World Bank created green bonds upon a request from multiple Swedish pension funds that wanted to make a change and invest in green projects (World Bank 2019). Hence, the World Bank along with multiple organizations, such as the ICMA and CICERO, have set the grounds and criteria as to which projects are eligible to receive proceeds from green bonds (World Bank 2019). In 2007, the European Investment Bank (EIB) has issued the world's first green bond under the name "Climate Awareness Bonds" (CAB) with a worth of EUR €600 million targeted at financing renewable energy (World Bank 2019; European Commission 2016). Then, in 2008, due to high demand, the World Bank issued its first green bonds with a worth of USD $440 million (European Commission 2016). The green bonds market is being managed by the Climate Bonds Initiative (CBI), an international non-profit organization based in the United Kingdom-London. It focuses on investors and on managing the $100 trillion climate bond market (CBI 2020). As a result, in order to support investors and governments, the CBI released the Climate Bond Standard and Certification Scheme in 2010. This scheme provides assurance to investors related to the integrity of green bonds towards the environment. It also acted as a simple and straightforward tool that helped governments in preference investments. Finally, the scheme supported investors' growing demand for the opportunities that the climate investments offered (CBI 2020). Nowadays, the green bond market has "labelled" and "non-labelled" green bonds. The labelled ones are issued and marketed as "green" while the non-labelled green bonds are do not have the green label but are issued by companies that operate in green industries such as solar companies (Pham 2016). The issues are governed

by second opinion providers and rating agencies. The green bond notion is now extended to having social, blue, and specific purpose bonds (World Bank 2019).

2.3 Green Bond Principles

Few years after the launch of the green bonds, a set of principles were put in place to determine whether a standard bond can be considered as a "green" bond. The World Bank and the ICMA have constructed the basis for the Green Bond Principles (GBP) (World Bank 2019). These principles are put in place to provide issuers guidelines on how to issue credible green bonds, support investors with transparent information, and aid underwriters with facilitating transactions. The GBP are set towards promoting integrity and full discloser in the green bonds market which translates to an increase in the capital allocation. As a matter of fact, issuers are constantly recommended to track and report the climate impact of their projects (ICMA 2018).

The GBP were last updated in June 2018 and has four fundamental principles categorized as the "use of proceeds, process for project evaluation and selections, management of proceeds, and reporting" (ICMA 2018, p. 3).

2.3.1 Use of Proceeds

The primary and the most crucial principle of the green bond is the use of its proceeds. The issuers must accurately describe in the green bond's legal documents where the proceeds of this issue are going to be used. The GBP specifies categories of green projects that are eligible for green bond funding. According to the CBI (2020), the green projects that fall under the solar, wind, marine, geothermal, bioenergy, forestry, buildings, water, waste, transport, or agriculture sectors are eligible for green bonds financing. Whereas, the hydropower,

shipping, and transmission and distribution sectors are still pending to be approved. The fisheries sector's approval is on hold and the land use has been rejected CBI (2020),

Figure 2. Projects under the Climate Bonds Taxonomy
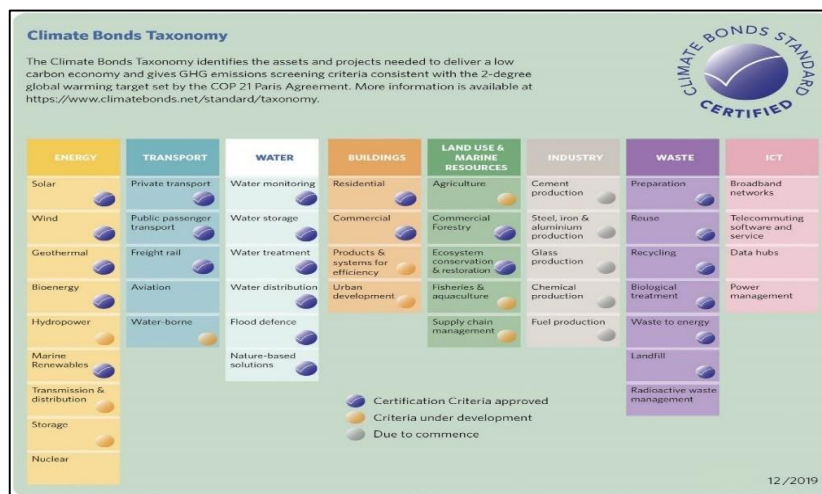
(CBI 2020, p. 2).

It is worth mentioning that in case there is a need to use all or part of the proceeds for refinancing, the ICMA (2018) recommends that issuers provide investors with an estimation of how much they require for financing compared to refinancing and which projects the issuers are anticipating will require refinancing.

2.3.2 Process for Project Evaluation and Selections

The second principle of GBP obliges green bonds issuers to provide information to investors on their sustainability goals, proposed projects that fall under the green projects criteria, what are the qualifying and/or disqualifying measures, and whether there are any environmental and social risk related to the projects. This can be achieved by listing the issuers' strategy and goals related to achieving environmental sustainability. In addition, the GPB

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recommends extreme transparency and that the issuer gets an external review to meet this principle (ICMA 2018).

2.3.3 Management of Proceeds

This principle requires green bond issuers to appropriately track the proceeds generated from green bonds. The ICMA (2018) states that as long as a green bond is outstanding, the remaining amount of the net proceeds must be constantly adjusted. This is to meet the needs of the qualified green projects taken during that specific period. Having this principle encourages issuers to support their management of proceeds by using auditors or a third party to authenticate their appropriate tracking process and how they are allocating the funds.

2.3.4 Reporting

Lastly, under the reporting principle, issuers must keep the information regarding the use of proceeds available at all times to the interested parties and have it constantly updated. The ICMA (2018) specifies that the issuers' annual report must include the list of green projects where the green bonds funds were used, the description of these projects, and the anticipated impact. In addition, when reporting, the ICMA encourages issuers to include quantitative, qualitative performance measures, and notable achievements in their green projects impact. Furthermore, when it comes to reporting the impact of certain green projects, the ICMA has set a specific format for doing so at both, project and portfolio level.

The GBP recommends issuers to get their green bonds projects and their associated green bonds issuances support by a pursue second party opinion, seek independent verification of specific set of criteria, receive certification from an external recognized organization, and have their bonds evaluated by skilled researchers and/or rating agencies (ICMA 2018). The

aforementioned Green Bonds Principles are constantly monitored and improved to ensure highest level of transparency and integrity.

2.4 SWOT Analysis

The green bond's market significant growth in just thirteen years grabbed the attention of market researchers and analysts. They dived into identifying the strength, weaknesses, opportunities, and threats of the green bond market using the SWOT analysis tool. It is imperative for investors and interested market participants to understand these key features as they could greatly impact a party's decision on whether to participate or not.

2.4.1 Strengths

The green bond market witnesses several strengths in many aspects. Firstly, it is distinctive from the broader conventional bond market in terms of how it explicitly highlights its main purpose (Tao 2016). As a result, the issuers can easily signal their green contributions to attract more investors. A study carried out by Tang and Zhang (2018) found that after green bonds issuance announcements, a company receives more attention from investors. Moreover, from a regional perspective, Maltais and Nykvist (2020) found that the Swedish market investors are interested in making a more socially responsible investment even if it comes at the expense of receiving lower returns compared to its non-green counterpart. Secondly, the green bond market holds a higher level of integrity compared to the market since it requires the involvement of a third party to audit the reporting process. Lastly, green bonds are tax exempted to encourage investors to take on SRIs which are sustainable and fight climate change (Climate Bonds Initiative (CBI) 2020; Segal 2020).

2.4.2 Weaknesses

One weakness of the green bond market lies in the absence of a clear definition of what can be labelled as "green" (Tao 2016). This is due to high level of ambiguity as a result of the complexity and integration of environmental aspects. This in turn comes at a cost of having definitive terms that set grounds of what issuers can consider as green projects. Moreover, since green bonds issuances are tied to specific projects, this can lead to either over or under funding (Giugale 2018. Lastly, issuing green bonds are costlier than the conventional ones as the GBP recommends companies to use a third party to monitor their management of proceeds as well as their reporting process.

2.4.3 Opportunities

With 51% growth from 2018 to 2019, the green bond market is offering several opportunities to the companies and its shareholders by reaching out to more investors. For instance, if a company issues a green bond, they will be able to reach out to green investors, the ones who are all about ESG investments, and investors who are in constant look for the next new investment choice (Tao 2016). In addition, when companies issue a green bond, it provides its shareholders with benefits. In fact, by looking at the cumulative abnormal returns (CAR), Tang and Zhang (2018) concluded that there is a positive response between the stock prices and the issuance of green bonds. In other words, the stock prices do increase after a firm issues its green bonds. Moreover, when companies issue green bonds and receive greater attention from investors, their stocks will be trade more frequently leading to an increase in their liquidity.

2.4.4 Threats

Currently, the green bond market participants are subject to potential threats in terms of credibility and growth hindering factors. Some issuers are expanding their definition of what they are naming "green". This is opening the doors of the potential threat of green-washing (MSCI ESG Research 2019). As stated in "Dictionary.Cambridge" (2020), Green-washing is a phenomenon where an entity is claiming to protect the environment while, in fact, it is not. As a result, if not monitored properly, the credibility of the green bonds market can be severely negatively impacted. Moreover, Deschryver and Mariz (2020) worked on identifying the barriers that each market participants are facing which can potentially hinder the growth of the green bond market. They identified five barriers that are contributing to slowing the growth of the market. Firstly, the issuer is not providing a clear definition regarding the financial benefits of the issued green bond. Secondly, the notion that issuers experience higher costs when issuing green bonds. Thirdly, green bonds issuances are not meeting the demand from investors in terms of diversity and liquidity. Lastly, unclear global standards that specifically state the ways for managing the proceeds

2.5 Green Bonds Market in 2020

Since it started, in 2008, the green bond market has witnessed significant growth. At the end of 2019, the issuance of green bonds globally has reached to USD 257.7 billion. This represents a growth of 51% from 2018 to include 1788 green bonds issued by 469 issuers. This increase was caused by the European market, Asia-Pacific, and North American accounting for 45%, 25%, and 23% respectively of 2019's total issuance (CBI 2020).

The United States (issued: USD $51.3bn), China (issued: USD $31.3bn), and France (issued: USD $30.1bn) were the leading issuers as they account for 44% of the 2019 total global green

bond issuance. Moreover, countries that joined the green bond market were "Barbados, Russia, Kenya, Panama, Greece, Ukraine, Ecuador, and KSA" (CBI 2020, p. 2). Figure 3 presents the 15 leading countries in 2019's green bonds issuance.

Figure 3. Top 15 countries issued green bonds in 2019
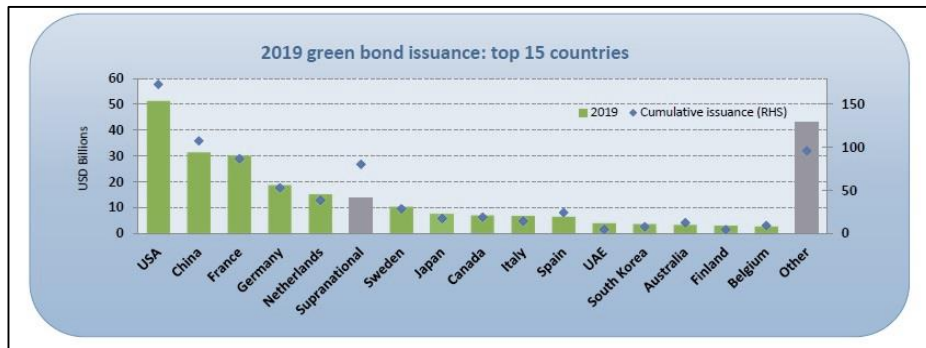
(CBI 2020, p. 1).

Moreover, CBI (2020) stated that the year 2019 was similar to the 2018 in terms of funds allocation which were mainly used towards energy and buildings to account for 31% and 30%, respectively. Figure 4 presents the 2018 and 2019 funds allocation side by side and a detailed 2019's funds allocation

Figure 4. Use of Proceeds
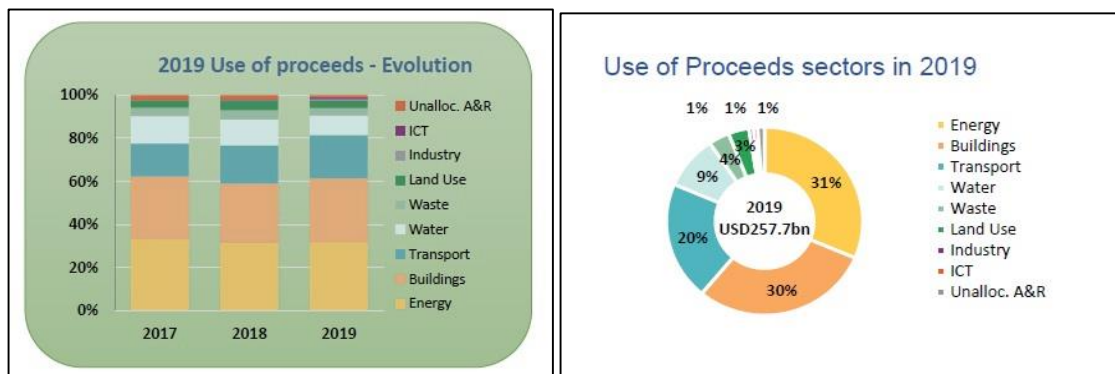
(CBI 2020, pp. 1 & 3).

In August 2020, CBI (2020) issued the mid-year report of 2020 green bond market summary. The global green bonds issuance of the first half of 2020 dropped by 26% compared to the first half of 2019. This decline in the green bonds' issuance is attributed to the COVID-19 pandemic (CBI 2020). Despite the decline, governments have focused on entering and supporting the green bonds market to combat this tragic pandemic. The sovereign issuance remained at the same level and the governments supported companies outstood to consist 24% of the total issues, an increase from 15% compared to the first half of 2019 (CBI 2020).

