UNIVERSITY OF VAASA

SCHOOL OF ACCOUNTING AND FINANCE

Viet Nguyen

HOW IMPLIED VOLATILITIES IN ENERGY SECTOR, CRUDE OIL AND STOCK MARKET AFFECT THE PERFORMANCE OF GREEN BOND?

Evidence from green bond market

Master`s Thesis in
Finance

Master's Degree Program in Finance

VAASA 2020

TABLE OF CONTENTS

TABLE OF FIGURES AND TABLES

ABBREVIATIONS

ARCH	Autoregressive Conditional Heteroskedasticity
CBOE	The Chicago Board Options Exchange
CBOT	Chicago Board of Trade
DJIA	Dow Jones Industrial Average
ESG	Environmental, Social, and Governance
ETF	Exchange Traded Fund
EVZ	EuroCurrency volatility index
FXE	EuroCurrency ETF
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GB	Green bond
GBP	Green Bond Principles
GVZ	Gold ETF volatility index
ICMA	International Capital Markets Association
OLS	Ordinary Least Squares regression
OVX	CBOE Crude oil ETF implied volatility index
SRVIX	CBOE Interest rate swap volatility index
TYVIX	CBOE/CBOT 10-year U.S. Treasury note volatility index
VIF	Variance Inflation Factors
VIX	CBOE Implied volatility index
VXN	CBOE Nasdaq 100 implied volatility index
VXXLE	CBOE Energy sector ETF implied volatility index
XLE	Energy Select Sector Index

UNIVERSITY OF VAASA
School of Accounting and Finance
Author: Viet Nguyen
Topic of the thesis: How implied volatilities in energy sector, crude oil and stock market affect the performance of green bond? Evidence from green bond market
Degree: Master of Science in Economics and Business Administration
Master's Programme: Finance
Supervisor: Jussi Nikkinen
Year of entering the University: 2015
Year of completing the thesis: 2020
Number of pages: 74

ABSTRACT

This study investigates the connection between the green bond and implied volatility indices from different financial markets such as energy, crude oil and stock market. More specifically, the study examines how these uncertainties from energy market (VXXLE), crude oil (OVX), and stock market (VIX) affect the performance of green bond where the performance is measured as returns. Since most of the green bond indices started to be computed in 2014, the sample period starts from October 2014 to January 2020.

The results of employed OLS regression models confirm the significant impact between green bond returns and VIX in majority of the models. Interestingly, the findings reveal that a negative linkage between OVX and green bond returns exists. However, the negative OVX-green bond relation is insignificant when the regression model is performed separately from other markets while it is barely statistically significant when considering two or more volatility indices simultaneously, with the uncertainty in energy and stock markets. This finding could indicate that the US VIX has a signaling effect and impact on OVX and suggest that the uncertainty could flow from the stock market to the crude oil market volatility. Furthermore, the results show that the VXXLE has only significant effect on green bond returns when considering individually and simultaneously with the OVX. The regression model 7 is also estimated with the GARCH(1,1) specification and show significant results suggesting that the volatility shocks are quite persistent and a large excess return value of not only positive but also negative will lead future forecasts of the volatility to be high for a prolonged period, for example in the periods of high volatility. Overall, the empirical findings show that VIX has the most significant effect on the green bond returns. However, the effect is quite small and considered as weak since the impact on green bond returns ranges between 0.4% and 0.5% when VIX increases by 1 percentage point suggesting that the volatility in fixed-income market might explain stronger effect and impact on the green bond performance and returns.

KEY WORDS: Green Bond, VIX, VXXLE, OVX.

1. INTRODUCTION

Green bond market has experienced an enormous annual growth of 50% since 2007. For instance, the European Investment Bank was the first multilateral development institution to issue a green bond (i.e. climate-awareness bond) with a value of 1 billion US dollars in 2007. The World Bank issued a second green bond in order to finance climate mitigation and adaption projects in its countries of operations, a year after. Ever since then, commercial banks, municipalities, and a few of the world’s largest corporations have followed closely in the same direction. The Paris Climate Agreement in 2015 had also its part to boost and moving financial resources to a climate-resilient economy by encouraging the interest among investors in alternative financial opportunities related to green projects and divestment from fossil energies. In 2017, the issuance of green bond has grown enormously from 1 billion US dollars in 2007 to 895 billion. In turn in the Nordic region, MuniFin is the most active Finnish bond issuer in international capital market, and also a first-ever green bond issuer in Finland where the MuniFin issued its fourth green bond in its history in 2019 worth 500 million euros with maturity of 10 years. In 2014, the total amount of green bond issuance was USD 36.6 billion. This volume more than tripled its previous year's level of USD 11 billion. This new market will lead to the growing demand of investors for financial investments that are beneficial not only environmentally but also economically. Thus, it is important to obtain a better understanding of the risk and return relationship of the market as the green bond market continues to grow. (Banga 2019; Reboredo 2018; MuniFin 2019; Pham 2016.)

As innovative financial instruments, the green bonds are novel fixed-income debt instruments to finance environmentally sustainable investments such as renewable energy, water and energy efficiency, sustainable waste management, sustainable land use, bio-energy, low carbon transports, and climate change adaption. (German Development Institute 2016.) For instance, many investors have begun to include climate change risk assessments into their investment strategies in a constant growth (Byrd & Cooperman 2018).

1.1. Purpose of the study

This study aims to extend the research and to provide further analysis on the suggested theme from the previous study of Pham (2016). More specifically, the goal of this study is to find answers to the research question that how uncertainty from different financial markets could affect to the performance of green bonds. In addition to the previous description, the research is motivated by the current awareness of climate change issues, recent growth in the trend of ESG and socially responsible investing which have increased the interest in alternative investment opportunities among investors. Previous study from Reboredo (2018) investigates the dependence between green bond market, stock market and energy commodity market using one green bond index, global stock market index (MSCI World Index) and S&P GSCI Energy Spot CME Index finding that green bonds tend to move weakly with the other financial markets but highly with the fixed-income markets. The purpose of this thesis is to study the relationship between green bonds and implied volatility indices in order to find results on how the uncertainty from different financial markets, including energy, crude oil, and stock markets, influence the green bond's performance measured as returns. Finally, this study intends to fill the gap of the novel research theme in green bonds since it is considered as a new fixed-income asset class which is growing and important for the current global economy and academic research and might bring new ideas for assessing risks related to green bonds.

1.2. Research hypotheses

As previously mentioned, since the continuous growth of green bond market, it is important to comprehend the market's risk and return behavior as suggested in the prior research from Pham (2016). Based on the literature on flight-to-quality phenomenon and prior studies, for instance, from Connolly, Stivers & Sun (2007) and Steeley (2006) relating to the negative relationship between stock-bond co-movements of return and implied volatility and stock-bond volatility relations, the expectation is that there is a negative or an inverse relationship between green bond returns and volatility indices.

The forthcoming hypotheses are formulated and motivated by the previous studies related to volatility analysis in green bond market and the relationship between different asset class returns such as stock indices and implied volatilities from Simon (2003), Giot (2005), Hibbert, Daigler & Dupoyet (2008), and Daigler, Hibbert & Pavlova (2012). Therefore, the first hypothesis is formed as follows:

H1: VIX has an impact on green bond return

The next hypothesis is formed based on the previous study that investigates the dependence between the green bond and financial markets. According to Reboredo (2018), dynamics in the energy market could affect the green bond's performance by influencing the environmentally friendly projects' economic viability which are funded by the returns gained from the green bonds and by the certain risks related to sudden changes in the energy prices:

H2: VXXLE has an impact on the green bond return
H2a : Both VXXLE and VIX simultaneously have an impact on the green bond return

According to the study from Nikkinen & Rothovius (2019), both OVX and VIX together are able to explain a huge proportion (69%) of the variability in energy sector uncertainty in which OVX has a larger role. In turn, Dutta (2018) finds adding VIX is vital because uncertainty could possibly run from the US VIX to volatility series of both crude oil and energy market. In addition, Dutta (2017) finds that renewable energy is significantly sensitive to uncertainty of oil price. In order to test the H3, H3a, H3b, and H3c the alternative hypotheses are formed as the following:

H3: OVX has an impact on the green bond return
H3a: Both VIX and OVX together have an impact on the green bond return
H3b: Both VXXLE and OVX affect the green bond return
H3c: VIX, VXXLE, OVX simultaneously have an impact to the green bond return

1.3. Contribution

The main contribution of this study is to show whether the implied volatility (the uncertainty) from different financial markets have an impact on the performance of the green bond. The performance is measured as returns. Again, as previously mentioned, the other intended contribution is also to provide further analysis of green bond's return-volatility relation in order to extend the previous literature from Pham (2016) and Reboredo (2018). Furthermore, the contribution of this study uniquely investigates the return-risk relation by including daily data of closing prices of MSCI Green Bond Index and various implied volatility indexes such as uncertainty in the energy sector, VXXLE, the US VIX representing the market wide uncertainty, and the crude oil market OVX, respectively. Lastly, this study limits to the chosen data and the time period.

1.4. Structure of the study

This study consists of a theoretical and an empirical part. The research is divided into eight chapters where the first briefly introduces to the study including the background, main purpose, hypotheses development, and the intended contribution. The second chapter provides further analysis of the literature review based on the previous studies. Chapter 3 and 4 present the theoretical framework of both conventional and green bonds, and different volatilities. Chapter 5 describes the range, formats, and sources of the data whereas chapter 6 presents the methodology used in this research. Empirical results are reported and analyzed in chapter 7. Finally, chapter 8 draws a conclusion for the study of this thesis in which the results are briefly presented and suggestions on a possible future research are introduced.

2. PREVIOUS STUDIES

Since the green bond research and theme are quite novel and in a constant growth, the most recent studies are briefly introduced in this chapter. In addition, the subsections summarize the most recent studies relating to green bonds and various studies of volatilities in different financial markets, and relationship between returns and volatilities.

2.1. Volatility of green bond market

According to Pham (2016), his paper is the first to analyze the green bond market's volatility behaviour by employing data on the S&P green bond indices' daily closing prices starting from April 2010 to April 2015. His empirical results based on the multivariate GARCH framework indicate that the green bond market's 'labeled' segment experiences large volatility clustering whereas the pattern of volatility clustering is considered weaker in the market's 'unlabeled' segment, respectively. In addition, the findings show that in the aggregate conventional bond market a shock tends to spillover into the market of green bond, where the spillover effect changes time to time. Thus, these results provide significant insights into this novel, growing, and promising market showing remarkable influences on the asset pricing, portfolio and risk management.

2.2. Stock market reaction to green bond issuance

Baulkaran (2019) studies the reactions in the stock market related to the green bond issuance announcements. The research results show that the cumulative abnormal returns are significantly positive. These findings suggest that shareholders consider this source of financing as value-enhancing where the funds gained from the green bond issuance are used to engage profitable green projects or risk mitigation purposes. Moreover, the regression analysis indicate that a negative investor reaction is observed among green bonds with higher coupon rates. For instance, the cumulative abnormal returns are positively linked with firm size, Tobin's Q, and growth, whereas a negative relationship is found between the cumulative abnormal return and operating cash flow, respectively. The value-enhancing feature of funds received from the green bonds show to be consistent with the firm growth in terms of the positive coefficient.

2.3. Green and conventional bonds, financial and energy markets

Banga (2019) studies the green bond market's potential as a source of climate finance for developing countries. His findings suggest that in developed and emerging countries, the green bonds are growing supported by the investors' increased climate-awareness. For developing countries, the full potential is considered as underappreciated since the market has remained in the early stages. For instance, the results indicate that the key barriers to the green bonds' development are the lack of appropriate institutional arrangements for management of green bond, the issuance's minimum size, and high transaction costs linked with green bond issuance. In the paper, he suggests the possible solutions as the efficient utilization of multilateral and national development banks as intermediary institutions for the management of local green bond. In order to deal with the previously mentioned challenges, the results suggest that the local governments need to support local green bond issuers by covering the high transaction costs linked with the issuance of green bonds.

Hachenberg & Schiereck (2018) study the potential price differences between green bond and conventional (non-green) bonds by matching daily i-spreads of green-labeled with the corresponding non-green-labeled bonds. More specifically, their interest drift to the question whether green bonds, as the new asset class, could possibly offer an attractive risk-return profiles in comparison to the conventional bonds. Their results show that AA-BBB rated green bonds as similar to the full sample trade barely tighter during the corresponding period in comparison to the respective issuers of non-green bonds. Additionally, financial and corporate bonds are considered to trade tighter compared to the equivalent non-green bonds whereas government bonds trade slightly broader. Finally, their results suggest that neither currency, nor issue size or maturity show significant impact on the pricing differences but rather industries such as government-related and financial issuers as well as ESG issuer ratings.

Reboredo (2018) investigates co-movement between the green bond and several financial markets such as stock and energy commodity markets. He finds that the green bond market closely follows with the corporate and Treasury bond markets. In contrast, the green bond market however weakly co-moves with the energy commodity and stock markets. For investors in the corporate and Treasury markets, the green bonds appear to have insignificant diversification advantages. However, benefits from diversification are remarkably targeted for investors in the energy and stock markets. The research results show that price spillovers from the corporate and Treasury fixed-income markets significantly affect the green bonds whereas the green bond prices are not impacted by the large price fluctuations in the energy and stock markets.

2.4. Energy sector, crude oil and stock market uncertainty

Risks related in the energy sector have been in the research interest for decades due to their fundamental value for global markets, societies and environment (Nikkinen & Rothovius 2019). According to their empirical results, the R^2 of their model is 69% showing that both crude oil (OVX) and stock market uncertainty (VIX) together are able to explain a large proportion, more than two thirds, of the variability in the energy sector uncertainty (VXXLE).

Earlier study from Dutta (2017) uses implied crude oil volatility (OVX), as a proxy for oil price uncertainty with oil, carbon price and renewable energy stock returns. He finds that crude oil price uncertainty runs to renewable energy and further concludes that renewable energy is extremely sensitive to oil price volatility. Thus, these results confirm economic theory that uncertainty can be highly contagious and spread between markets, in this situation to the renewable energy equities. Liu, Ji & Fan (2013) examine short- and long-term cross-market uncertainty transmission implied by OVX and other volatility indexes such as stock market (VIX), euro/dollar exchange rate (EVZ), and gold

(GVZ), respectively. Their results show that the OVX is significantly affected by other market volatilities indicating that investors' volatility expectation in the crude oil market becomes more sensitive to uncertainty shocks from other markets during periods when the global economic condition is supremely unstable. Moreover, Maghyereh, Awartani & Bouri (2016) investigate the connection between oil and equities in eleven major stock exchanges globally in the time period between 2008 and 2015. Their findings indicate that the relationship between equity markets and crude oil is found due to bi-directional information spillovers between the two markets. In turn, Dutta (2018) examines whether uncertainty in the market of crude oil has an impact on the US energy sector market's volatility using the corresponding implied volatility indexes. The results show that a long-run relationship between the implied volatilities in the crude oil and stock market exists. In contrast, the causality test also indicates the existence of short-run linkages between the implied volatilities in the international crude oil and the US energy sector stock markets.

2.5. Relationship between return and implied volatility

Simon (2003) examines the Nasdaq volatility index, VXN, during the period including both the inflation of the Internet bubble and its bursting. The findings indicate that the VXN appears to have a strong asymmetrical reaction to positive and negative index returns, as similar to the findings of previous studies of implied volatility. Giot (2005) studies the relationships between implied volatility indices (VIX and VXN) and stock index returns. More specifically, the S&P 100 and Nasdaq 100 represent the stock indices whereas the VIX and VNX are the volatility indices. The results confirm that there is a negative and statistically significant connection between the stock returns and implied volatility indices. For long positions, there is also some evidence of expectations on forward looking positive (negative) returns which are triggered by the implied volatility indices' supremely high (low) levels.

In turn, Hibbert et al. (2008) investigate the short-term dynamic linkage between the returns of S&P 500 (Nasdaq 100) index and changes in the implied volatilities at the daily and intraday level. The findings indicate that the results are not sufficiently explained by the leverage and volatility feedback hypotheses. In addition, the findings suggest that the traders' behavior is consistent with the empirical results of a strong daily and intraday negative relationship between return and implied volatility. Further, the results show that the negative relation between return and implied volatility is most closely related to large changes in the index returns where the strength of the relationship is coherent with the skew of implied volatility.

Finally, Daigler et al. (2012) compare the connection between return and volatility for the euro currency to the corresponding relation for the equity market by investigating the sign, symmetry, and strength of the relationship. They use the euro-currency exchange-traded fund (FXE) and its related option implied volatility index (EVZ) since prior studies only use equities and/or realized volatility. For the equity study, findings indicate a negative asymmetric return-volatility relationship for implied volatility with a strong relation during periods of extreme market fluctuations. In contrast, the results indicate that for the euro-currency the return-volatility relationship is weak and asymmetric, with either a positive or negative sign. All in all, these findings expand the original concept which was limited to equities. For instance, the results show that the relationship between return and implied volatility is surprisingly weaker than expected and in some occasions, the euro-currency is shown to have positive asymmetric returns.

3. BONDS

In this chapter, the theoretical framework of conventional and green bond is introduced. Since the existence of wide range of different bond securities in the aggregate bond market and different factors affecting to the bond's price, this thesis is only focusing on the conventional bonds such as notes, Treasury and corporate bonds and briefly describing the main characteristics relating to bond pricing. The main bond pricing features include coupon, interest rate, maturity, and par value of the bond. In the first section with its subsections, the basic idea of the bond and its features, bond types, and a brief description of bond pricing are determined. Later, a new fixed income asset class of green bonds, credit rating agencies and their ratings are presented.

3.1. Characteristics of bond

A bond is a debt security issued with borrowing arrangements. The borrower of bond issues, or in other words, sells a bond to its lender (i.e. holder) for a certain amount of cash. The bond holder receives specified payments which are known as coupon payments on predetermined dates required by the bond arrangements. For instance, an ordinary coupon bond issuer is obligated to make semi-annual interest payments to the bondholder for the life of the bond. The interest payments are determined by the coupon rate of the bond. At the end of the bond's life, the issuer pays back the debt to the bond holder in bond's principle (which is also known as its par value or face value). The annual interest payment is calculated as the bond's par value times the coupon rate. Overall, main features that are included in the bond contract between the bond issuer and holder are the coupon rate, face value of the bond, and maturity date. Generally, bonds are issued with coupon rates set just high enough to attract investors to pay the face value when buying the bond. However, a zero-coupon bond is issued without the coupon payments. In this scenario, an investor will receive the par value at the due date of the bond but without the interest payments until maturity date. Thus, this bond has a zero-coupon rate and is issued at the price below its par value. In addition, the return of investor is only based on the difference between the issue price and the payment of face value at maturity. (Bodie, Kane & Marcus 2011: 426.)

3.1.1. Treasury bonds, notes and corporate bonds

Bonds can be distinguished in to different types based on their time to maturity. For instance, the maturity for a Treasury note ranges between 1 and 10 years whereas Treasury bonds are issued with time to maturity ranging from 10 to 30 years. These are also known as long-term bonds and traded in the fixed-income market. Respectively, short-term debt securities are known as Treasury bills maturing in a year or less. (Bodie et al. 2011: 426; Brealey, Myers & Allen 2016: 48.)