Figure 5. Green Bond Issuances Comparisons
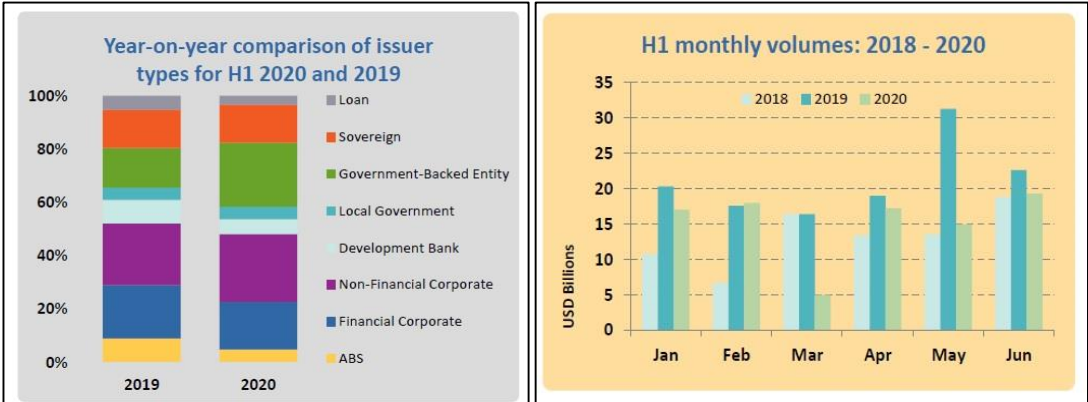
(CBI 2020, pp. 1 & 3).

Chapter 3: Literature Review

3.1 Introduction

The ever-growing capital market with its diverse types of markets and securities trigger the need to understand how their volatilities are correlated and linked to each other. The importance is derived from the fact that investors, portfolio managers, policymakers, and many other market participants are in constant search and strive to secure an optimal portfolio. As a result, researchers are continuously developing models and conducting studies to analyze the relationship between two or more markets or even industries.

The literature review aims to provide an overview of the currently available studies that are relevant to the topic. This section will be divided into four subsections. The first will present several studies that focused on comparing between the green and the conventional bonds market in different aspects. The second will discuss the development of the Dynamic Conditional Correlation Multivariate GARCH (DCC MGARCH) model. The third section will present studies that have applied the DCC MGARCH model as a method to examine whether there are co-movements and volatility linkages between different markets, within the same market, and even across industries. The last section will state the research hypothesis and the research gap that this paper attempts to fill.

3.2 Green versus Conventional Bonds Literature

This section will present the studies that focused on comparing the green and non-green bonds markets in many aspects such as correlation factors, issuing convenience, pricing differences, premiums, yield spreads, and volatilities.

Broadstock and Cheng (2019) conducted a study to identify the factors that determine the correlation patterns between green and conventional bonds markets. In their study, they apply the DCC multivariate GARCH model to get the correlations and then they apply the Dynamic Model Averaging to determine the factors of the correlations. They select daily data from 28th November 2008 to 31st July 2018 for 8 macroeconomic variables. The researchers found that there is evidence that both, green and non-green bonds marketa, experience sensitivity to particular macroeconomic variables. These macroeconomic variables are fluctuations in the capital market volatility, vagueness in the economic policy, the economic activity on daily basis, oil prices, and, lastly, the specific measures related to good and bad announcements related to green bonds.

Gianfrate and Peri (2019) carried out a research to test whether issuing green bonds are as convenient as issuing their conventional counterparts. They selected data consisting of 3055 bonds out of which 121 are green bonds. These bonds are issued from the time period of 2013 to 2017 and are European. To answer their question, they used propensity score matching method. They concluded that issuing green bonds to finance green projects are more convenient than issuing conventional ones. This is attributed to the fact that the issuers will pay investors lower returns for green bonds compared to the conventional ones. In fact, Giangrate and Peri (2019) stated that the additional costs that the issuer encounters when issuing green bonds are insignificant compared to the amounts that will be saved, which they estimate to be around 15 to 21 basis points, due to paying a lower interest rate. Moreover, their study suggests that green bonds carry greater benefits for corporate issuers as they continue to be traded in the secondary market. As a result, they confirm that issuing green bonds to combat climate matters does not penalize the financial issuers.

Nanayakkara and Colombage (2019) looked at examining pricing difference between green and conventional bonds. In the study, they apply the credit spread as a tool to test whether investors are willing to buy green bonds at a premium compared to similar conventional ones. The researchers used a panel data regression with a hybrid method to capture the difference in daily prices between both bonds issued in the 2016 and 2017. Moreover, the credit spreads were measured using the Option-Adjusted spread (OAS) while adjusting for any special bonds criteria along with universal and macroeconomic aspects that affect the spread. They found that when a comparable issue of both bonds takes place, green bonds are sold with a premium of 63 basis points than its comparable issues of traditional bonds. The researchers attribute this premium to the higher demand of investors in the market. Moreover, they suggest that this premium should encourage more issuers to tap into the green bonds market as it's a source for a lower cost capital.

Furthermore, Zerbib (2019) conducted a research study between green and non-green bonds to examine the impact of the social motives, such as environmental preferences, on the prices of the bond market. In his paper, he selected the bonds that were issued from July 2013 to December 2017. Using matching method and then a two-step regression method, he computed the yield differentials between both types of bonds. The researcher adopts the green bond premium as a tool to recognize the impact of the environmental preferences on the prices. The conclusion of this study was that green bonds' yield are lower than the traditional ones. Moreover, they found that across the entire selected sample, the yield premium, on average, is -2 basis points for the green bonds compared to the non-green ones. The research found that this lower yield in the green bonds are more seen in the financial bonds and the ones with low rating. Lastly, he stated that, based on the results, investors with

environmental preferences have low impact on the bond prices which can hinder the growth of the green bond market.

Moreover, Ehlers and Packer (2017) focused on analyzing how the "green" label affects the pricing of a bond issued by the same issuer. They carried out their study by selecting issuers that issued fixed rate green and traditional bonds in USD and Euro at a similar issuance and maturity date between 2014 and 2017. By comparing their credit spreads at the time of issuance, the research concluded that, with green bonds, the issuers were able to receive funds at lower spreads (by 18 basis points) than with the non-green ones. The findings supported the existing literature stating that there is high demand for green bonds compared to supply and, hence, the green bonds are sold at a premium.

However, Lacker and Watts (2020) refuted studies (e.g. Nanayakkara and Colombage 2019 and Ehlers and Packer 2017) that say green bonds are sold at premium. In their paper, they mainly investigated whether investors are willing to forgo wealth in exchange of making more socially responsible investments. However, in the process, they wanted to test whether green and non-green bonds are priced differently. To carry out the analysis, they used Bloomberg's "green" labelled municipal bonds and applied matching procedure to match each green bond to a non-green one extracted from Mergent database. They were matched in terms of having the same issuer, issue date, rating, not being callable, coupon rates, and have maturity of one year. Their final sample consisted of 640 comparable green and non-green bonds. They found that investors are not willing to forgo wealth to take up a socially responsible investment. In addition, they found that, holding risk and return factors constant, there is no significant evidence supporting that green and traditional bonds experience differences in pricing and that an investor considers both bonds as substitutes. As a result,

they have concluded that what they called as greenium, the premium of a green bonds, equals to zero.

Moreover, Hachenberg and Schiereck (2018) conducted a study questioning whether green bonds are priced differently and whether are providing better investment opportunities than the conventional ones. To answer this question, they carried out their analysis using a sample between the beginning of October 2015 till the end of March 2016. Then, to determine if the green bonds are cheaper or more expensive than a similar traditional bond using the I-spreads of Bloomberg which included 7032 green bonds and 14,064 conventional bonds. Similarity between the two types of bonds were considered in terms of the issuer, raking, maturity, currency, and whether the coupon is fixed or floating. Hachenberg and Schiereck (2018) concluded that, on average, the green bonds are not trading very differently from the conventional ones. However, for A, AA, and BBB rated green bonds, they were trading tighter than the conventional ones. Moreover, the researchers concluded that green bonds issued by governments are traded more than the comparable conventional bonds. On the other hand, corporate green bonds are traded less than the conventional one. Lastly, they also conclude that the factors that significantly impact the pricing differences are not the issue size, maturity, and currency but rather the industry and ESG ratings.

Febi et al. (2018) carried out a study that analyzes the impacts of liquidity risks on the yield spreads for the green and non-green bonds. The authors adopted two liquidity estimates; LOT liquidity and bid-ask spread. They selected a sample of 64 bonds labelled "green" trading on the London Stock Exchange and Luxembourg Stock Exchange and 56 traditional bonds trading on the Luxembourg Stock Exchange. They ensured that only plain vanilla bonds are included to make the study more comparable. Febi et al. (2018) concluded that, on average,

the green bonds were more liquid than its non-green counterpart from 2014 to 2016. Moreover, when using regression, they found that the yield spread is positively related to both measures but when applying fixed-effects model, on the LOT liquidity was related to green bonds. Finally, Febi et al. (2018) found that the LOT effect is not lasting but is rather decreasing over the last few years. This in turn indicates that the liquidity risk for the green bonds is becoming insignificant and provide a promising future for the green bond market growth.

Moreover, Reboredo (2018) carried out a study to investigate the green bond's co-movements with other financial markets. The financial markets used in the comparison were fixed income, stock, and energy commodity. The author stated the reason for comparing these markets is that investors who are interested in green bonds are more likely to have assets from the aforementioned markets in their portfolios. Reboredo (2018) relied on the static and dynamic capula functions approach were used with daily data from October 2014 to August 2017 to understand the degree of the co-movement under any market conditions between green and the other financial markets. Moreover, the data consisted of indices to represent each market. The researcher concluded that green bonds market experiences a significant co-movement with the fixed-income market, i.e. corporate and treasury and an insignificant co-movement with the stock and energy commodity market. As a result, Reboredo (2018) states that, unlike stock and energy markets, investors in the fixed-income market will not yield diversification benefits from investing in green bonds. Moreover, by applying the Value-at-Risk (VAR) and Conditional Valua-at-Risk (CoVaR) approach, the study concluded that the green bonds market experiences significant price spillovers from the fixed income market

whereas it does not when any substantial price changes in stock and energy markets take place.

Pham (2016) carried out a research to gain better knowledge on the risk and return of the green bond market using the daily prices from April 2010 to April 2015 of multiple S&P green bond Indices. Then, using a multivariate GARCH model and the S&P U.S. Aggregate Bond Index, to represent the conventional bonds, the researcher found that green bonds market witnessed large volatility clustering while the conventional bond experienced a small one. Pham (2016) also found that there is a volatility spillover effect from the conventional to the green bond but it is not fixed. It is worth mentioning that this study was the first to study the green bond's market volatility and compare it to its non-green counterpart.

3.3 Multivariate GARCH Model Development

This section presents the literature behind the development of the Multivariate GARCH model as it is essential in carrying out the analysis of this paper. In the beginning, the paper will start with providing a background on GARCH model and then moves to explain how MGARCH model differs from GARCH.

3.3.1 What is GARCH?

The GARCH model, developed by Tim Bollerslev in 1986, is the Generalized ARCH model. This model is an extension of the ARCH model which was developed in 1982 by Robert F. Engle. The GARCH model stands for Generalized Autoregressive Conditional Heteroskedasticity and is applied to examine the volatility in the financial markets and carry out economic forecasting. To better understand the GARCH model, this paper will briefly explain the ARCH model and how GARCH is different from it.

The ARCH model "explicitly recognizes the difference between the unconditional and the conditional variance allowing the latter to change over time as a function of past errors" (Bollerslev 1986, p. 308). In other words, the ARCH model informs whether the time series data under study has a non-constant variance (heteroskedastic) that depends on its own past periods. Moreover, when analyzing the data, ARCH follows an autoregressive (AR) process that relies on previous values to forecast the future one. The autoregressive lag order is denoted as p. Engle (1982) developed the following ARCH (p) equation considering a conditionally normal distribution:

$$\gamma_t | \psi_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \gamma_{t-1}^2 + \cdots + \alpha_p \gamma_{t-p}^2 \tag{1}$$

where α_0 is the constant, α_1 is the coefficient at ARCH process order 1, and γ_{t-1}^2 is the error variance term of the previous period. It is worth mentioning that in ARCH the α_0 must be a positive value that is greater than zero and α_1 must be a positive number falling between zero and one (Adeleye 2019).

Bollerslev (1986) argues that the ARCH model lacks the ability to take into consideration the effect of the error variance terms beyond the specified p order. Moreover, he stated that, empirically, when applying the ARCH model, it often requires a higher number of lags in the conditional variance equation. As a result, a random lag structure is usually applied to avoid having non-parsimonious model that contradicts with the negative variance measure. To overcome these issues, Bollerslev developed the GARCH model. Unlike the ARCH model that considers previous samples variance, the GARCH model incorporates lagged conditional variances. It applies not only the autoregressive (AR) process for the error variance but also

the moving average (MA) process for the past variance itself. The autoregressive process related to ARCH terms is denoted as q and the moving average related to the GARCH terms process is denoted as p. The moving average represent the number of lags the variance to be included. The GARCH (p,q) model is presented in the following equation (Bollerslev 1986):

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}, \qquad (2)$$

where α_0 is the constant, α_i is the coefficient at ARCH terms (ε_{t-i}^2), β_i is the coefficient at GARCH terms. In the GARCH model, p lag order can be equal or greater than zero, the q lag order must be greater than zero, α_0 must be greater than zero, and α_i and β_i coefficients must be greater or equal to zero. The sum of the α_i and β_i coefficients must be less than one, however, when it is more than one, IGARCH must be applied (Adeleye 2019).

Baybogan (2013) explained that the advantage of the GARCH model comes from it being more parsimonious and since it considers huge amount of information, the GARCH (1,1) model is usually sufficient and provides the required information.

The GARCH model and its variants is widely used by financial experts to determine asset pricing, advise on which asset will yield a higher return, and forecast the returns concurrent investments. GARCH model helps investors and portfolio managers when it comes to allocating funds, mitigating and handling risk, and optimize diversification benefits (Kenton 2020).

Since it is development, the GARCH model had variety of extensions such as EGARCH, GJR GARCH, also known as TGARCH, EGARCH, MGARCH, and many more (Brooks

2014). Each model was developed to overcome certain issues. This paper will focus on providing literature on the MGARCH only as it will be used to carry out this study.

3.3.2 What is MGARCH?

MGARCH stands for Multivariate GARCH and it permits the conditional covariances of the variables in question to have a dynamic nonrigid structure. It addresses the movement of the covariances over time and, hence, are more complex than the univariate GARCH model (Brooks 2014). The MGARCH has a variety of models such as the VECH, the diagonal VECH, BEKK models, and conditional correlation models. The conditional correlation models are further derived to three models known as Constant Conditional Correlation (CCC), Dynamic Conditional Correlation (DCC), and Varying Conditional Correlation (VCC) multivariate GARCH models (Brooks 2014). These are constructed to analyze the volatilities and study the co-movements across markets and industries so that investors, portfolio managers, and policymakers have full understanding when it comes to investment decisions (Sclip et al. 2016).

Out of all models, this paper will focus on defining the DCC MGARCH model as it is the model which will be applied to carry out the analysis. Briefly, the DCC MGARCH model has the distinctive mixed features of a univariate GARCH model and, the more complex, multivariate GARCH model (Brooks 2014). The following chapter (Chapter 4) will explain and define the DCC MGARCH model in details and clarify how it works.

3.4 DCC Multivariate GARCH Applications Across Markets.

This section presents the literature that have applied the DCC MGARCH model in their analysis to examine the conditional correlation and the volatility linkages between the same, two or more markets, or across industries and countries.

Park, Park and Ryu (2020) carried out a study to closely look at the green bond and stock market volatility spillover and their sensitivity towards shocks. To represent each market, the researchers used the returns of the S&P 500 Index for the stock market and the S&P 500 Green Bond Select Index for the green bond. The time period was from January 2010 to January 2020. Using BEKK and DCC multivariate GARCH models to test for spillover effect, they concluded that even though the stock and the bond market have a certain level of volatility spillover, both markets do not respond to the other market's negative shocks in a great extent. Moreover, using the sign and size bias test to examine the asymmetric volatility, they found that while both markets are highly sensitive to negative shocks but only the green bond is sensitive towards positive shocks too.

Saiti and Noordin (2018) did a study to understand to which extent the equity investors in Malaysia yield diversification benefits when adding traditional and Islamic equities from Southeast Asian region and the largest ten equity indices to their portfolios. To answer this question, they use the DCC multivariate GARCH model. In their study, they select the returns of the MSCI Malaysia index to represent the traditional stock returns in Malaysia, the MSCI indices in the Southeast Asia, Japan, China, Hong Kong, and India to represent the conventional and Islamic stock market in the same region, and the MSCI indices in the U.S., UK, Canada, France, Germany, and Switzerland to represent the two stock markets internationally. The data selected was the daily closing prices from 29th June 2007 to 30th June 2016. They found that the indices of the Asian and international Islamic stock markets experience either more or less volatility than their traditional counterparts. Moreover, from analyzing the correlation, they found that the MSCI indices of Japan for both stock markets yield greater diversification benefits than Southeast Asia region, Hong Kong, China, and

India. Lastly, on an international level, they found that U. S's MSCI indices for both stock markets provide greater diversification benefits than the UK, Canada, France, Germany, and Switzerland.

In addition, Saiti et al. (2019) conducted a similar study to Saiti and Noordin (2018) but they focused on the traditional equity investors in the Chinese market. They investigated three Islamic stock indices and other 10 indices related to different sectors in the Shanghai Stock Exchange. The researchers adopted the DCC multivariate GARCH model and selected daily data from 28th August 2009 to 29th September 2017. They found that the select Islamic indices experience lower volatility that their conventional counterparts. Moreover, from analyzing the correlation, they found that conventional equity investors in China greatly yield diversification benefits from adding the Islamic stock indices to their portfolio.

Talbi, Boubaker, and Sebai (2017) carried out a study to know whether there was a financial contagion between multiple emerging and developed countries stock markets during the subprime crises of the U.S. The study adopted a DCC-MGARCH (1,1) model and an adjusted correlation approach to test whether there was contagion. They examine 63 markets and gather their daily returns for these markets' stock indices. The period ranged from 2nd January 2003 to 31st December 2013 and was divided into pre and post the financial crisis. The DCC-MGARCH (1,1) model, they found that there was contagion effect for the majority of the emerging and developed countries during the U.S. crisis. In fact, they found that the contagion effect impacted the emerging market more.

In addition, Hassan et al. (2017) have constructed a study that investigates the conditional correlation between Sukuk and traditional bonds and analyze their volatility linkages. The study looks specifically at both securities' markets in Europe, U.S., and emerging markets

for the period between 2010 to 2014. The study attempts to find whether Sukuk acts in a different way than the conventional bonds do regarding co-movements, volatility, and dynamic correlation and to note what determines and affects their dynamic conditional correlation. To carry out their analysis, Hassan et al. (2017), adopts the DCC multivariate GARCH model and select daily data from 1st January 2010 to 31st December 2014. For the conventional bonds, they select six corporate indices designed by Bloomberg and for Sukuk they construct an index by applying Bloomberg standards and criteria. The researchers found that Sukuk and traditional high-rated bonds experience minor reaction of conditional volatility towards market shocks. Moreover, compared to the U.S. and EU high-rated bonds, they found that Sukuk's returns are significantly less volatile. In additional, they concluded that there is a positive time-varying conditional correlation between both markets and that their dynamic correlation increases during recessions. Lastly, through analyzing how market factors impact correlations, they found that there is a behavioral change in the sukuk-bond relationship.

Similarly, Sclip et al. (2016) also studied the co-movements and volatility between Sukuk and the global stocks market after the financial crisis. This study was considered to be the first that examines the co-movements between the two markets. They select DCC multivariate GARCH model and select daily data from 1st January 2010 to December 2014. Using the MSCI criteria and methodology, they construct an international market capitalization weighted index where only greatly liquid sukuks with excess amount of USD 200 million and that has, at least, one credit rating. For stocks market, they selected 5 global and 5 emerging MSCI Indices. They found that there is a significant correlation between the sukuk market and the U.S. and EU stock indices with no evidence of flight to quality

phenomenon associated with sukuk. Moreover, they concluded that, during financial crisis, volatility linkages increase between sukuk and regional market indices. In addition, they state that, since sukuk experience lower volatility than equity, investors with a perfectly diversified equity portfolio could avail diversification benefits. However, during financial crisis, sukuk acts as a hybrid security between bonds and equity as they experience high volatility and dynamic correlations at that time.

Furthermore, Papaioannou et al. (2017) examined the correlation and volatility between three markets, namely the electricity, financial, and energy commodity markets. They focused the study during the time of the U.S. subprime crisis and the Greek government debt crisis to analyze the volatility spillover effect of these events on the electricity, financial, and energy commodity markets. They selected daily prices from April 2008 to March 2014 making a total of 2,160 observation. Using the DCC multivariate GARCH model to document the co-movement during market circumstances changes, the researchers found that the correlations and linkages between the aforementioned markets have changed in structure due to essential policies that are dominant in these markets and due to the existing the financial crisis in Europe. Moreover, they found that the financial and commodity markets experienced volatility spillover. However, this was not the case for the electricity market in Greek.

Oliveira et al. (2018) did a study to investigate the volatility spillover impact from and to the Brazilian stock market. They select daily prices of multiple Brazilian and U.S. indices to represent different securities for the period between 2014 to 2016 that was labelled as the most volatile since the subprime crisis. They applied DCC Multivariate GARCH and other models (BEKK and t-Copulas). The researchers reached to a conclusion that the volatility in the Brazilian stock market is mainly caused by the portfolio rebalancing made by portfolio

managers who are investing in Latin America. Moreover, they also found that the U.S. monetary policy causes volatility in the Brazilian Stock Market. On the other hand, they found evidence that the commodity markets and the U.S. bonds market experience volatility produced by the Brazilian Stock market.

3.5 Research Hypothesis

This paper's hypothesis is constructed as per the following:

H0: The global green bonds market will not experience dynamic conditional correlation with the broader global conventional bonds market and, hence, investors could gain diversification benefit

H1: The global green bonds market will experience dynamic conditional correlation with the broader global conventional bonds market and, hence, investors would not yield diversification benefits.

3.6 Research Gap

Green bonds market is a relatively a new one. As a result, as presented earlier, most studies that undertook to compare green bonds market to its comparable conventional bonds market have focused on correlation factors, issuing convenience, pricing differences, premiums, yield spreads, and volatilities.

Beside Pham (2016) and Reboredo (2018), the literature presented earlier provide an evidence on the lack of studies related to examining the time-varying conditional correlation between both markets and their volatility linkages. This paper aims to fill the gap in the literature in this matter. It also aims to contribute to the existing literature related to examining the dynamic conditional correlation and volatility linkages between the aforementioned markets using the DCC Multivariate GARCH model.

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Chapter 4: Econometric Methodology

4.1 Introduction

This paper aims to answer whether a dynamic conditional correlation exists between the green and non-green bonds market. In addition, it examines the conditional volatilities of both markets looking to see if there is evidence of volatility linkages. In order to do so, this paper adopts a model called the Dynamic Conditional Correlation that allows assessing both at the same time. In this section, we will start off by describing the model and the data adopted in this paper. Then, in a chronological order, this section presents the steps required to carry out our analysis such as the preliminary test, finding the best univariate GARCH model, reaching to the DCC results. Afterwards, the section presents how to calculate volatility linkages and carry out structural break analysis.

4.2 DCC Multivariate GARCH

The Dynamic Conditional Correlation (DCC) was proposed by Engle (2002). This model, as discussed in chapter 3, is a type variation of the multivariate GARCH model. In fact, it is an extension of the Constant Conditional Correlation (CCC) model where the conditional correlations are constant overtime. However, since many studies concluded that the conditional correlations also experience time variation and are not always constant, the DCC was developed to allow for the conditional correlation to be time-varying (Brooks 2014). In fact, Sclip et al. (2016) stated that the DCC is a more reliable model than the CCC when it comes to portfolio management and assets allocation. As seen in chapter 3, many studies have relied on this model to model the conditional correlation between two variables. According to Engle (2002), the formula for the DCC is the following:

$$H_t = D_t R_t D_t \tag{3}$$

H_t is the variance-covariance matrix. D_t is the N × N diagonal conditional standard deviation matrix which is obtained from the univariate GARCH model of each individual time series in question. It is expressed as $diag\ (\sqrt{h_{it}})$. The univariate GARCH model follows equation (2) stated in chapter. Since we have two time series, our $D_t = diag\ (\sqrt{h_{1t}}, \sqrt{h_{2t}})$ is the 2 × 2 diagonal conditional standard deviation matrix which is obtained from the univariate GARCH model of each individual time series in question $\begin{bmatrix} \sigma_{GBt} & 0 \\ 0 & \sigma_{CBt} \end{bmatrix}$.

R_t represents the dynamic conditional correlation matrix $\begin{bmatrix} 1 & \rho_{GBt} \\ \rho_{CBt} & 1 \end{bmatrix}$. It has the following formula:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{4}$$

$$Q_t = \overline{Q}\ (1 - \alpha - \beta) + \alpha\ (\varepsilon_{t-1}\grave{\varepsilon}_{t-1}) + \beta Q_{t-1} \tag{5}$$

$\overline{Q}$ is the matrix of the unconditional correlation of the standardized residuals $\grave{\varepsilon}$. $Q_t^{*}\ \{\sqrt{q_{ii,t}}\}$ is the diagonal matrix which includes the square roots of the diagonal figures of $Q_t = \{q_{ii}\}_t$ (Lahrech & Sylwester 2011) and is represented as per the following (Andersson-Säll & Lindskog 2019):

$$Q_t^{*} = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 \\ 0 & \sqrt{q_{22}} & 0 \\ 0 & 0 & \sqrt{q_{nn}} \end{bmatrix}$$

The positive matrix of Q_t ensures that the dynamic conditional correlation matrix (R_t) and all elements to be equal to less than one in absolute terms. The covariance element between the two variables at time t (ρ_{ijt}) is calculated as $q_{ijt}/\sqrt{q_{ii,t}q_{jj,t}}$ (Lahrech & Sylwester 2011). The α and β parameters in the DCC model provides an indication on whether the data sets

in question experience time varying conditional correlation and whether there is spillover between the two markets (Yadav 2020). Moreover, they provide information on the persistency of the short-term and long-term volatility effect of both variables. It is important to mention that the value of α and β parameters should be greater than zero but their sum ($\alpha + \beta$) should be less than 1(Sclip et al. 2016).

This paper adopts the DCC model to estimate the conditional variance-covariance matrix H_t in two stages. The first stage is to estimate the volatility of the green bond market index and the conventional bond market index using different types of univariate GARCH models. The models that we are examining and selecting from are GARCH, GJR GARCH, and EGARCH. Based on the selected GARCH model, the time-varying conditional correlation (R_t) process will differ accordingly (Lahrech & Sylwester 2011). In the second step, we divide the market returns by their estimated standard deviations generated in the first step to calculate the standardized residuals ε_{it} using equation (6) which is in turn used to estimate the α and β parameters.

$$\varepsilon_{it} = m_{it}/\sqrt{h_{it}} \tag{6}$$

The first step and the second step will be explained in details in the following subsections.