Both Treasury notes and bonds make coupon payments semi-annually. In addition, they are purchased from the Treasury in their face value of 100 US dollars but commonly the par value is 1000 US dollars. Despite of the denominations of 1000 USD, the bond's bid and ask prices are quoted as a percentage of the par value. The bid price which is known as the price that the bond can be sold to a dealer. The ask price is slightly however higher and is the price where the bond can be bought from a dealer, respectively. (de La Grandville 2001: 17.)

Corporations are able to borrow money through bond issuance as the government. Some of these bonds are traded on the NYSE Bond platform but majority of them are traded on over-the-counter market. This market includes a computer quotation system linking a network of bond dealers. Practically, the bond market may be slightly narrow since there are few investors interested in trading a certain issue in regardless of time. The corporate bonds share similar characteristics as the government bonds and are rated for their creditworthiness by the bond-rating agencies such as Moody's, Standard & Poor's, and Fitch. More specific details of credit ratings are presented later in the subsection of this chapter. As previously mentioned, the characteristics for the corporate bonds are price, coupon, and time to maturity. (Bodie et al. 2011: 427–428.)

3.1.2. Bond pricing

Bond's coupon and principal payments all occur months or years in the future. An investor who would be willing to pay for a claim to these payments depends on the bond's price and its dollar value to be received in the futures compared to the dollar value today. This feature related to bond pricing is called as present value which depends on market interest rates. The interest rate can be separated into nominal and real interest rates. For instance, the nominal interest rate equals the sum of a real interest rate and a premium above the real rate to compensate for expected inflation. The market interest rate is also known as the discount rate. Since most bonds are not riskless, the discount rate will include an extra premium. This premium is based on the bond related risk factors such as default risk, call risk, tax attributes, and liquidity. For simplicity, the theoretical bond price can be calculated by using one interest rate to discount cash flows of any maturity. However, in practice it is worth noting that there may be different discount rates for cash flows in various time periods. In order to value a debt security such as a bond, the expected cash flows are discounted by the appropriate discount rate. The bond's cash flows include coupon payments until maturity date and the final payment of par value. Thus, the theoretical bond value can be calculated as follows in equation 1. (Bodie et al. 2011: 432–433.)

$$\text{Bond value} = \sum_{t=1}^{T} \frac{\text{Coupon}}{(1+r)^t} + \frac{\text{Par value}}{(1+r)^T} \tag{1}$$

where

∑ = sum of coupon payments from time t to T

T = maturity date

r = interest rate

In addition to the previous, the first term on the right-hand side of equation 1 is called as the present value of an annuity or annuity factor whereas the second term is called the present value factor of the final payment of the bond's par value. Therefore, the price of the bond can be calculated as in the equation 2 below.

(2) $$\text{Bond price} = \text{Coupon x } \frac{1}{r}\left[1 - \frac{1}{(1+r)^T}\right] + \text{Par value x } \frac{1}{(1+r)^T}$$

Before ending the first subsection of the chapter 3, some additional noteworthy considerations are described as follows. Overall, there are many factors that may affect to fluctuations in the price of the bond. To name a few important variables that may play a significant role in the variation of the bond's price are, for example, the negative relationship between bond price and yield to maturity relating to changes in the interest rates, the convexity based on the sensitivity on the fluctuations in the interest rates, the duration relating to bond's various payments in terms of time to maturity, inflation, and the term structure of interest rates as known as the yield curve. As previously mentioned in the beginning of this chapter, this thesis mainly focuses in giving a brief description of the theoretical background on bond's characteristics, types and its pricing but does not take the risk management issues of the bond into account on the fixed-income market. For broader knowledge of the previously described variables, the following literature in question is available in Brealey et al. (2011: 46–75).

3.1.3. Credit rating agencies and credit ratings

Credit rating agencies assess credit ratings in order to determine credit risk. There are three largest and best-known, i.e. the Big Three, credit rating agencies in the international markets which are Standard & Poor's (S&P), Moody's, and Fitch Group. Credit rating agency's task is to evaluate the corporations' creditworthiness by issuing a credit rating for their bonds. Banks also make their own credit ratings but, however, these credit ratings are not as public as the credit rating agencies. (Hull 2015: 544.)

The corporations will benefit from these credit ratings on the global financial markets when selling their bonds to investors. The higher the corporation's credit rating, the more attractive and safer investment, investors consider the corporation's bonds. For instance, when the corporation acquires financing with a high credit rating, it is in a more favorable situation compared to the corporation with a lower credit rating. In terms of favorable, it means that the corporation has an opportunity to borrow at lighter terms, for example, with a lower interest rate compared to unfavorable, where it has higher borrowing costs, respectively. (Bodie et al. 2011: 449.)

Table 1 below presents credit ratings from two major credit rating agencies. The Standard & Poor's determine its credit ratings with signs of plus and minus whereas the Moody's highlights its corresponding ratings by numbers from 1 to 3 in which the number one is the best, respectively. Top four classes, starting from BBB (the Standard & Poor's) and Baa (the Moody's) moving up belong to the class of investment grade. For investors, these classes have low credit risks. Classes below the investment grade are called as speculative classes which are also known as junk bonds or high yield loans, due to their higher credit risk. In practice, loans with a speculative credit rating will lead to an increased financial risk. For instance, in 2009 the corporations whose bond's credit ratings were in the speculative class, faced payment difficulties, which played one of the major roles in the global financial crisis. However, defaults in payments do not necessarily mean bankruptcy since it is not caused solely on payment difficulties. For example, the situation may also be that the corporation has not managed to cope with its interest payments or it might have drifted into debt restructuring which is known as "Chapter 11" in the United States. (Knüpfer & Puttonen 2014: 157–159.)

Table 1. Credit ratings from Standard & Poor's and Moody's (Knüpfer & Puttonen 2014: 157).

Moody's	**Standard & Poor's**	**Description**
Aaa	AAA	The highest credit rating where corporation's solvency is extremely strong in paying its loans and interest rates.
Aa (1,2,3)	AA (+/-)	Corporation has strong solvency to pay off its loans and interest rates, but is quite riskier compared the top class.
A (1,2,3)	A (+/-)	Corporation has a good chance of meeting its debt obligations. However, negative changes in the economy and environment can weaken its solvency.
Baa (1,2,3)	BBB (+/-)	Corporation has solvency in normal conditions. However, negative changes in the economy and environment might risk its solvency.
Ba (1,2,3) B (1.2,3) Caa (1,2,3) Ca (1,2,3)	BB (+/-) B (+/-) CCC (+/-) CC (+/-)	Corporation's current solvency is speculative. Corporation's current solvency is vulnerable. Corporation's solvency is currently poor. Corporation's solvency is currently very poor.
C (1,2,3) D	C (+/-) D	Corporation is approaching or close to bankruptcy. Corporation is not able to meet its payment obligations.

3.2. Green bonds

Green bonds, also known as climate bonds, are considered to be relatively a new fixed income asset class that share similar characteristics as the conventional corporate and government bonds related to pricing and rating. However, the speciality of green bonds which differs them from the conventional bonds is that their returns are tied by the issuer for projects with environmental benefits linked with a climate friendly and sustainable economy. In January 2014, the publishment of Green Bond Principles (GBP) by the International Capital Markets Association (ICMA) is to set rules for a bond to be labeled as green. This enables investors to distinguish the environmental benefits of the fixed income asset classes over alternative investments since the establishment of the GBP. (Reboredo 2018.)

According to the Climate Bonds Initiative (2017), the difference between labeled and unlabeled bonds supported by the GBP, encouraged for a significant growth in green bond issuance which increased from 3 billion USD and 11 billion USD in 2012 and 2013, respectively, to 37 billion USD in 2014, 43 billion USD in 2015, and 81 billion USD in 2016. Still, green bonds represent less than 1% of the bond market regardless of rapid growth of the green bond market. Furthermore, green bonds show to have a relatively small fraction, approximately 17%, of unlabeled climate-aligned bonds.

The main focus of the green bonds is on funding renewable energy project consisting of 45.8% of the issuance in 2015 and allocating in energy efficient projects of 19.6%, low-carbon transport of 13.4%, sustainable water projects of 9.3%, and waste and pollution projects of 5.6%. The primarily issuers of green bonds locate in private sector entities, for example, corporations, public sector entities such as national and local government or a state entity, and supranational entities, for instance, the World Bank, and the European Investment Bank. Moreover, the average maturity of the green bonds is between 5 and 10 years and are issued mostly in currencies of US dollar and euro. (European Commission 2016.)

The green bonds are considered to become as a well-established sustainable investment instruments and gaining popularity among environmentally-conscious market participants such as investors. In addition, the investors' interest in green bonds are also thriving from the awareness of the potentially significant influence caused by the climate change through government policies and corporations that encounter climate related risks. For instance, in 2015, under the Paris Climate Agreement which globally obligated a broad set of countries to shift to a climate-resilient economy. Thus, the green bond market is expected to boom by attracting the interest of diverse issuers and a wide range of investors such as mutual and pension funds, insurance corporations, small and medium-sized institutions, and individual investors. For example, various stock exchanges around the world, in Italy, London, Luxembourg, Mexico, Oslo, Shanghai, and Shenzhen, have established certain segments of green bond market in purpose to boost this market. Moreover, the contribution of previously mentioned market segments is the willingness to improve liquidity, transparency, and green bonds' reputation as a start to scale up the requirement of financial resources for greening the global economy. (Reboredo 2018.)

In order to reflect the price dynamics of the broad set and increasingly large universe of green bonds, various green bond indexes were developed. According to Reboredo (2018), there are currently four global green bond indices in which each has its own methodology and criteria in adding bonds in components of the corresponding index. All of the four green bond indexes were launched around in 2014 since most of the indexes started to be computed after the publication of the GBP. The providers of the green bond indexes are Bloomberg Barclays MSCI, the S&P Dow Jones, Solactive AG, and the Bank of America Merrill Lynch.