4.3 Data

In order to understand the characteristics of the green bond index relative to the greater conventional bond index on a global level, we consider high frequency time series data for both bonds' market performance indicators. This paper adopts weekly prices to carry out the study (see e.g. Christoffersen et al. 2013, Lahrech & Sylwester 2013, Pesaran & Pesaran 2010, and many more). This paper selects Bloomberg Barclays MSCI Global Green Bond

Index (Ticker: GBGLTRUU) and Bloomberg Barclays Global Aggregate Total Return Index (LEGATRUU) to represent the global green and broader conventional bonds markets, respectively. In this paper, we denote the global green bond index as GB and the global conventional bond index as CB. The sample was obtained from Bloomberg and it covers the period from 17th October 2014 to 18th September 2020 leaving us 310 observations for weekly returns.

4.3.1 Bloomberg Barclays MSCI Global Green Bond Index (GB)

Bloomberg Barclays MSCI Global Green Bond Index (GBGLTRUU) was established in June 2013. It is established with a main objective of representing the market in a precise manner providing the green bond market's participants the ability to assess the risk and returns of this bond under a clear framework related to investment decisions. This index provides market stakeholders MSCI ESG Research independent assessment for the green bonds securities to determine whether they are in line with the four Green Bonds Principles (GBP) discussed in chapter 2. Moreover, this index follows certain fixed-income criteria selected by Bloomberg to ensure transparency and accurate market representation. Lastly, this index includes variation of sub-indices in its form such as credit quality, area, currencies, maturities, and many more (*MSCI* ESG Research 2019). In addition, the objective of this index is to provide a significant amount of transparency on how the proceeds are being used, a clear definition on what to be considered as green bonds to combat greenwashing, and a platform for investors to find the green bonds with a label (*MSCI* ESG Research 2019). The GB index is involved in the treasury, corporate, government, and securitized bonds sector. It is a multi-currency index with bonds that have a minimum of one year maturity and that must have the principal and interest in these currencies "Americas: CAD, CLP, MXN, USD

EMEA: CHF, CZK, DKK, EUR, GBP, HUF, ILS, NOK, PLN, RUB, SEK Asian-Pacific: AUD, CNY*, HKD, IDR, JPY, KRW, MYR, NZD, SGD, THB" (*MSCI* ESG Research 2019, p. 9). Furthermore, as stated in "Environmental-Finance" (2020), the GB index was selected as the best index for the last four years and for the year 2020.

4.3.2 Bloomberg Barclays Global Aggregate Total Return Index (CB)

The Bloomberg Barclays Global Aggregate Total Return Index (LEGATRUU), also known as Agg, was established in 1973. It acts as a benchmark when measuring the global fixed-rate, graded bond markets. It includes many different types of bonds from the developed and emerging markets such as government, government-related, corporate, asset-backed, mortgage-backed, and commercial mortgage-backed securities (SSGA 2020). Similar to GB, it is a multi-currency index which includes twenty-four currencies (Bloomberg 2020). In order to ensure that there is no overlapping in the data between this index and the GB index, we spoke to a Bloomberg representative, Gary Jamison, and we also obtained a list of the securities under the CB index. As per these two, this paper can confirm that the GB index is not included under the CB index.

In figure 6 for the weekly prices for GB and CB, we can see that both indices have stochastic upward trend or, in other words, there is no constant mean. Moreover, from the graph, it is evident that both indices experience co-movement as they move upward or downward at the same time.

Figure 6. Weekly prices for GB amd CB
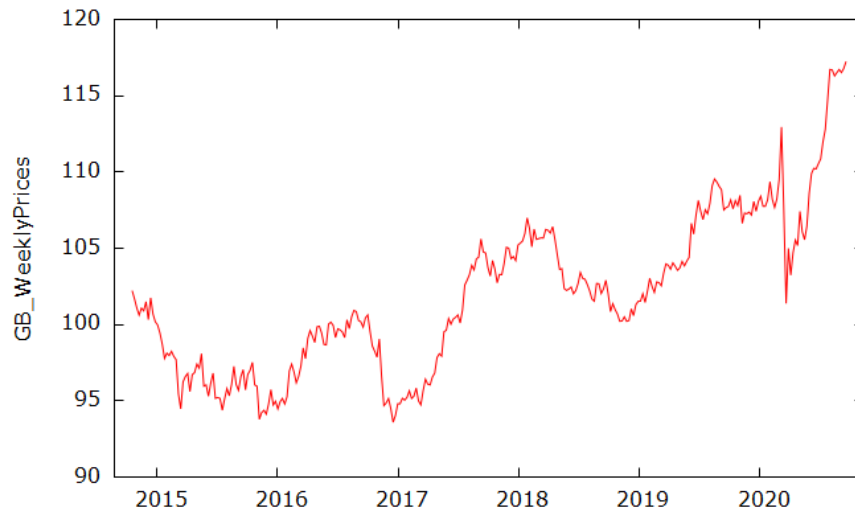
Panel A: Bloomberg Barclays MSCI Global Green Bond Index
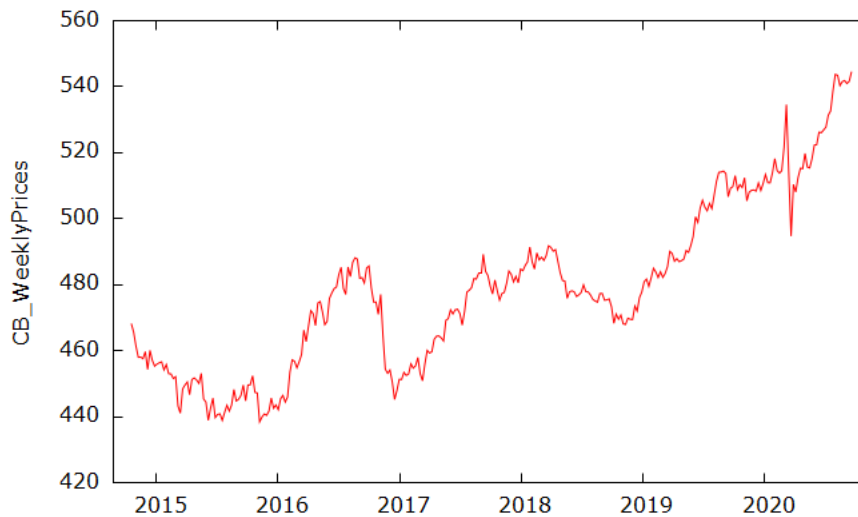
Panel B: Bloomberg Barclays Global Aggregate Total Return Index

Note: Panel A represents the weekly prices for Bloomberg Barclays MSCI Global Green Bond Index (GB). Panel B represents the weekly prices for Bloomberg Barclays Global Aggregate Total Return Index (CB). Time frame is from 17/10/2014 to 18/09/2020.

It is worth mentioning that both indices are comparable as GB copies the fixed income's eligibility conditions that are implemented in CB (MSCI ESG Research 2019). These conditions aim towards guaranteeing accurate representation, predictability, and the potential of investment potential.

4.3.3 Weekly returns

In order to carry out analyzing the dynamic conditional correlations between both markets, we first need to convert the weekly prices to returns. This can be done in two ways. The first is by using the arithmetic mean which adopts the percentage change formula (Daly 2008):

$$R_{i,t} = \left(\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}\right) \tag{7}$$

The second is by taking the log of the prices using the following formula (Park, Park & Rye 2020):

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{8}$$

where $P_{i,t}$ is the current close price at the current t period and $P_{i,t-1}$ is the close price for the previous t period.

In this paper, we will use equation (8) to transform our data into return. This is because the logarithmic returns are better than the arithmetic returns as they do take into consideration compounding over multiple periods (Miskolczi 2017). These weekly returns will be used and considered our main data from now onwards to carry out all our analysis. The graphical presentation of the weekly returns is seen in Panel A and Panel B under figure 7 in chapter 5.

4.3.4 Descriptive statistics

The descriptive statistics is designed to provide a brief summary on the key features of the data we are adopting. In table 1, the summary of the weekly return's descriptive statistics is presented. It shows that the mean of GB and CB indices are close to zero indicating that the mean is reverting back. Moreover, we can find that the median has a higher value than the mean indicating skewness. The skewness will be further discussed in section 4.2. Moreover, the standard deviation of the GB and CB indices state that the GB experience 0.9% deviation from mean and CB experience 0.7% deviation from the mean. Lastly, the unconditional correlation between the two indices is 0.92 meaning that both experience a very strong positive correlation.

Table 1
Summary statistics of weekly returns

	Bloomberg Barclays MSCI Global Green Bond Index (GB)	**Bloomberg Barclays Global Aggregate Total Return Index (CB)**
Descriptive Statistics		
Mean	0.00047997	0.00050997
Median	0.00075192	0.00077486
Minimum	-0.058653	-0.039076
Maximum	0.035004	0.031242
Standard Deviation	0.0091845	0.0077232
Unconditional Correlation	0.92959846	

4.4 Normality Test

The normality tests are designed to determine whether a particular set of data has a normal distribution. The normal distribution indicates that the data in question has specific features such as a symmetric bell shape where the mean equals the median and 68% of the data set lies within 1 standard deviation from the mean. There are plenty of normality tests and they

can be carried out through regression, Chi-squared, distribution, moment, spacings, and many others (Yap & Sim 2011). This paper will focus on adopting the moment tests such as skewness, kurtosis, and Jarque-Bera (1981) test for the data set and standardized residuals (see e.g. Park, Park & Ryu (2020); Reboredo (2018); Hassan et al. (2017); Lahrech & Sylwester (2013); Pham 2016; Sclip et al. (2016), and many others).

The skewness informs on how the data set in question is distributed and what is its shape. A normal distribution has skewness that is equal to zero and have the mean, median, and mode equal to each other.

Moreover, kurtosis measures the peak of the series at the mean and how fat the distribution tails are. A normal distribution has its kurtosis equal to three and is described to Mesokurtic. If it is larger than three, the distribution has fat tails and is described as Leptokurtic (Brooks 2014).

Skewness and kurtosis figures are obtained from the descriptive statistics generated by Gretl. Lastly, the Jarque-Bera (1981) hypothesis test is the following:

$$H_0 = the\ time\ series\ has\ a\ normal\ distribution$$

$$H_1 = the\ time\ series\ does\ not\ have\ normal\ distribution$$

$$Reject\ H_0\ if\ p-value\ \leq\ \propto,$$

$$where \propto is\ the\ significance\ level\ at\ 1\%, 5\%, or\ 10\%$$

The Jarque-Bera test result is obtained from running the normality test for each variable using Gretl.

Any result that does not have skewness equal to zero, kurtosis of three, and reject Jarque-Bera null hypothesis indicates the data set is not normally distributed. Moreover, with regards

to the standardized residuals, should they turn out to be not normally distributed, the Quasi-Maximum Likelihood (QML) function must be applied instead of Maximum-Likelihood function (Lahrech & Sylwester 2011).

4.5 Preliminary tests

This section presents the methodology of the preliminary tests that determine specific features of the data set in use such as stationarity, volatility clustering, autocorrelation, and ARCH tests. These tests, and more specifically, the autocorrelation and ARCH tests provide an answer whether an ARCH effect exists or not. The results will in turn provide us with an insight on whether the data for GB and CB can be modeled using different types of GARCH models.

4.5.1 Stationarity Test

A time series is described as stationary when it has a constant mean, variance, and autocovariance at each specified lag. On the other hand, a non-stationary data is when a data series exhibit a trend (Lahrech 2019). There are multiple stationarity tests such as ADF originated by Augmented-Dickey-Fuller (1979), KPSS originated by Kwiatkowski et al. (1992), and PP originated by Philipps-Perron (1988) (Reboredo 2018). The stationarity test used in this paper is the Augmented Dickey-Fuller (ADF) (1979) unit root test (see e.g. Park, Park & Ryu (2020); Reboredo (2018); Hassan et al. (2017); Lahrech & Sylwester (2011); Pham 2016; Sclip et al. (2016); Liow et al. 2009, and many others). The ADF figure is obtained by Gretl statistical software. The hypothesis for the ADF test is:

$$H_0 = the\ time\ series\ has\ a\ unit\ root\ (non-stationary)$$

$$H_1 = the\ time\ series\ does\ not\ have\ unit\ root\ (stationary)$$

$$Reject\ H_0\ if\ p - value\ \leq \propto,$$

$$where \propto is\ the\ significance\ level\ at\ 1\%, 5\%, or\ 10\%$$

4.5.2 Volatility Clustering Test

Volatility clustering, also known as volatility pooling, refers to when the financial time series experience volatility in clusters. In other words, large changes in returns, either positive or negative, have the tendency to be followed by large changes and small changes in returns, either positive or negative, tend to be followed by small changes. Brooks (2014) clarifies that this phenomenon is driven by the fact that the information which impacts the prices tend to come in clusters rather than equally spread out over time. Gaunersdorfer, Hommes and Wagener (2008, p. 28) stated that "volatility clustering arises as an endogenous phenomenon, caused or amplified by the trading process itself through heterogeneity, adaptive learning, and the evolutionary interaction between fundamentalists and technical analysts".

To identify whether the series in question experience volatility clustering, this paper relies on graphing the returns and squared returns. This approach was used by many studies (see e.g. Park, Park & Ryu (2020); Papaioannou et al. (2017); Pham (2016), Sclip et al. (2016); Lahrech & Sylwester (2013) and many others).