Figure 1 below presents the dynamics of the four green bond indices. It can be seen that all of the four indices closely follow with each other and show to have similar temporal patterns in terms of volatility with upturns and downturns from 2016 moving forward and during 2015.

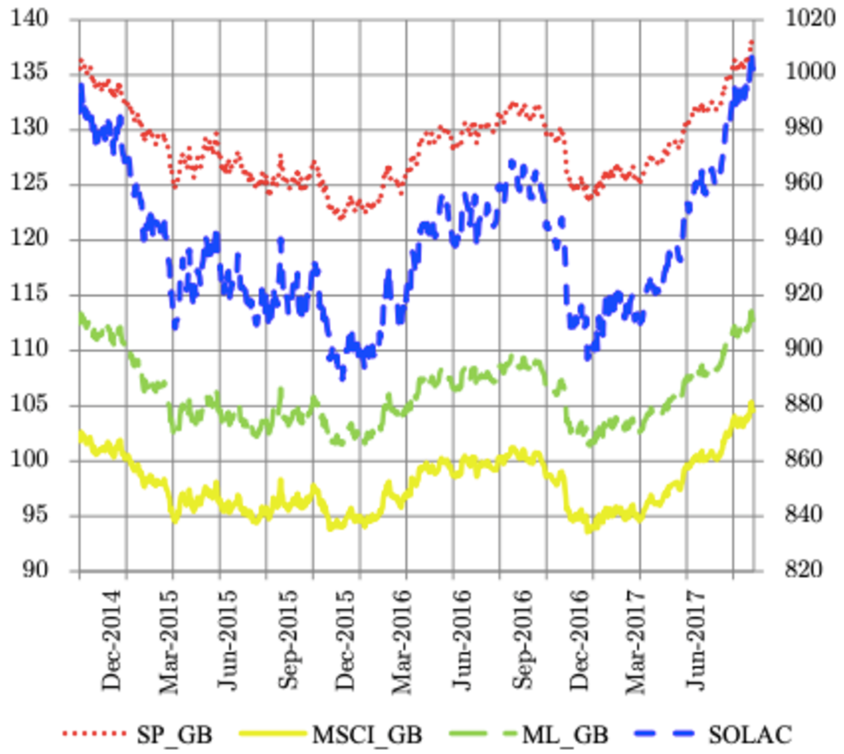

Figure 1. Daily green bond price indexes from October 2014 to August 2017. The prices of SOLAC are on the right axis (Reboredo 2018).

3.3. Bloomberg Barclays MSCI Green Bond Index

The Bloomberg[1] Barclays MSCI Green Bond Index offers investors a robust and objective measure of the global market for fixed income securities issued in a purpose on funding projects relating to direct environmental benefits. This index is defined as a multi-currency market value-weighted benchmark and is consisting of corporate, government-related and securitized bonds which are labeled as green by the MSCI ESG Research including of alternative energy, energy efficiency, green building and climate adaption, pollution prevention and control, and sustainable water. In addition, the index includes fixed rate coupon payments. Furthermore, the index was launched in November 2014, calculated in US dollars, and is rebalanced monthly. However, it does not

[1] Bloomberg is known as a global leader in fixed income indexing whereas MSCI is the world's largest ESG (environmental, social and governance) provider in equity indexes and research. They both have collaborated and introduced a new family of Green Bond Indices. (Bloomberg MSCI, 2019.)

have a 1-year minimum as time to maturity and bonds are held until final due date of maturity. (Bloomberg MSCI 2017; Reboredo 2018.)

As previously mentioned, the four green bond indices show to follow closely with each other and show same features in temporal patterns in terms of volatility with downturns and upturns during 2015 and from 2016 moving forward. Therefore, this study focuses only on one green bond index, the Bloomberg Barclays MSCI Green Bond Index, due to the similarities in terms of co-movements with other green bond indices.

4. VOLATILITY

In this chapter, the theoretical backgrounds of different volatilities are described. First, the definition of volatility is explained following to the presentation of implied volatility and the popular VIX index which estimates the future expected volatility in the market. Even though the VIX index is the most widely quoted measure for volatility, there are also available for several other stock markets and their volatility indices globally. For instance, the stock market index of UK known as the FTSE 100 Index and its volatility index of FTSE 100 VIX Index, DAX and VDAX in Germany, respectively. Moreover, these volatility indices reach out to different markets such as crude oil, and energy sector. Therefore, the volatility indexes of crude oil and energy sector and stock-bond volatility relations are briefly introduced in the latter part of this chapter.

4.1. Definition of volatility

The volatility of a variable, denoted as σ, is defined as the standard deviation of the return of a market variable such as equity and commodity prices, interest and exchange rates provided by the variable per time unit when the return is expressed using continuous compounding. Generally, the unit of time is one year for volatility in option pricing. Thus, the volatility is the standard deviation of the continuously compounded return per year. However, the volatility used in risk management is measured in one day as the unit of time. Therefore, the volatility is defined in this case as the standard deviation of the continuously compounded return per day. More specifically, the volatility, e.g., of a stock is a measure of market participants' uncertainty on the future stock returns. The volatility of the stocks typically ranges between 15% and 60%. In addition, the volatility tends to be much higher on trading days compared to nontrading days. Thus, nontrading days are not included in the calculations of volatility. (Hull 2018: 213, 239; Hull 2015: 325.)

In equation 3, the value of a variable, e.g. a stock, S_i at the end of day i and its continuously compounded return per day for the stock on day i is defined as the following:

(3) $$\ln\left(\frac{S_i}{S_{i-1}}\right)$$

This is slightly similar to equation 4:

(4) $$\frac{S_i - S_{i-1}}{S_{i-1}}$$

For an alternative definition for the daily volatility of a variable is thus the standard deviation of the proportional change in the variable during a day. This alternative definition is commonly used in the risk management. (Hull 2018: 214.)

4.2. Implied volatility

Generally, risk managers calculate volatilities from historical data. However, they also try and keep track on implied volatilities. For instance, the volatility of the underlying asset price, a stock price, is a parameter which cannot be directly observed in the Black–Scholes–Merton option pricing model. Therefore, the implied volatility of an option is the volatility giving the option's market price due to substitution into the pricing model. The implied volatilities are used in order to follow up the market's opinion about the volatility of a specific stock. Historical volatilities reflect the past whereas the implied volatilities are forward looking. (Dumas, Fleming & Whaley 1998; Canina & Figlewski 1993.)

4.3. VIX index

The Chicago Board Options Exchange's (CBOE) innovation of VIX, is an index, similar to the Dow Jones Industrial Average (DJIA), calculated in real-time basis throughout each trading day. However, the VIX index differs from the DJIA index as it measures the volatility but not price. The VIX index is known as the most popular index. More specifically, this index is formed by the implied volatility of 30-day options on the S&P 500 calculated from a wide range of calls and puts. The first trades in futures contract on the VIX started in 2014 whereas trading in options on the VIX begun in 2006. However, the CBOE have calculated the implied volatilities since January 1986, but in its current form of the VIX started in 2003. Volatility is regularly traded by investors. For instance, by trading options on the S&P 500 is a bet on the future level of the S&P 500 and also the volatility of the S&P 500. But, a futures or options contract on the VIX is a bet only on the future market volatility over the next 30 calendar days, respectively. The definition for one contract is on 1,000 times the index. (Whaley 2013; Whaley 2009.)

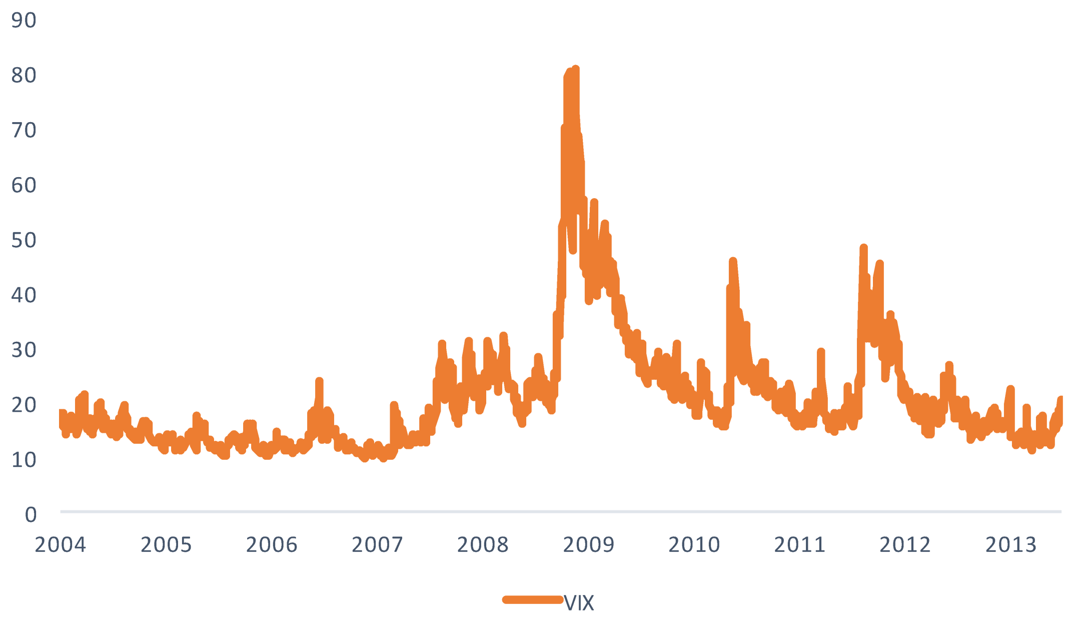

Figure 2. The VIX index from January 2004 to June 2013.

The VIX index is also known as the fear index as it measures the investor uncertainty. Figure 2 above shows the VIX index from January 2004 to June 2013. Between 2004 and mid-2007, the VIX index remains stable ranging between 10% and 20%. However, the index reaches 30% during the second half of 2007 and a record high 80% in October and November 2008 due to the aftermath of global financial crisis and the Lehman's bankruptcy. In the early 2010, the index corrects back to the normal level, but rapidly increases again as the spikes reach in May 2010 and the second half of 2011 due to stresses and uncertainties in the financial markets. (Brealey et al. 2011: 565; Hull 2015: 342.)

4.4. Energy sector and crude oil volatility

Since oil is considered as an important production input for the global economy, variations in oil price could bring uncertainty by impacting the aggregate economic development and growth (Dutta 2018). According to Vo (2011), an increase in oil price levels will lead to higher production costs by affecting inflation, consumer confidence, and thus economic growth.

Globally, several of the world's largest corporations reach in the energy sector such as Royal Dutch Shell, Exxon Mobil, and even the smallest can be found in the top 20 of the Fortune 500 corporations. Thus, understanding the energy sector and oil price uncertainties are important and inevitable since these risks play a large role in the overall economy. For instance, the importance of acknowledging these uncertainties' dynamics and sources that the energy and crude oil markets encounter are not only for the corporations themselves but also for investors in managing the corresponding uncertainties and hedging against risks within the sector. For measuring the uncertainty in the industry of energy and crude oil, the CBOE published implied volatility indexes of VXXLE and OVX, respectively. Next, the previously mentioned volatility indices are briefly introduced. (Nikkinen & Rothovius 2019.)

4.4.1. VXXLE index

The implied volatility index of VXXLE is published by the CBOE on March 16, 2011 and is formed by the options market prices on Energy Select Sector Index (XLE) Exchange Traded Fund (ETF). This index includes large energy sector companies, for example, Chevron Corporation, Exxon Mobil, Schlumberger NV, and Conoco Phillips. Therefore, the implied volatility index of VXXLE measures the future stock price uncertainty of the energy sector companies, specially, the market's expectation of 30-day volatility. (Ruan & Zhang 2019; Nikkinen & Rothovius 2019; Dutta 2018.)

More specifically, the XLE index follows closely a market-cap-weighted index of US energy companies in the S&P 500. This index is considered as the first and currently the largest energy ETF worth of $13.76 billion assets under management. The XLE index was launched in December 1998 for the possibility to offer liquid exposure to the large oil and gas industries with low holding costs. However, the trading volume of XLE options were slightly low during the first six years from December 1998 but became highly active since 2005. In 2019, the average daily dollar volume for XLE is $792.38 million. During the time period between 2005 and 2016, the average trading volume was approximately 46,000. Similar to the VIX index, the VXXLE is also considered as an important indicator as the investor fear index in energy equity investments. (Ruan & Zhang 2019.)

4.4.2. OVX index

Crude oil volatility index, OVX, is a measure for uncertainty in the crude oil market and is considered as a new volatility derivative published by the CBOE during the global financial crisis in 2008. This first crude oil index tracks the market's expectation of 30-day volatility of crude oil prices by the well-known methodology, from the CBOE Volatility Index to options on the Oil Fund of United States, consisting a wide range of strike prices. The Oil Fund of the United States is an exchange-traded security intended to follow up crude oil price changes. More specifically, the procedure is practically done by holding cash and short-term futures contracts where the performance of the Fund is designed to track, as near as possible, the spot price of West Texas Intermediate light, sweet crude oil, less the expenses from the United States Oil Fund. (Liu et al. 2013.)

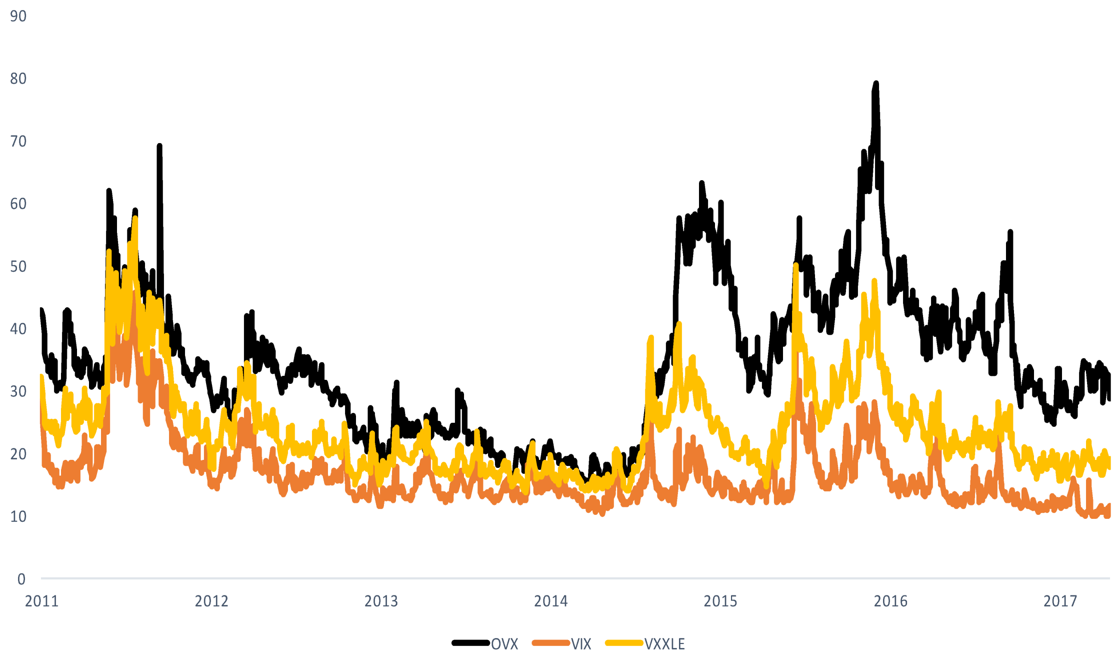

Figure 3. Volatility indexes from March 2011 to June 2017.

Figure 3 above presents the previously introduced volatility indexes of VIX, VXXLE, and OVX. A positive correlation and co-movement can be seen between the three volatility indexes. Furthermore, the graph shows several major upward movements which seem to be a consequence of either economic or political events. The first spike appears during the beginning of 2011 and can be considered due to the political crisis in the Middle East as a result of a remarkable increase in the oil price uncertainty. The second spike occurs in August 2011 relates to the US and European debt default risk. Also, several spikes are observed in the VIX of crude oil market in the period between 2015 and 2016. During the 2015–2016 period, the oil industry is in a downturn and thus an increase occurs in the oil volatility index. The consequences behind the turmoil might be in connection with the strong US dollar, declining demand, oversupply of crude oil or nuclear deals in the Middle East during the period 2015–2016. (Dutta 2018.)

4.5. Stock-bond volatility relation

In general, bonds are considered as safe asset classes based on the assumption that theoretically the government or a country cannot go bankrupt. In light with this assumption, the bonds can be seen as less risky assets compared to the stocks suggesting that the bond volatility is lower in comparison to the stock volatility. The assumption and theory are consistent with the findings from Johnson & Young (2004) showing that during the 30-year period of the study for Swiss market, the stock market volatility has averaged about four times higher than the bond market. Moreover, the results from Schwert (1989, 1990) and Reilly, Wright & Chan (2000) show that for the U.S. market, the average stock volatility is nearly three times higher in comparison to the bond market. However, Johnson & Young (2002) indicate that for the UK market the stock market volatility is slightly less, only about twice higher compared to the bond market.

Connolly et al. (2007) find that the co-movements of cross-country stock returns tend to be stronger (weaker) as a result of days of high (low) implied volatility and on days that experience large (small) changes in the implied volatility. In contrast, co-movements of stock-bond returns tend to be significantly positive (negative) as a result of days of low (high) implied volatility and on days that encounter small (large) changes in implied volatility. These findings seem to be rational since the higher the risk or volatility the more investors look for safe assets. This is known as the flight-to-quality phenomenon where investors shift their capital out from high-risk investments into less risky investments, such as U.S. Treasury bonds specially during the periods of increased uncertainty. For instance, Huang, Wu, Yu & Zhang (2015) suggest that the previously described flight-to-quality hypothesis is supported by their results indicating that some investors raise their U.S. Treasury bonds holdings at times of confronting increased political uncertainty.

Johnson & Young (2004) find that the bond market volatility to stock market volatility ratio in Switzerland has been grown in terms of long-term trend. Still, this trend is considered negligible. In some occasions, the volatility of bond market draw close to the volatility of stock market. However, bond market volatility had only a small share compared to stock market volatility in several time periods. This could suggest that the stock market-bond market volatility relation is supremely unstable. Additionally, the finding is supported by the results of large fluctuations in the beta and correlation coefficients associated with the bond and stock market returns. For instance, many beta and correlation coefficients are negative, during the periods of late 1970s and 1980s, and early 2000s, showing an inverse relationship between bond returns and stock returns. Even though prior researchers have shown that the US bond market volatility has grown in relation to the volatility of stock market, the findings are however different in terms of the markets in Switzerland. Finally, the results suggest that it is unsafe in assuming that trends in market volatility are same or universal in the developed countries' securities markets.

5. DATA

This chapter presents the data used in the empirical research of this thesis. The first subsection of data focuses on describing the data, their formats, range, and sources. Later, the descriptive statistics are introduced.