In addition, the ARCH test determines whether an ARCH effect exists in the residuals of a financial time series. This test proves whether volatility clustering exists in a numerical matter (Papaioannou et al. 2017). When the data in question has ARCH effect, it means that there is an Autoregressive Conditional Heteroscedasticity or, in simple words, the time series experience conditional volatility. To carry out this test, we regress the weekly returns against a constant using the Ordinary Least Squares (OLS) model in Gretl. Then, this paper tests for

ARCH effect from the regression results obtained by Gretl software using the suggested lag order by Gretl. The test used for ARCH effect is called LaGrange Multiplier. The hypothesis is a per the following:

$$H_0 = the\ time\ series\ has\ no\ ARCH\ effect$$

$$H_1 = the\ time\ series\ has\ ARCH\ effect$$

$$Reject\ H_0\ if\ p-value\ \leq \propto,$$

$$where \propto is\ the\ significance\ level\ at\ 1\%, 5\%, or\ 10\%$$

4.5.3 Autocorrelation Test

The Autocorrelation test informs about the level of similarity of a certain financial time series and its past version of itself (Smith 2020). This test is crucial in determining whether we can apply GARCH model to our time series. This paper uses the Ljung-Box to test for autocorrelation in the residuals and squared residuals. This approach was used by many studies (see e.g. Park, Park & Ryu (2020); Reboredo (2018); Pham (2016), Sclip et al. (2016); Lahrech & Sylwester (2013) and many others The Ljung-Box provides a quantitative measure of the volatility clustering (Chen 2002). The formula for Ljung-Box is the following (Brooks 2014):

$$Q^* = T(T+2) \sum_{k=1}^{m} \frac{\hat{\tau}_k^2}{T-K} \sim \chi_m^2 \tag{9}$$

we apply the same methodology as stated under the ARCH effect test for the weekly returns only, however, we select the autocorrelation test from the regression results obtained by Gretl software using the suggested lag order by Gretl. With regards to the squared residuals, we first calculate the indices' squared returns and then repeat the same steps. The hypothesis for the Ljung-Box is as per the following:

$$H_0 = the\ time\ series\ has\ no\ autocorrelation$$

$$H_1 = the\ time\ series\ has\ autocorrelation$$

$$Reject\ H_0\ if\ p - value\ \leq \propto,$$

$$where \propto is\ the\ significance\ level\ at\ 1\%, 5\%, or\ 10\%$$

In conclusion, the results of the preliminary tests will dictate whether GARCH models can be used to model the data.

4.6 First Step: Selecting the Best Univariate GARCH Model

This section presents the steps that lead us to determine the best type of univariate GARCH model for modeling the volatility of each of the time series. We start off with selecting the p,q orders for the ARMA model through the ACF and PACF functions, run the regression for all possible orders for the different types of GARCH models, and lastly, select the best model out of all based on the Akaike Information Criterion.

4.6.1 Selecting ARMA (p,q) Orders

In an attempt to find the type of the univariate GARCH model, we first start off with identifying the p,q orders for ARMA. This is to examine the mean equation of the GARCH model. Selecting these orders will be determined by AutoCorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) using a statistical graph called the correlogram. The ACF presents the values of the autocorrelation of a series and its own lagged figures. It is used to determine the q order. In addition, the PACF presents the values of the residuals' correlations that moves to the next level. It determines the p order (Lahrech 2019).

In this paper we obtain the correlogram graph for GB and CB weekly returns though Gretl using maximum lag value of 24 and Barlett standard errors. The correlogram graph has upper

and lower interval bars at 95% interval. As a result, any lag that exceeds or crosses the bar and is statistically significant at 5% significance level will be taken into consideration for the ACF and PACF order.

4.6.2 Choosing the best ARMA Model

Selecting the best model depends on how much it is capturing information and reducing the loss of it. After finding the possible p,q orders for ARMA, we will use the ARIMA model in Gretl and test out all the possible models. The weekly returns of GB and CB will be the dependent variables. The selection of the best model depends on having the lowest Akaike Information Criterion (AIC). The AIC is used to evaluate multiple possible models against each other and decide which one best fits the data. It is calculated based on the number of independent variables used in the model and the maximum likelihood estimate (Bevans 2020). Then we will examine the selected model's parameters and test for white noise in its residuals (Lahrech 2019).

4.6.3 White Noise Testing

The white noise is defined as having a mean equal to zero and a static variance indicating no autocorrelation between lagged version of itself (Brooks 2014). Once we obtain the model with the lowest AIC, we need to conduct white noise test in its residuals. To do so, from the ARMA results from Gretl, we will save the residuals and plot its correlogram to examine its ACF and PACF bands. If all the suggested lag order by Gretl, 24 lags, are within the 95% interval band, then we can determine that the data has white noise. The hypothesis for white noise is:

$$H_0 = the\ time\ series\ is\ white\ noise$$

$$H_1 = the\ time\ series\ is\ not\ white\ noise$$

$$\text{Reject } H_0 \text{ if } p - value \leq \propto,$$

$$where \propto is \ the \ significance \ level \ at \ 1\%, 5\%, or \ 10\%$$

In case the best model turns out to have autocorrelation lags that are significant at 5%, we will need to run ARMA model again using the new suggested p,q orders according to the ACF and PACF until we reach the state of white noise.

4.6.4 Testing Symmetric and Asymmetric GARCH Models

Once we find our best ARMA model using AIC and check for white noise in its residuals, we move to estimating the univariate GARCH model using STATA statistical software. This paper shifts to STATA because Gretl does not incorporate the MA part of ARMA when running the GARCH model. For testing the GARCH models, this paper adopts the standard symmetric GARCH model and two asymmetric model such as GJR-GARCH and EGARCH. The formulas for GJR-GARCH and EGARCH are shown in equation (10) and (11) (Brooks 2014):

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{10}$$

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left| \frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right| \tag{11}$$

For the mean equation in GARCH and EGARCH, the best selected ARMA model from the previous steps will be used. Then, for the ARCH (q) and GARCH (p) terms, we will use the p,q orders (1,1), (1,2) (2,1), and (2,2).

When conducting the regression for the GB weekly returns, the dependent variable will remain as the GB weekly returns while inserting the best ARMA (p,q) orders under model 2 tab and continuously changing the ARCH (q) and GARCH (p) orders to the ones stated

earlier. Once the testing for the symmetric GARCH model is done, we switch to EGARCH and test again. Then, for CB weekly returns, this paper repeats the same steps.

4.6.5 Selecting the best GARCH Model

After testing the different types of GARCH models using the suggested p,q orders, just like selecting the best ARMA model, this paper relies on AIC to select the best GARCH model to be used in the DCC.

4.7 Second Step: Estimating the DCC GARCH Model Parameters

After we estimate the best GARCH model to model our data, this paper calculates the standardized residuals according to equation (6). Once we have the results, we check for the normality of the standardized residuals by assessing the skewness, kurtosis, and Jarque-Bera test.

Based on the normality results of the standardized residuals, we run the DCC-GARCH model using the STATA statistical software using either Maximum Likelihood or Quasi Maximum Likelihood. In the equation section of DCC in STATA, we add the returns of GB and CB as the dependent variables and use the p,q orders of the best GARCH model that was estimated in the previous step. After obtaining our DCC, STATA (n.d.) recommends using the Wald test to ensure that the DCC is a good fit for our data and that it does not need to be reduced to a CCC model. For the same purposes, Karanasos, Yfanti and Karoglou (2016) used this test. The command on STATA is "test _b[Adjustment:lambda1] = _b[Adjustment:lambda2] = 0" (p. 4) and the hypothesis is the following:

$$H_0 = Lambda\ 1 = Lambda2 = 0,$$

$$(the\ model\ needs\ to\ be\ reduced\ to\ CCC)$$

$$H_1 = Lambda\ 1 = Lambda2 \neq 0,$$

$$(the\ model\ does\ not\ need\ to\ be\ reduced\ to\ CCC)$$

$$Reject\ H_0\ if\ p - value\ \leq \propto,$$

$$where \propto is\ the\ significance\ level\ at\ 1\%, 5\%, or\ 10\%$$

4.7.1 Dynamic Conditional Correlations

Once we confirm that our model is better off fitted DCC, we carry forward with our analysis to predict the variances for the GB and CB and their covariance using the command "predict h2* if e(sample), variance". Then, we move towards calculating the conditional correlation using the correlation formula:

$$r_{x,y} = \frac{\sum(x_i - \bar{x})\,(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2(y_i - \bar{y})^2}} \tag{12}$$

4.8 Volatility linkages

In examining the volatility linkages, we rely on analyzing the univariate conditional variance's graphs for GB and CB. In addition, numerically, we calculate and exam the correlation coefficients of the univariate conditional variance. This method was adopted by many studies (see e.g. Hassan et al. (2018); Sclip et al. (2016); Lahrech & Sylwester (2013), and many more).

4.9 Structural Break

The time series data is said to exhibit structural break when there is a sudden change in its pattern at a certain point of time (Brooks 2014). Understanding when a structural break took place gives an insight on the behavior of the data in question. This paper adopts Chow test to determine whether our data experienced a significant change that needs to be addressed. Initially, we will need to determine the date of the sudden change in the pattern. We do so by

graphing both of the conditional variances obtained from the DCC model. Then, using Gretl,

we carry out a linear regression using OLS, select the Chow test in the regression outcome,

and insert the date of the structural break. The Chow test hypothesis is:

$$H_0 = The\ time\ series\ has\ no\ structural\ break$$

$$H_1 = \ The\ time\ series\ has\ structural\ break$$

$$Reject\ H_0\ if\ p - value\ \leq \propto,$$

$$where \propto is\ the\ significance\ level\ at\ 1\%, 5\%, or\ 10\%$$

Chapter 5: Results and Discussions

5.1 Introduction

This paper aims to answer whether a dynamic conditional correlation exists between the green and non-green bonds market. In addition, it examines the conditional volatilities of both markets looking to see if there is evidence of volatility linkages. This section presents the results and provide interpretation of the figures with discussion related to the literature. The results are presented in chronological order as stated in chapter 4.

5.2 Normality Test for the Data Set

In chapter 4, this paper adopts the Skewness, Kurtosis, and Jarque-Bera test to determine the normality of the distribution. As indicated in table 2, the skewness of the GB and its conventional counterpart are slightly negative. This means that the majority of the data is skewed to the left presenting a long tail on the left side and a fat tail on the right side of the distribution line. This is supported by the fact that the median has a slightly greater value than the mean. Moreover, with regards to kurtosis, the GB and CB have an excess kurtosis of 8.1 and 4.7, respectively, which indicate that both series have a bell shape that is leptokurtic instead of Mesokurtic. This means that investors holding GB and CB will experience irregular positive or negative extreme returns and ultimately subjecting themselves to kurtosis risk (Kenton 2019). Lastly, the *p*-value of the Jarque-Bera (1981) test for normality is statistically significant at 1%.

Since the skewness is less than zero, kurtosis is greater than three, and the null hypothesis of the Jarque-Bera test is rejected, we can conclude that the returns of both indices, GB and CB, are not normally distributed indicating that their data experience asymmetric distribution.

This finding is consistent with many studies that uses time series (see e.g. Park, Park & Ryu 2020; Reboredo 2018; Hassan et al. 2017; Lahrech & Sylwester 2013; Pham 2016; Scilp 2020, and many others). In fact, Sheikh and Qiao (2009) stated that, with financial time series, the returns are proven to be not normally distributed. It is worth mentioning that even though both do not have normal distribution, the CB was closer than GB to being normally distributed. This paper will later conduct a normality test for the standardized residuals to determine whether to use Maximum Likelihood (ML) or Quasi-Maximum Likelihood (QML) estimator.

Table 2
Normality tests of weekly returns for GB and CB indices

	Bloomberg Barclays MSCI Global Green Bond Index (GB)	Bloomberg Barclays Global Aggregate Total Return Index (CB)
Test for Normality		
Skewness	-1.1956	-0.82366
Excess Kurtosis	8.1701	4.7204
Jarque-Bera	936.047	322.862
p-value	<0.00001***	<0.00001***

Note: The *** beside *p*-values figures under the Jarque-Bera test indicates that they are statistically signification at 1%.

5.3 Preliminary Tests

This section presents the results of preliminary tests in terms of stationarity, normality, volatility clustering, autocorrelation, ARCH effect to determine whether GARCH models are applicable to both data set (Yadav 2020).

5.3.1 Stationarity Test

According to the ADF unit root stationarity test results in table 3, it is evident that the weekly prices for the GB and the CB are not stationary as the *p*-value is greater than 10%. In this case, it is said that the data has a unit root. On the other hand, using equation (8), the returns of GB and CB are stationary as the *p*-value is less than 1% significance level. The return data is now described as a one that does not have a unit root and is stationary at order 1. In fact, this is consistent with numerous studies where their raw data was not stationary and then became stationary at first order (see e.g. Park, Park & Ryu (2020); Reboredo (2018); Hassan et al. (2017); Lahrech & Sylwester (2013); Pham 2016; Sclip et al. (2016); Liow et al. 2009, and many others). In figure 7, we can also see that the returns of GB (Panel A) and CB (Panel B) have a mean that is reverting back. Brooks (2014) states that stationarity is a key feature of a time series data set that must be examined. This is due to multiple reasons. Firstly, stationarity can significantly affect the data's behavior and properties in terms of shocks' persistence. Secondly, relying on non-stationary data can lead to bogus regressions. Finally, if a regression analysis is carried out using non-stationary data, then the results will be inaccurate and result in limitations.

Table 3

Unit Root test of weekly prices and returns for GB and CB

	Bloomberg Barclays MSCI Global Green Bond Index (GB)	Bloomberg Barclays Global Aggregate Total Return Index (CB)
Augmented Dickey-Fuller (ADF) test		
Prices		
ADF statistics	0.393231	0.603894
p-value	0.9827	0.9899
Returns		
ADF statistics	-14.7892	-15.2338
p-value	<0.00001***	<0.00007***

Note: The *** beside *p*-values figures indicate that they are statistically signification at 1%.