5.1. Data

The data for the Barclays MSCI Green Bond Index is gathered from Bloomberg whereas the data for various volatility indices are collected from Datastream (Thomson Reuters). This thesis uses daily closing prices for the overall dataset to be comparable and thus there is no need for major adjustments. As previously mentioned, The Bloomberg MSCI Green Bond Index is used as it serves as a tool to follow closely the performance of increasingly large green bond universe and its market. The green bond index allows investors to compare the green bond's returns and volatility with alternative investments. Furthermore, the daily closing prices of different market volatility indices, such as VIX as a measure of the US stock market uncertainty, VXXLE as an indicator of the uncertainty in the energy sector, and OVX representing the uncertainty of crude oil market, are included.

Again, since many green bond indices started to be computed mostly after the GBP's publication, time series of the dataset of daily closing prices start from October 2014 to January 2020 including 1384 observations and the selected time period is matched with the data of volatility indices in order to ensure that they are comparable.

The daily data of closing prices for green bond index and volatility indices are transformed by taking a natural logarithm. In order to transform daily closing prices of green bond index to daily log returns, the formula is formed as the following:

(5) $$\mathrm{R}_{\mathrm{GB,t}} = \ln\left(\frac{\mathrm{GB_t}}{\mathrm{GB_{t-1}}}\right)$$

where

$R_{GB,t}$ = Daily natural log return of green bond index from day t-1 to day t
GB_t = Price of green bond index at day t
GB_{t-1} = Price of green bond index at day t-1

whereas daily natural log changes are obtained by closing prices of variable *i* such as volatility indices (VIX, VXXLE, OVX) by the following formula:

(6) $$\Delta V_{i,t} = \ln\left(\frac{V_{i,t}}{V_{i,t-1}}\right)$$

where
$\Delta V_{i,t}$ = Natural log change in daily closing price of variable i from day t-1 to day t
$V_{i,t}$ = Price of a variable i at day t
$V_{i,t-1}$ = Price of a variable i at day t-1

The data transformations above are performed for simpler idea in interpreting the results of the forthcoming regression models. This is also known as the log-log model where a coefficient of an estimate, e.g. β1, is the elasticity of dependent variable, in this case the daily returns of green bond index and with respect to the independent variables such as the volatility indices, respectively. For instance, the interpretation of the log-log model is defined as a one percentage change in the independent variable *i* affects the green bond return by the amount of percentage change in the beta coefficient (Wooldridge 2002: 45–46).

Figure 4 below illustrates the historical price development of green bond index and volatility indices for the chosen time period from October 2014 to January 2020. The positive co-movement between the volatility indices can be observed. The MSCI green bond index moves with a stable growth whereas VIX, VXXLE, and OVX indices are more volatile and show more fluctuations.

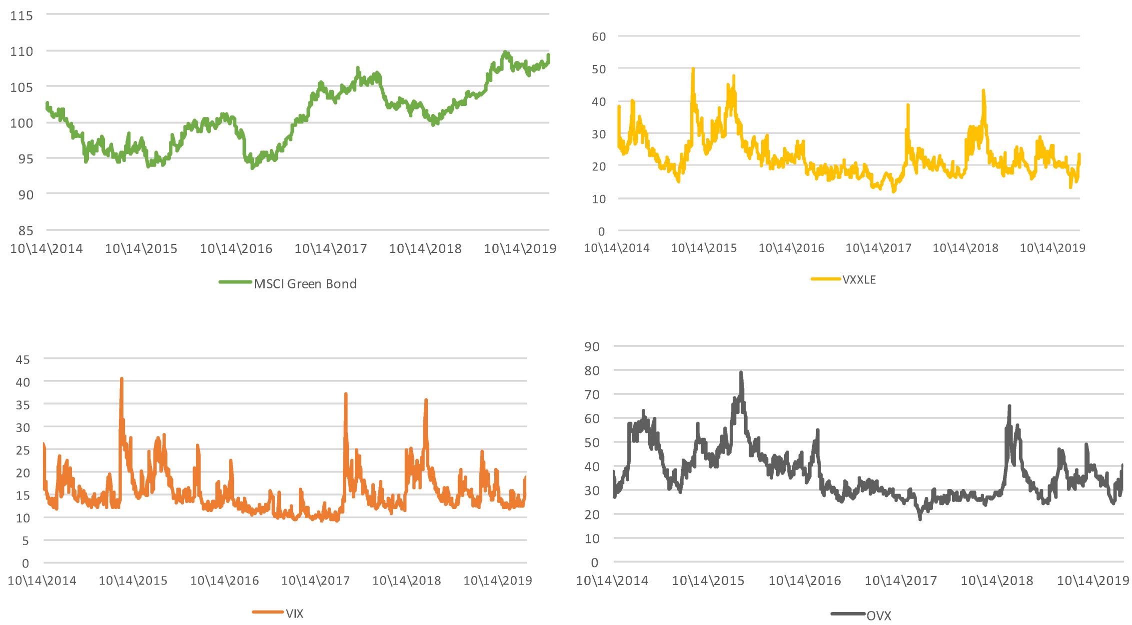

Figure 4. Historical index developments for MSCI Green Bond, VXXLE, VIX, and OVX.

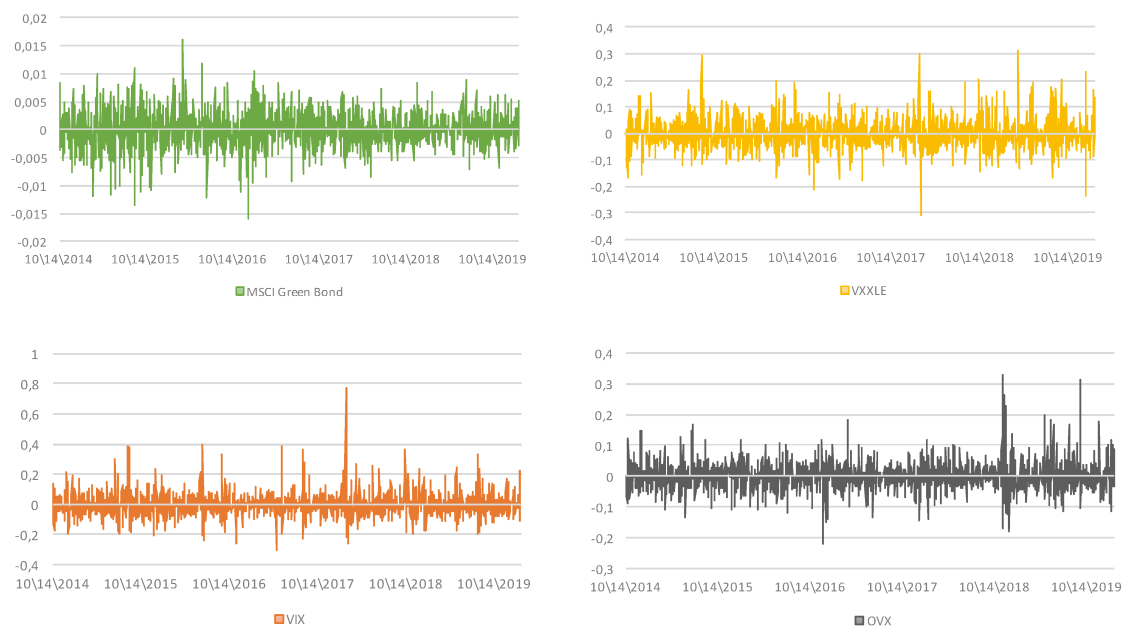

Figure 5. Dynamics of index returns for MSCI Green Bond, VXXLE, VIX, and OVX.

Figure 5 above presents the movements of daily natural log returns and changes for the green bond and volatility indices of VIX, VXXLE, and OVX for the chosen time period between October 14, 2014 and January 31, 2020. Again, the returns for volatility indices show slightly similar patterns as in Figure 4 as positive co-movements with more fluctuations and are more volatile compared to the green bond index returns. In addition, the dynamics of the returns in Figure 5 illustrate that the indices are stationary[2]. This is important due to the requirement of stationarity in time series data and regression analysis. Thus, this dataset is allowable to be used in the forthcoming regression models.

5.2. Descriptive statistics

Table 2 below presents the descriptive statistics for the daily closing prices of green bond index and different volatility indices. In turn, Table 3 below shows the descriptive statistics for daily natural log returns of green bond, VIX, VXXLE, and OVX. For all the indices, average daily returns are close to zero whereas the corresponding standard deviations reveal that green bonds are less volatile compared to the uncertainty in energy sector, crude oil, and stock markets.

In Table 3, all volatility indices are positively skewed, except the green bond index which shows a negative skewness. Also, kurtosis among the variables are all above three which indicate that the natural log returns and changes in volatility indexes are not normally distributed. Under the null hypothesis, the returns of green bond and volatilities are normally distributed. Evidence from Table 2 and Table 3 show large values of Jarque-Bera and the tests are strongly suggesting the contrary in which the null hypotheses are rejected for all of the indices as they do not follow a normal distribution.

[2] The stationarity is tested with the unit root test rejecting the null hypothesis at 1% level. See Appendix 1 for more details.

Table 2. Descriptive statistics for prices of green bond and volatility indices.

	MSCI_GB	VXXLE	VIX	OVX
Mean	100.89	22.68	15.15	36.48
Median	100.71	21.02	14.04	33.72
Maximum	109.73	49.77	40.74	78.97
Minimum	93.55	11.71	9.14	17.86
Std. Dev.	4.21	5.99	4.25	10.35
Skewness	0.15	1.19	1.52	0.99
Kurtosis	1.98	4.48	6.37	3.66
Jarque-Bera	65.27	452.78	1189.15	255.38
Observations	1384	1384	1384	1384

Table 3. Descriptive statistics for returns of green bond and volatility indices.

	MSCI_GB	VXXLE	VIX	OVX
Mean	0.000	0.000	0.000	0.000
Median	0.000	-0.002	-0.003	-0.001
Maximum	0.016	0.309	0.768	0.328
Minimum	-0.016	-0.310	-0.300	-0.219
Std. Dev.	0.003	0.057	0.081	0.048
Skewness	-0.152	0.519	1.309	0.770
Kurtosis	4.598	6.181	11.478	7.960
Jarque-Bera	152.63	645.51	4540.37	1555.22
Observations	1384	1384	1384	1384
Correlation matrix				
MSCI_GB	1			
VXXLE	0.08	1		
VIX	0.11	0.72	1	
OVX	0.00	0.52	0.35	1

Finally, the correlation matrix in Table 3 above indicates that green bond market returns show low linear dependence with uncertainties in the stock, crude oil, and energy markets. However, higher dependence and co-movements are shown among the volatility indices, especially uncertainties between the energy sector and stock market and crude oil and energy markets, which are expected. The seriousness of dependency among the variables are investigated in the subsection of chapter 7.

6. METHODOLOGY

This thesis methodology is assessing to extend the suggested research topic from Pham (2016) by studying the relationship between green bonds and various market uncertainties, and how these volatilities affect the performance of green bonds. The following ordinary least squares regression below is used in order to find any relationship between the performance of green bond market and different market uncertainties. These uncertainties are measured by various volatility indexes, such as VXXLE, VIX, and OVX. Furthermore, the dataset is already transformed by taking the natural logarithms as described previously. Thus, the regression models can be used directly without further adjustments.

6.1. OLS regression

This thesis's methodology follows and is motivated by the previous studies related to the return-volatility relation including Simon (2003), Giot (2005), Hibbert et al. (2008), and Daigler et al. (2012). In order to study the return-volatility relationship between green bonds and different market uncertainties for assessing Pham's (2016) suggested future research, the following regression models are to test the H1, H2, and H3 by individually exploring the linkage between the green bond returns and volatility indices. For instance, Giot (2005) examines the relationship between stock index returns and implied volatility indices by using the OLS analysis. Thus, one of the well-known methodologies employed in previously mentioned empirical studies, a linear regression model, known as the ordinary least squares (OLS), is formed as the following:

(7) (M1) $R_{GB,t} = \beta 0 + \beta 1(\Delta VXXLE_t) + \varepsilon_t$

(8) (M2) $R_{GB,t} = \beta 0 + \beta 1(\Delta VIX_t) + \varepsilon_t$

(9) (M3) $R_{GB,t} = \beta 0 + \beta 1(\Delta OVX_t) + \varepsilon_t$

where $R_{GB,t}$ is the daily natural log return of green bond index from time t to T, ΔVIX_t, $\Delta VXXLE_t$, ΔOVX_t are the daily natural log changes of volatility indices of US stock market, energy sector, and crude oil market from time t to T. The β0 coefficient represents as an intercept term whereas β1 is the slope coefficient, and ε_t is the error term from time t to T, respectively.

Liu et al. (2013) show that the US VIX acts as a driving force for crude oil volatility index. Moreover, Maghyereh et al. (2016) find that the causality significantly runs from the US VIX to OVX. In order to contribute to the literature of uncertainty transmission by examining the connection between crude oil and equity volatilities and testing the H3a, the regression model is formed as the following:

(10) (M4) $R_{GB,t} = \beta 0 + \beta 1(\Delta VIX_t) + \beta 2\,(\Delta OVX_t) + \varepsilon_t$

As previously mentioned in the research hypotheses of chapter 1, based on Dutta's (2018) study, adding VIX is vital since uncertainty could flow from the US VIX to both crude oil and energy sector equity market volatility series. Moreover, as previously described in the H3 in which OVX and VIX explain a large proportion of VXXLE, the relationship between VXXLE and OVX together are explored. Therefore, to test the H2a, H3b, H3c the regression models are formed as follows:

(11) (M5) $R_{GB,t} = \beta 0 + \beta 1(\Delta VXXLE_t) + \beta 2(\Delta VIX_t) + \varepsilon_t$

(12) (M6) $R_{GB,t} = \beta 0 + \beta 1(\Delta VXXLE_t) + \beta 2\,(\Delta OVX_t) + \varepsilon_t$

(13) (M7) $R_{GB,t} = \beta 0 + \beta 1(\Delta VXXLE_t) + \beta 2(\Delta VIX_t) + \beta 3(\Delta OVX_t) + \varepsilon_t$

7. EMPIRICAL RESULTS

This chapter presents the results of the regression models used in the empirical research. The results will be analyzed and demonstrated by tables in order to add readability and to test the research hypotheses of this thesis. The first subsection reports the variance inflation factors and the results of the VIF values are explained. Lastly, the results of green bond markets and the corresponding hypotheses are tested and analyzed in the second subsection. In order to run the regression models and obtain the empirical results, the statistical software, EViews, is used.

7.1. Variance inflation factors

The correlation matrix in Table 3 shows that the correlations among volatility indices are positively correlated, especially a high co-movement is observed between VIX and VXXLE, 0.72, and OVX and VXXLE, 0.52, respectively. This might indicate a multicollinearity issue and thus assessments are needed to be done. In order to identify the possible multicollinearity, a measurement of expressing the degree is defined as each independent variable is explained by the set of other independent variables. In other words, each independent variable becomes a dependent variable and is regressed against the remaining independent variables. One of the most common measures for identifying and assessing both pairwise and multiple variable collinearity is the variance inflation factor (VIF). As a general rule of thumb or a common cut-off threshold for the VIF, is a value of 10. (Hair, Black, Babin & Anderson 2014: 196, 200.) Therefore, the previously described method in detecting the multicollinearity issue is performed as follows in Tables 4–6.

Table 4. VIF values for VXXLE.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		VXXLE	
Constant	0.000001	1.01	-
VIX	0.0003	1.23	1.22
OVX	0.0008	1.22	1.22
Observations	1384	1384	1384

Notes: VXXLE is a dependent variable whereas VIX and OVX are independent variables, respectively.

Table 5. VIF values for VIX.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		VIX	
Constant	0.000002	1.07	-
VXXLE	0.004	1.65	1.56
OVX	0.003	1.56	1.56
Observations	1384	1384	1384

Notes: VIX is a dependent variable whereas VXXLE and OVX are independent variables, respectively.

Table 6. VIF values for OVX.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		OVX	
Constant	0.000001	1.04	-
VXXLE	0.002	4.26	4.15
VIX	0.001	4.18	4.15
Observations	1384	1384	1384

Notes: OVX is a dependent variable whereas VXXLE and VIX are independent variables, respectively.

From Table 4 to Table 6 it can be observed that based on the cut-off threshold for VIF of the value of 10, the suspected multicollinearity among the independent variables, and between the dependent and independent variables are within tolerable limits since all of the VIF values are clearly below 10. Therefore, the dependent and independent variables are not considered to affect the multicollinearity issue and thus these variables are allowable when used in the forthcoming regression models.

7.2. Results of green bond performance

Table 7 reports the estimates of regression results for testing the hypotheses by individually performing the regression models, as in models 1–3, between the green bond index daily natural log returns and the volatility indices. These regression models are defined previously in chapter 6 and presented in three different models. All of the three models have the VIF values of 1 which indicate that there is no multicollinearity among the variables and the regression models can be used without issues. An interesting finding is that the OVX has an opposite, a negative sign in its coefficient estimate which could rise an issue of multicollinearity. However, the VIF value is still 1 and since there are 1384 observations there are no multicollinearity among the variables.

Table 7. OLS Regression results 1.

	MSCI_GB		
Variable	(M1)	(M2)	(M3)
Constant	0.0001	0.0001	0.0001
	(0.0173)	(0.0014)	(0.0001)
ΔVXXLE	0.0045***		
	(0.0017)		
ΔVIX		0.0046***	
		(0.0014)	
ΔOVX			-0.0002
			(0.0019)
R^2	0.01	0.01	0.00
Adj. R^2	0.01	0.01	0.00
F-statistic	8.41	17.59	0.01
VIF[3]	1.00	1.00	1.00
Observations	1384	1384	1384

Notes: This table reports the results from the following three regression models (Eq. 7–9):

(M1) $R_{GB,t} = \beta 0 + \beta 1(\Delta VXXLE_t) + \varepsilon_t$

(M2) $R_{GB,t} = \beta 0 + \beta 1(\Delta VIX_t) + \varepsilon_t$

(M3) $R_{GB,t} = \beta 0 + \beta 1(\Delta OVX_t) + \varepsilon_t$

where MSCI_GB is the daily natural log return of the MSCI green bond index (dependent variable) from day t until day T, $\Delta VXXLE_t$, ΔVIX_t, ΔOVX_t are the (independent variables) daily natural log changes of different financial market volatility indexes such as energy sector, stock market, crude oil from day t until day T. In turn, ε_t is the error/residual[4] term from day t until day T. The sample period is 10/14/2014–1/31/2020. The standard errors presented in the parentheses are corrected using the Huber-White estimator. ***, **, * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

[3] More details for VIF values are presented in Appendices 2–3.
[4] The residuals show neither serial correlation nor heteroskedasticity. See Appendix 8.

In model 1 and 2, the results of the changes in the energy sector (ΔVXXLE) and stock market (ΔVIX) are statistically significantly affecting the performance of the green bond index in terms of high significance levels and figures of F-statistics. Thus, the null hypothesis can be rejected and the results are consistent with the alternative hypotheses H1 and H2. The results suggest that as one percentage point increase in the VXXLE and VIX, increases the green bond return by 0.45% and 0.46%, respectively. Although the results are statistically highly significant at 1% level, the effects on the green bond performance are slightly weak since the estimated returns are close to zero. These results are consistent with the previous study from Reboredo (2018) who finds that the green bond prices weakly co-move with energy commodity and stock markets. In addition, the co-movement between green bond and stock market (0.11) and energy sector (0.08) show to be weak in terms of the correlation matrix in Table 3. Thus, based on the regression results and the co-movements between the green bond returns and changes in VXXLE and VIX could indicate weak dependencies and influences on the performance of green bonds.