5.3.2 Volatility Clustering Test

Figure 7, presents the time series plot for the GB and CB returns and squared returns. All graphs for both indices clearly show volatility clustering. For example, we can see that the low volatility in 2019 was followed by low volatility and the high volatility that started in the beginning of 2020 continued to be high up to April 2020. Moreover, Panel A and B are following a white noise process which means that both variables are independent, distributed with a mean equal to zero, have an identical variance, and there is no correlation with other variables in the series itself. Moreover, this conclusion is supported by the numerical test of ARCH-LM test in table 4.

It is worth mentioning that, in March 2020, both bonds indices experienced the highest level of volatility since the past six years.

The findings of this paper is also consistent with many studies (see e.g. Park, Park & Ryu (2020); Papaioannou et al. (2017); Pham (2016), Sclip et al. (2016); Lahrech & Sylwester

(2013) and many others). In fact, Cont (2007) stated that the returns of financial time series data often demonstrate volatility clustering feature.

Figure 7. Time series plot of GB and CB regular and squared weekly returns

Panel A: GB Weekly Returns

Panel B: CB Weekly Returns

Panel C: GB Squared Weekly Returns

Panel D: CB Squared Weekly Returns
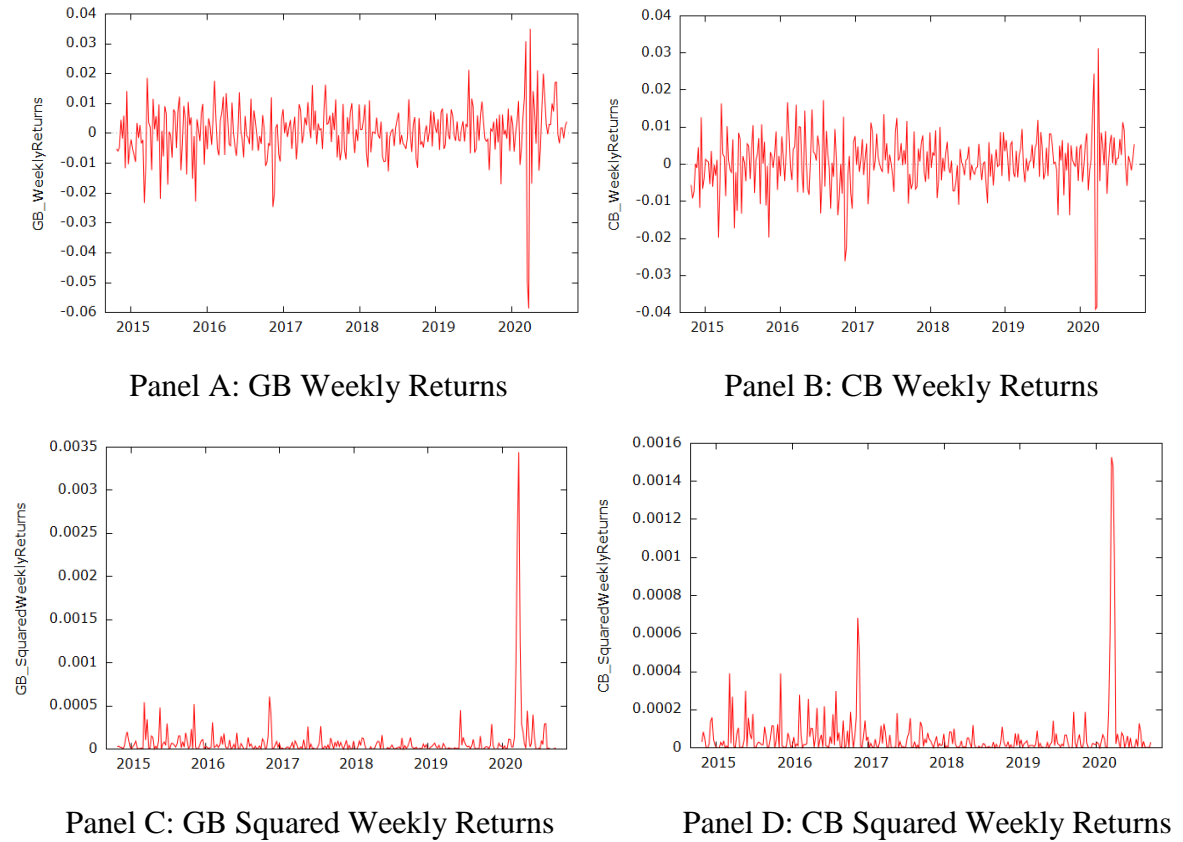
Note: The sample period 17/10/2014 to 18/09/2020. Panel A and B present the weekly returns of GB and CB while Panel C and D present the weekly squared returns.

Table 4
ARCH Effect for weekly
returns

	Bloomberg Barclays MSCI Global Green Bond Index (GB)	Bloomberg Barclays Global Aggregate Total Return Index (CB)
Test for autocorrelation		
LM for returns (14)	145.353	137.253
p-value	<0.00006***	<0.00002***

Note: The lag order 14 was used as per Gretl's suggestion. The ***, **, and * beside *p*-values figures under the Lagrangean Multiplier test indicates that they are statistically significant at 1%, 5%, and 10%.

5.3.3 Autocorrelation Test

The Ljung-Box test for autocorrelation results of the returns and squared returns are shown in Table 5. The p-value of the Ljung-Box test for the squared returns is less than 1% significance level which allows us to reject the null hypothesis of no autocorrelation in the green and conventional bonds' indices. In other words, the results provide evidence that both, the green and its non-green counterpart, experience autocorrelation at a 1% significance level. While the p-values for returns and squared returns for both bonds are statistically significant, the squared returns experienced a higher level of significance. This indicates that the returns tend to continue in increasing in terms of autocorrelation overtime showing persistency. The high level of significance of the returns and squared returns, also numerically supports the fact that both indices experience volatility clustering as discussed in the previous section. This conclusion was also found in many studies, however, there was a variation in the number of lags selected (see e.g. Park, Park & Ryu (2020); Reboredo (2018); Hassan et al. (2017); Lahrech & Sylwester (2013); Pham 2016; Sclip et al. (2016); and many others).

Table 5

Autocorrelation for weekly returns and squared returns

	Bloomberg Barclays MSCI Global Green Bond Index (GB)	Bloomberg Barclays Global Aggregate Total Return Index (CB)
Test for autocorrelation		
Ljung-Box for returns (14)	23.6132	27.3468
p-value	0.051*	0.0173**
Ljung-Box for squared returns (14)	176.365	167.853
p-value	<0.00003***	<0.00001***

Note: The lag order 14 was used as per Gretl's suggestion. The ***, **, and * beside *p*-values figures under the Ljung-Box test indicates that they are statistically significant at 1%, 5%, and 10%.

In conclusion, since the weekly returns of the Bloomberg Barclays MSCI Global Green Bond Index (GB) and Bloomberg Barclays Global Aggregate Total Return Index (CB) experience stationarity at the first order, volatility clustering, ARCH effect, and autocorrelation we can conclude that a GARCH model can be applied to model the data for both variables (Park, Park, & Ryu 2020).

5.4 First Step: Selecting the Best Univariate GARCH Model

This section will present and discuss the results of selecting the best univariate GARCH model to model our data using DCC. In the beginning, the section will start with presenting the results of the best ARMA model selection process to reach the optimal mean equation of the GARCH model. Then, using the best ARMA model, the paper will conclude what is the best GARCH model to carry out our research.

5.4.1 Selecting ARMA (p,q) Orders

As stated in chapter 4, this paper will rely on the PACF and ACF to determine the possible ARMA p,q orders for both GB and CB. With reference to figure 8, the correlogram shows

the possible PACF (p) and ACF (q) orders for the GB and CB through witnessing the bars that are crossing the 95% signification interval band. Hence, we can conclude that the possible orders for the GB are (2,2), (2,8), (8,2), and (8,8) while the possible orders for CB are (2,2), (2,4), (2,8), (8,2), and (8,8)

Figure 8. Correlogram plot of GB and CB weekly returns
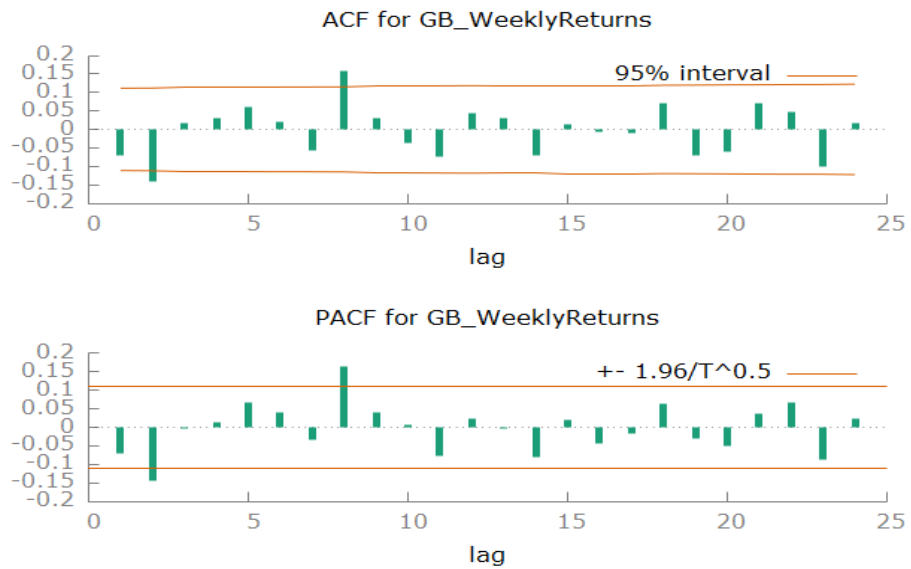
Panel A. GB Weekly Return Correlogram
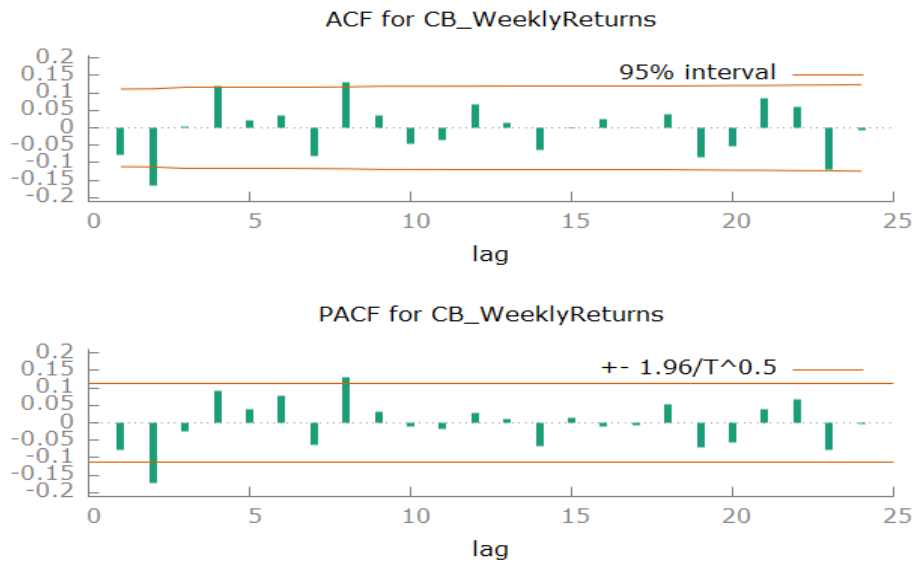
Panel B. CB Weekly Return Correlogram

Note: The maximum lag orders are 24 and the Barlett standard errors is applied. Panel A and B presents the weekly returns of GB and CB, respectively.

5.4.2 Choosing the Best ARMA Model

Table 6 presents the AIC for the possible suggested ARMA (p,q) orders. From the table, we

find that the ARMA (8,8) model for both indices, GB and CB, has the lowest AIC value.

Hence, we conclude that ARMA (8,8) best explain each index.

Table 6

Akaiki Information Criterion for each ARMA (p,q) order

	Bloomberg Barclays MSCI Global Green Bond Index (GB)	Bloomberg Barclays Global Aggregate Total Return Index (CB)
ARMA (p,q) orders		
(2,2)	-2,029.385	-2,138.897
(2,4)	N/A	-2,139.786
(2,8)	-2,027.305	-2,136.710
(8,2)	-2,024.914	-2,136.059
(8,8)	-2,035.952	-2,141.152

5.4.3 White Noise Test

The p,q orders of ARMA models are only confirmed once we ensure that model's residuals exhibit white noise (Pukkila, Koreisha & Kallinen 1990). Hence, in our case, in order to ensure that ARMA (8,8) has captured all the available information accurately in the GB and CB, figure 9 presents their correlogram to show the white noise test results on the residuals of the model. Since all bars are within the Barlett standard errors 95% interval up to 24 lags. Hence, this paper will accept the null hypothesis that the GB and CB demonstrates white noise in their ARMA (8,8) model's residuals. This means that the residuals of the ARMA (8,8) model for the mean equation in GARCH are random and independent. This conclusion is favorable as it informs us that this paper has incorporated all possible information related to the mean equation.

Figure 9. Correlogram plot of GB and CB ARMA (8,8) Residuals.
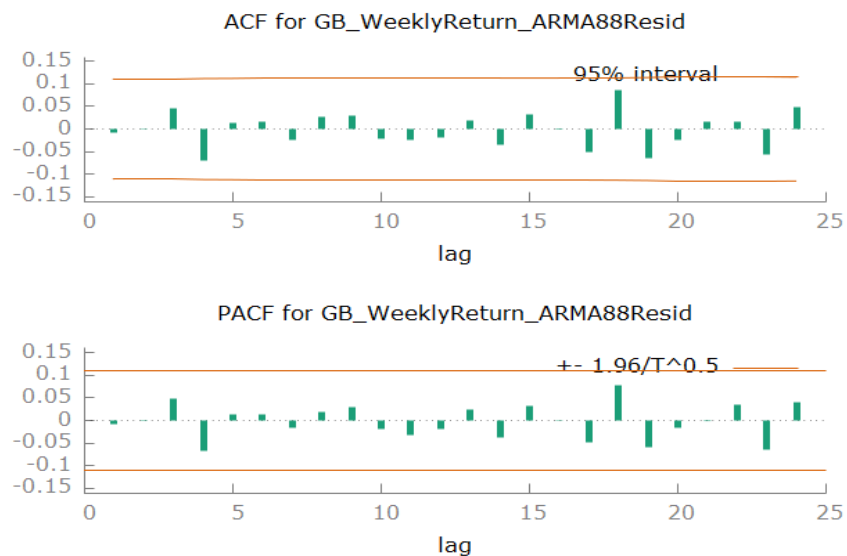
Panel A. GB Weekly Return ARMA (8,8) Residuals
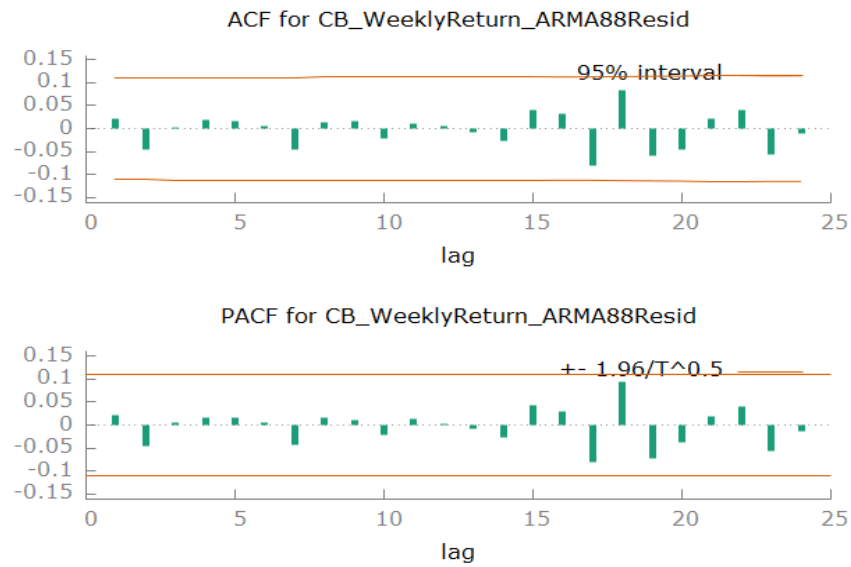
Panel B. CB Weekly Return ARMA (8,8) Residuals

Note: The maximum lag orders are 24 and the Barlett standard errors is applied. Panel A and B presents the ARMA (8,8) residuals of GB and CB, respectively.

5.4.4 Testing Symmetric and Asymmetric GARCH Models

As stated in chapter 4, this paper will attempt finding the best GARCH model that will best fit our data. Table 7 presents the AIC for each ARMA (8,8)-GARCH, GJR GARCH, and EGARCH (p,q) orders.

Table 7
Akaiki Information Criterion for each ARMA(8,8)-GARCH models

(p,q) orders	Bloomberg Barclays MSCI Global Green Bond Index (GB)			Bloomberg Barclays Global Aggregate Total Return Index (CB)		
	GARCH	GJR-GARCH	EGARCH	GARCH	GRJ-GARCH	EGARCH
(1,1)	-2114.106	-2113.865	-	-2198.130	-2204.033	-2181.481
(1,2)	-2127.157	-	-	-2205.780	-2205.118	-
(2,1)	-	-	-	-2192.290	-	-
(2,2)	-	-	-	-	-	-

5.4.5 Selecting the best GARCH Model

Based on the AIC's lowest value from table 7, the best GARCH model to examine the volatility of the GB and CB is the standard symmetric GARCH model. The selection of the GARCH model rather than the asymmetric GJR ang EGARCH is consistent with Pham (2016) who found, through asymmetric leverage effects test, that the two indices of the labeled and unlabeled green bond and the conventional bond index do not exhibit asymmetric features. However, with regards to the green bond market, our findings are inconsistent with Park, Park, and Ryu (2020) who found that the green bond market exhibits asymmetric volatility characteristics. On a side note, Hassan et al. (2018) who did not conduct a study related to the green bonds or conventional bonds but rather on Sukuk found that fixed income markets do not exhibit asymmetric features.

Moreover, we find that the GARCH with (1,2) p,q orders. This result is inconsistent with Pham (2016), where she concluded that based on, Schwartz Information Criteria, the optimal mean equation is the one without any lags and the volatility equation adopts GARCH (1,1) order. It is worth mentioning that since we selected the GARCH model, then we are assuming that the negative and the positive shocks have the same impact on the GB and the CB (Lahrech 2019).

Table 8 presents the conditional mean and the conditional variance coefficients for GB and CB. For the GB, we notice that the coefficients of the mean equation are statistically significant at 1% and 5% except for the 6th lag of the autocorrelation process in the mean equation. Moreover, the coefficients in the conditional variance equation all are statistically significant at 1%. In fact, since the ARCH term value, denoted by α_1, is positive and statistically significant at 1%, it indicates that the GB's volatility has a certain level of

sensitivity to market events (Sclip et al. 2016). In other words, we can say that, on average, the lags of shocks positively affect the variance of the GB.

For the CB, it is evident that the coefficients in the conditional mean equation are all statistically significant at 1% and 5%. In addition, the coefficients for the conditional variance equation are all statistically significant at 1%. In the ARCH term value, denoted by α_1, also indicate that the lags of shocks positively affect the variance of the CB.

Looking at the coefficients of GB and CB for α_1 side by side, we can see that GB has a higher value than CB. This indicates that GB is more sensitive and has higher reaction to the market events than the CB does. On the other hand, the coefficients of β_1 for GB and CB shows that GB has a lower value than CB. This indicates that GB exhibit less persistence in its conditional volatility than CB does. This was not completely the case in Pham (2016) where the GB had a higher value in its ARCH and GARCH terms than CB indicating that GB experience higher volatility than CB.

Table 8
Univariate ARMA(8,8)-GARCH(1,2) Model

	Bloomberg Barclays MSCI Global Green Bond Index (GB)		Bloomberg Barclays Global Aggregate Total Return Index (CB)	
	coefficients	p-value	coefficients	p-value
ω	0.0006698	0.108	0.0010051	0.010***
φ_1	-0.8328972	0.000***	-0.7877518	0.000***
φ_2	-0.1958702	0.002***	-0.2271889	0.000***
φ_3	0.5020018	0.000***	0.4777806	0.000***
φ_4	0.9422896	0.000***	1.015241	0.000***
φ_5	0.480309	0.000***	0.4763743	0.000***
φ_6	-0.0805075	0.183	-0.1282118	0.031**
φ_7	-0.7548911	0.000***	-0.6950092	0.000***
φ_8	-0.8638138	0.000***	-0.8490662	0.000***
θ_1	0.7776581	0.000***	0.7075635	0.000***
θ_2	0.1339162	0.012**	0.1456486	0.010***
θ_3	-0.5664265	0.000***	-0.5468919	0.000***
θ_4	-0.849186	0.000***	-0.9239395	0.000***
θ_5	-0.4074386	0.000***	-0.3543759	0.000***
θ_6	0.1573356	0.001***	0.2721098	0.000***
θ_7	0.7625208	0.000***	0.7062902	0.000***
θ_8	0.9057791	0.000***	0.8667424	0.000***
ω	0.000000367	0.561	-0.000000071	0.831
α_1	0.3902874	0.000***	0.2803102	0.000***
α_2	-0.3796948	0.000***	-0.2830357	0.000***
β_1	0.9821066	0.000***	1.003189	0.000***

Note: ω is for the constant, φ_i is for the AR, θ_i is for MA, α_i is for the ARCH terms, β_1 is for the GARCH terms. The *** and ** next to the coefficients' *p*-value figures indicate that they are statistically significant at 1% and 5%, respectively.

5.5 Second Step: Estimating the DCC GARCH Model Parameters

5.5.1 Normality Test for Standardized Residuals

Based on our best selected model for GB and CB, we calculate the standardized residuals according to equation (6) and test them for normality. Table 9 shows the standardized residuals normality test.

Table 9

Normality Test for the standardized residuals

	Bloomberg Barclays MSCI Global Green Bond Index (GB)	Bloomberg Barclays Global Aggregate Total Return Index (CB)
Test for Normality		
Skewness	-0.054753	-0.16809
Excess Kurtosis	0.49288	0.26756
Jarque-Bera test	3.29271	2.38447
p-value	0.192752	0.303542

Since the skewness is very close to zero, kurtosis is almost equal to 3, and, most importantly, the null hypothesis of normal distribution in the Jarque-Bera test is accepted for GB and CB, we can conclude that the returns of both indices, are normally distributed. In this case, this paper will carry forward in estimating the DCC-GARCH model using the Maximum Likelihood estimator.

5.5.2 DCC-GARCH Model Results

The DCC-GARCH results suggest that between GB and CB are presented in table 10. By looking at the results, we find that the ARCH and GARCH terms for the GB and CB are all statistically significant at 1%. This indicates that the DCC-GARCH model captures the univariate GARCH model extremely well.

Moreover, we find the DCC parameters, α and β, are fulfilling the DCC conditions in having a value that is greater than zero and a sum that is equal less than 1. The alpha parameter informs us about the GB's reaction to a shock in the CB and vice versa whereas the Beta parameter informs us about the persistency of the volatility following a shock. In table 10, we find the α parameter is positive and is statistically significant at 1% significance level.

This informs us that the standardized residuals from the periods before are persistent. In other words, we can say that there is a short-term volatility spillover between GB and CB. This result is consistent with Reboredo (2018) who found strong evidence of spillover between the green and conventional bonds markets. The β parameter is almost zero and is not statistically significant. This means that the persistency of a shock in both markets relative to other is low and fades away quickly. The result of this paper is somehow inconsistent with Pham (2016) who found that both parameters to be statistically significant and was able to conclude that there is evidence of time-varying conditional correlation between the green bond and the conventional bond market.

Table 10
DCC-GARCH (1,2)

	Bloomberg Barclays MSCI Global Green Bond Index (GB)		Bloomberg Barclays Global Aggregate Total Return Index (CB)	
	coefficients	p-value	coefficients	p-value
ω	0.0008187 (0.0003768) 0.3505426	0.030**	0.0007707 (0.0003356) 0.2697797	0.022**
a_1	(0.0669162) 0.3410849	0.000***	(0.0551323) 0.247534	0.000***
a_2	(0.063134) -0.8872776	0.000***	(0.0430488) -0.5851797	0.000***
b_1	(0.0497543)	0.000***	(0.123407)	0.000***
Correlation (GB, CB)	0.9227338	0.000***		
DCC Parameters				
α	0.3174347	0.000***		
β	0.0890062	0.480		
Log-Likelihood Function	2464.863			

Note: ω is for the constant, a_1 and a_2 are for the ARCH terms, b_1 is for the GARCH terms. The *** and ** next to the coefficients' *p*-value figures indicate that they are statistically significant at 1% and 5%, respectively. The amounts in the brackets are the standard errors.

Moreover, this paper conducts the Wald test to check whether the DCC model needs to be reduced to CCC for better analysis. The results in table 11 allows us to reject the Wald test's null hypothesis at 1% and conclude that the CCC model would be too restrictive to model our data. This result is consistent with Karanasos, Yfanti and Karoglou (2016)'s finding who then carried on their research using DCC.

Table 11

Wald test for DCC

	DCC-GARCH(1,2)
Chi-square test	23.40
p-value	0.0000***

Note: *** indicates significance level at 1%

5.5.3 Dynamic Conditional Correlations

Based on the DCC estimated model, this paper moves forward with estimating the conditional correlations values between GB and CB. Table 12 and figure 10 present the conditional correlations descriptive statistics and graph, respectively.

This paper finds the conditional correlations between GB and CB are time-varying, positive, and are on the high side. The highest conditional correlation was on 13th March 2013 with a value of 0.988 and the lowest was on 5th May 2017 with a value of 0.622. On average, the conditional correlation is at 0.923. Moreover, we find the conditional correlations between GB and CB are not normally distributed (Jarque-Bera test) and do exhibit heteroskedasticity (ARCH-LM test).

Table 12

Summary statistics of Dynamic Conditional Correlations

	Dynamic Conditional Correlation
Descriptive Statistics	
Mean	0.92319
Median	0.93161
Minimum	0.62155
Maximum	0.98823
Standard Deviation	0.046171
Jarque-Bera test	2470.1
p-value	0***
ARCH-LM test	4.38585
p-value	0.0362***

Note: *** indicates 1% significance level.

Figure 10. Dynamic Conditional Correlation between GB and CB
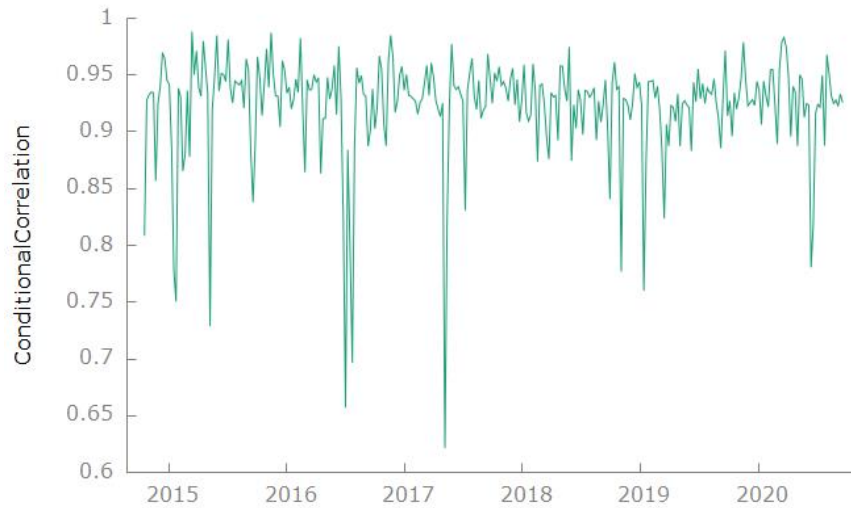
5.6 Volatility Linkages

In figure 11, the conditional variance from the univariate GARCH (1,2) model for GB and

CB is presented. In this figure, we can see that GB is more volatile than CB. Moreover, the

figure demonstrates how both variables experience volatility at the same time indicating a

certain level of co-movement between the two markets. This is also consistent with Pham (2016). Moreover, using a different methodology, Reboredo (2018) found that the green bond market experience co-movements with the conventional one. In fact, this co-movement is explained by Broadstock and Cheng (2019) who found that both markets are sensitive to the same macroeconomic factors. This finding also supports our usage of the DCC model in our analysis.

We must note that there is an unprecedent volatility shock in March 2020 that was not witnessed over the past 6 years. This is most likely attributed to the stressing time of the COVID-19. In fact, Hassan et al. (2018) found that, when a stressful event takes place, the security prices become drastically more volatile as many investors tend to sell what they consider as being less liquid and buy a safer and more liquid securities.

In addition to the graphical analysis, we examine the volatility linkages between GB and CB in a numerical manner using the pairwise correlation tool on the univariate GARCH conditional variances. This paper concludes that, on a global level, the conditional variance of the GB and CB experience high and strong positive correlation at a value equals to 0.922. This means both markets experience volatilities during similar periods. This could be attributed to the fact that the green bond is a submarket of the broader one. This result informs us that investing in both assets will not yield diversification benefits. This finding is consistent with Roberedo (2018). Lahrech and Sylwester (2013) stated in these cases investors lose the chance to minimize their risks. Hence, we can conclude that they cannot be included in the same portfolio.

Figure 11. Univariate GARCH (1,2) Conditional Variance Plots
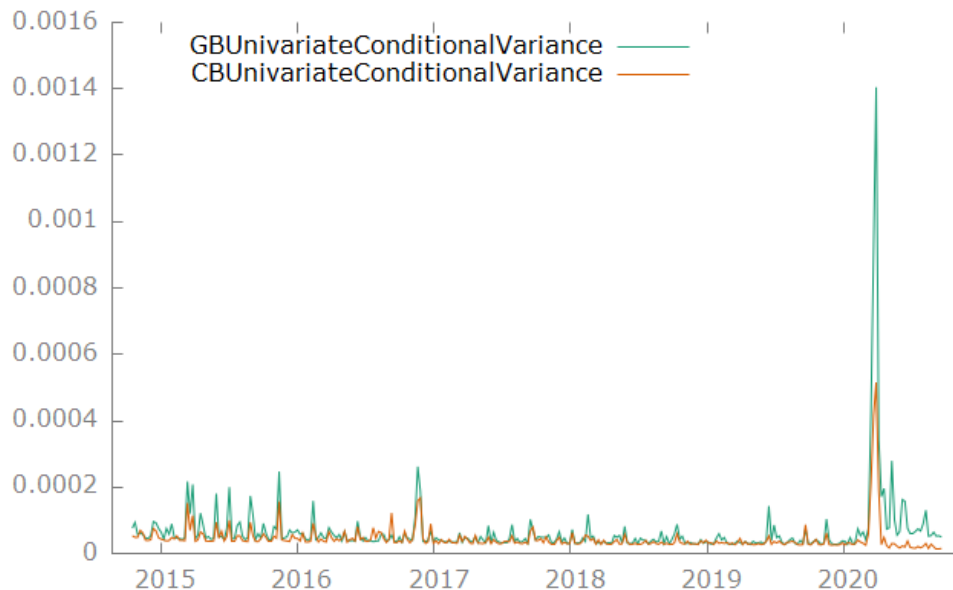
Note: The green line represents GB and orange line represents CB.

5.7 Structural Break

If we look closely at the returns (figure 7) or the conditional variance graphs (figure 11), it is noticeable that, from the end of January 2020 till June 2020, GB and CB started experiencing volatilities. In fact, there was a sudden change in the pattern during March 2020, more specifically, the 27th March 2020 which was never witnessed at any point over the past six years. This is due to the COVID-19 pandemic and the increased of cases forcing many countries to start lockdown. The lockdowns, known as The Great Lockdown, created the world's worst economic state since The Great Depression of 1928 (IMF 2020). The Chow test results of the conditional variance for GB and CB are presented in table 13. The p-value of the F-statistics allows us to reject the null hypothesis of no structural break and conclude that on 27th March 2020 a structural break took place.

Table 13

Structural break test for GB and CB

	Bloomberg Barclays MSCI Global Green Bond Index (GB)	Bloomberg Barclays Global Aggregate Total Return Index (CB)
Test for stuctural break		
Chow test	15.1948	5.9587
p-value	0.0001***	0.0152***

Note: *** indicates statistically significant at 1%

5.8. Summary of the findings

The data of the global indices do not exhibit normal distribution. Moreover, they show that they are stationary at the first order of integration and appear to have volatility clustering. Hence, a GARCH model was applied to model the volatility. This chapter found that GB and CB were best explained by an ARMA (8,8) for the mean equation of the GARCH model and concluded that their residuals exhibit white noise. Then, the chapter tested different orders and different symmetric and asymmetric GARCH models and found that, based on AIC, GARCH (1,2) model is the best fit for the variance equation. Running the ARMA (8,8)-GARCH (1,2), the results showed that GB is more sensitive and has higher reaction to market events than CB does. In addition, GB exhibit less persistency in its conditional volatility than CB does. Moreover, the DCC-GARCH showed while there is short-term volatility spillover between GB and CB, the persistency of a shock in both markets relative to the other is low and fades away quickly. In addition, this chapter found evidence of time varying, positive, and strong conditional correlation between GB and CB and experience volatility linkages. Lastly, there was a structural break for both indices on 27th March 2020.

The results of this section allows use to reject our null research hypothesis and conclude that

investing in both bonds at the same time will not yield diversification benefits.

Chapter 6: Conclusion

6.1 Introduction

Driven by the importance to adhere to the Paris Agreement in combating climate change and the ever-growing awareness of having sustainable economies, market participants are now tapping into the green bond market more than ever before. With 51% growth from 2018 to 2019, many leading asset management entities are joining the green bond market and are becoming part of organizations that pressure companies to reduce their $CO2$ emission. The rapid growth the green bond market is witnessing called for an immediate and extensive research on its comparability with the conventional market. This paper aimed at analyzing both markets to answer its main question: "On a global level, do green bond market experiences time-varying conditional correlation with conventional bond market?"

In carrying out this research, the paper relied on green bond and conventional bond market global indices to represent each market. The Bloomberg Barclays MSCI Global Green Bond Index (GBGLTRUU) was selected to represent the global green bond market and the Bloomberg Barclays Global Aggregate Total Return Index (LEGATRUU) was selected to represent the global conventional bond market. The data used was the weekly prices of both indices obtained from Bloomberg. The time frame of the data was for six years from 17th October 2014 till 18th September 2020 making a total of 310 observations.

6.2 Summary of the Study

The first chapter is the introduction. It started by providing a background of the study and discussing the main characteristics of the green bond market. Then, the chapter addressed the significance of the study. Afterwards, this chapter identified the aim and objectives of this

paper. Next, it stated the research questions of this paper. Lastly, it listed the structure of the thesis.

The second chapter provided an overview of the green bond market. Firstly, the chapter began with the historical information of the green bond market. Secondly, it discussed the four Green Bond Principles (GBP). Thirdly, the chapter conducted SWOT analysis of the green bond market. Lastly, it provided the current state of the green bond market by presenting the top 15 leading countries and its current statistics compared to the previous years.

The third chapter focused on presenting the literature review. In the beginning, the chapter presented multiple research studies that were related to comparing green to conventional bonds. Then, the chapter introduced the general framework of the GARCH model and its extension the multivariate GARCH model. Afterwards, it presented studies that analyzed the dynamic conditional correlation using the DCC MGARCH model. Lastly, the chapter states the research hypothesis and gap.

The fourth chapter, presented the econometric methodology that this paper followed to answer the research questions. In the beginning, the chapter thoroughly discussed how the DCC Multivariate GARCH model works. Then, it described the data, introduced the two indices used in this paper, and presented the descriptive statistics of our data. Afterwards, it stated the preliminary tests required to carry out the analysis. Next, the chapter thoroughly described the methodology to find the first of the DCC MGARCH model. Lastly, it thoroughly described the second step of the DCC MGARCH model.

The fifth chapter presented the results following the same chronological order as mentioned in the methodology. In the beginning, it presented the results from the preliminary results.

Then, it presented the results and provided detailed discussion for DCC's first step. Next, the chapter presented the results and conducted detailed discussion for DCC's second step. Lastly, it provided a summary of the findings.

6.3 Summary of the Findings

This study is looking at understanding whether a dynamic conditional correlation exists between the green bond and the conventional bond markets on a global level. Based on the methodology adopted, this paper found that both indices do not exhibit normal distribution. In addition, through several tests, the study concluded that the GB and CB are stationary at the first order and exhibit volatility clustering indicating that a GARCH model is applicable to model the data for both indices. Through several steps, this paper found that GB and CB were best explained by an ARMA (8,8)-GARCH (1,2). The results showed that GB is more sensitive and has higher reaction to market events than CB does. In addition, GB exhibit less persistency in its conditional volatility than CB does.

Then, from the estimation of the univariate GARCH model, this paper found that the estimated standardized residuals to be normally distributed and, hence, this paper proceeded with using Maximum Likelihood function in the DCC model. The findings from the DCC model showed that the α and β parameters are both greater than zero and their sum is less than 1. The alpha parameter was statistically significant indicating, on a global level, a short-term volatility spillover between GB and CB. However, the beta parameter was not statistically significant and almost zero in value indicating that, on a global level, the persistency of a shock in both markets relative to the other is low and fades away quickly. The appropriation for using DCC rather than CCC model to model the data was supported by rejecting the Wald test's null hypothesis and concluding that CCC would be too restrictive

to model the variables. This paper found that, on a global level, the conditional correlation between GB and CB are time-varying, positive, and are on the high side with an average of 0.923. Moreover, this paper found that both indices experience co-movements and volatility linkages meaning they both experience volatilities during similar periods. Lastly, we note that there was a change in the volatility pattern during March 2020 resulting in a structural break. The Chow test confirmed that the structural break took place on the 27th March 2020 which represents the time when majority of the countries started their lockdowns. In conclusion, this paper state that investing in both bonds at the same time will not provide diversification benefits.

6.4 Implications and Recommendations

This paper has multiple implications on market participants and policy makers. First of all, this study provides investors and portfolio managers with the required information to understand how the two financial instruments work together. Hence, investors and portfolio managers would be to make educated decisions when it comes to constructing optimal diversified portfolios. Secondly, this paper allows portfolio managers to consider risk management practices based on the analysis of the GB and CB's conditional volatilities. Thirdly, with the exponential growth the green bond market is witnessing, this paper provides market participants with information related to the characteristics of the newly established market. This paper will in turn acts as a foundation when it comes to deciding on whether to allocate funds in the green bond market or not.

Based on the findings, this paper does not recommend investors to hold both types of bonds at the same time. This is due to the fact that both bonds, on a global level, exhibit strong positive time varying conditional correlation. Hence, investing in GB and CB at the same

time will not yield diversification benefits. Moreover, at this stage, this paper recommends investors who are interested in adding green bond to their portfolio to do so with a level of caution. This is because the green bond market is relatively new with lots of uncertainties and is experiencing a higher level of volatility over the past six years compared to its counter-part.

With that being said, due to the importance of the green bond market in maintaining and achieving sustainability goals, the paper recommends and encourages governments and policymakers to establish regulations that aim towards lowering the risks associated with the Green Bonds market. Doing so, could result in having a more engaging market that reduces the higher level of volatility and provide a more stable economic diversity. Lastly, this paper recommends policymakers to establish policies, regulations, and practices that aims at increasing the differentiating strategies the green bond market and the conventional bond market in order to attract wider range of investors to the green bond market.

6.5 Limitations of the Study

This paper encountered few limitations due to the fact that the green bond market is still in its emerging phase. Firstly, there was very limited number of studies that studied the characteristics of the green bond market's volatility. Secondly, the studies that compared the green bond market to the conventional bond market were done on their issuing convenience, pricing difference, premiums, and yield spreads. This in turn made comparing the results of this paper to previous literature very limited. Thirdly, the time frame of this study is only for six years of weekly data limiting this paper to 310 observations. Lastly, this paper did not take into consideration any micro or macroeconomic factors that might have impacted the findings.

6.6 Future Research Suggestions

This paper suggests several research topics that can be carried out in the future. First, this paper suggests extend this study to cover longer period of time to allow taking into consideration the impact of different economic factors on green bonds performance. Secondly, this paper can also be extended to include macroeconomic factors as explanatory independent variables in the DCC model to note any changes in the findings. Thirdly, this paper recommends comparing the volatility of the green bond market and the conventional bond market in the UAE as it is the only country in the MENA region that has been recognized as one of the top 15 leading countries in issuing Green Bonds. Lastly, this paper suggests conducting a study to examine whether a dynamic conditional correlation exists between green bonds and green sukuk given the fact that Green Sukuk that are governed by Sharia laws.

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