In contrast, the regression result for the estimate of OVX shows no significant effect on the performance of green bonds in terms of low figures of F-statistics and t-statistics (the t-values can be obtained by dividing the estimates by the standard errors which are in the parentheses). This result suggests that changes in the crude oil volatility does not affect the returns of the green bonds when the regression model is performed separately from other markets as in model 3. Therefore, H3 is not supported and the corresponding null hypothesis is not rejected and remain valid. Later, the results are obtained by the regression models that include additional volatilities in order to capture any significance if the volatilities both together simultaneously affect the green bond's performance.

Table 8. OLS Regression results 2.

	MSCI_GB		
Variable	(M5)	(M4)	(M6)
Constant	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
ΔVXXLE	-0.0003		0.0062***
	(0.0021)		(0.0019)
ΔVIX	0.0047***	0.0053***	
	(0.0017)	(0.0015)	
ΔOVX		-0.0033*	-0.0041*
		(0.0019)	(0.0021)
Observations	1384	1384	1384
R^2	0.01	0.01	0.01
Adj. R^2	0.01	0.01	0.01
F-statistic	8.80	10.23	5.99
VIF[5]	1.55	1.14	1.32

Notes: This table reports the results from the following three regression models (Eq. 10–12):

(M4) $R_{GB,t} = \beta 0 + \beta 1(\Delta VIX_t) + \beta 2\,(\Delta OVX_t) + \varepsilon_t$

(M5) $R_{GB,t} = \beta 0 + \beta 1(\Delta VXXLE_t) + \beta 2(\Delta VIX_t) + \varepsilon_t$

(M6) $R_{GB,t} = \beta 0 + \beta 1(\Delta VXXLE_t) + \beta 2\,(\Delta OVX_t) + \varepsilon_t$

where MSCI_GB is the daily natural log return of the MSCI green bond index (dependent variable) from day t until day T, $\Delta VXXLE_t$, ΔVIX_t, ΔOVX_t, are the (independent variables) daily natural log changes of different financial market volatility indexes such as energy sector, stock market, crude oil from day t until day T. In turn, ε_t is the error/residual[6] term from day t until day T. The sample period is 10/14/2014–1/31/2020. The standard errors presented in the parentheses are corrected using the Huber-White estimator. ***, **, * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

[5] More details for VIF values are presented in Appendices 4–6.
[6] The residuals show neither serial correlation nor heteroskedasticity. See Appendix 8.

Table 8 above presents the results for regression estimates which are obtained by three different regression models of M4, M5, and M6. The VIF values are still within the tolerable limits since they all are clearly below 10 and slightly changes from the previous results in Table 7. Thus, the regression models are allowable to be used. Now, the regression models include two volatilities from two different market in order to test hypotheses H2a, H3a, and H3b with a simultaneous effect on the green bond returns.

In the regression model 5, ΔVIX remains still highly significant at 1% level and slightly increases the green bond return from 0.45% to 0.47% when ΔVXXLE is included in the model. However, the ΔVXXLE becomes insignificant and approaches close to zero and has a negative coefficient. Thus, the H2a is not supported whereas its null hypothesis remains valid and is not rejected, respectively. This result is partially inconsistent with the prior study from Dutta (2018) where he finds that uncertainty from the US VIX could possibly flow to energy sector market volatility. But, the results from regression model 4 are consistent with Dutta's finding where the uncertainty in the US VIX flows to the crude oil market volatility. Therefore, the H3a is supported. Still, the interesting finding of a negative coefficient in OVX suggests that there might be a negative relationship between changes in OVX and the green bond returns. Based on the regression results, one percentage point rise in VIX increases the green bond's return by 0.53% whereas the same amount increase in OVX could reduce the returns of green bond by 0.33%. Then, the total net return is approximately 0.20%.

The results in model 6 show that ΔVXXLE is highly statistically significant when ΔOVX is included in the same model. Also, changes in OVX remains significant at 10% level with a negative sign in its coefficient. This supports the alternative hypothesis H3b. Again, the correlation between VIX and VXXLE (0.72) is higher compared to correlation between VXXLE and OVX (0.52) and therefore it might explain the insignificance for VXXLE in model 5 when VIX is included but the contrary when VIX is replaced by OVX. The interpretation of the results in model 6 indicates as VXXLE rises by one percentage point, the return of green bond increases by 0.62% which has the most impact at this point. Simultaneously the OVX reduces the green bond returns by 0.41% and thus the total net return for the green bond is approximately 0.21%.

Overall, the results in Table 8 are slightly stronger but remain approximately similar to the results reported in Table 7. For instance, the changes in VIX becomes positively stronger which has the most impactful effect on the green bond returns. Also, the F-statistics are higher than presented in the first part of the regression results. Finally, the results in Table 8 indicate also consistency with the prior studies from Liu et al. (2013) showing that the US VIX has an impact on crude oil volatility index and the research from Maghyereh et al. (2016) who find the causality running from the US VIX to OVX.

Table 9 below reports the regression estimates and results obtained by the regression model 7. For the model 7, all three volatility indices, VIX, VXXLE, OVX are included in order to find whether there is any simultaneous impact on the green bond's returns. The results for model 7 are still approximately similar to the prior results in Table 8. The VIF values are less than 1.76 and clearly below the cut-off threshold of 10. Thus, the regression model 7 is allowable to be used.

The uncertainty in stock market, ΔVIX, remains positively statistically significant in model 7. Moreover, the crude oil volatility is barely significant with a negative coefficient whereas uncertainty in the energy market is insignificant. These findings are similar to the previous results in Table 8 when VXXLE is included with the VIX in which VXXLE becomes insignificant. The possible reason might be as VIX has the dominant role as the uncertainty flows from the US VIX to the other markets such as energy and crude oil volatilities. In this case, only for the crude oil market which is partially consistent with earlier study from Dutta (2018) finding that the uncertainty flowing from the US VIX to the volatility of crude oil market. Thus, the H1 is still supported in terms of the regression models 2, 4, 5, and 7. However, H3c is not supported and the comparable null hypothesis is not rejected and remains valid.

Table 9. OLS Regression results 3.

	MSCI_GB
Variable	(M7)
Constant	0.0001
	(0.0001)
ΔVXXLE	0.0015
	(0.0021)
ΔVIX	0.0046***
	(0.0017)
ΔOVX	-0.0039*
	(0.0021)
Observations	1384
R^2	0.01
Adj. R^2	0.01
F-statistic	6.95
[1]VIF	<1.76
AR1	-0.0152
	(0.0275)
AR2	0.0424
	(0.0265)
AR3	-0.0461*
	(0.0269)
ARCH0	0.0000000803**
	(0.0000000393)
ARCH1	0.0277***
	(0.0058)
[2]GARCH1	0.9652***
	(0.0073)

Notes: This table reports the results from the following regression model (Eq. 13):

(M7) $R_{GB,t} = \beta 0 + \beta 1(\Delta VXXLE_t) + \beta 2(\Delta VIX_t) + \beta 3(\Delta OVX_t) + \varepsilon_t$

where MSCI_GB is the daily natural log return of the MSCI green bond index (dependent variable) from day t until day T, $\Delta VXXLE_t$, ΔVIX_t, ΔOVX_t are the (independent variables) daily natural log changes of different financial market volatility indexes such as energy sector, stock market, crude oil from day t until day T. In turn, ε_t is the error/residual[7] term from day t until day T. The sample period is 10/14/2014–1/31/2020. The standard errors presented in the parentheses are corrected using the Huber-White estimator.

[7] The residuals show neither serial correlation nor heteroskedasticity. See Appendix 8.

***, **, * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

[1]VIF values in more details are provided in Appendix 7.

[2]GARCH(1,1) residuals were tested and show neither serial/auto correlation nor ARCH effect. More details of the test results using the Ljung-Box test and ARCH LM test are provided in Appendix 9 and 10.

The research results of Table 9, confirm that the US VIX seems to have an impact on the volatility of crude oil market and that the causality runs from the US VIX to OVX, are still in line with the previous studies from Liu et al. (2013) and Maghyereh et al. (2016), respectively.

The regression model 7 is also estimated with three autoregressive terms and GARCH(1,1)[8] specification. Both the ARCH1 and GARCH1 parameters are positive as expected and highly significant at 1% level. In addition, the sum of the coefficients of the ARCH1 and GARCH1 parameters (0.0277+0.9652) is close to one, indicating that volatility shocks are quite persistent. Since the GARCH1 parameter is significant, a large excess return value of not only positive but also negative will lead future forecasts of the volatility to be high for a prolonged time period. For instance, in the periods of time of high volatility. The null hypotheses of residual tests are not rejected and remain valid. Thus, the residual tests of the GARCH(1,1) show that there are neither serial/auto correlation nor ARCH effect by using the Ljung-Box test, and the ARCH LM test (with 1 and 3 lag terms) respectively.

Overall, based on the regression estimates and results the F-statistics and t-values suggest that the VIX has the most significant effect on the green bond returns in most of the regression models 2, 4, 5, and 7. The positive co-movement between green bond return and VIX remains approximately the same in the models 2, 4, 5, and 7 but the effect seems to be quite weak since the impact of it to the green bond returns are roughly from

[8] See Engle (1982) and Bollarslev (1986) for generalized autoregressive (GARCH) models in general, and Bauwens & Laurent (2006) for the literature on multivariate GARCH models cited there.

0.4% to 0.5% when VIX increases by 1 percentage point. Lastly, the results suggest the opposite for the expectations on the negative relationship between green bond returns and volatility indices. In contrast, the crude oil volatility, OVX, makes an exception where it is however consistent with the expectation of an inverse relationship between green bond returns and volatility index. These findings could indicate that since the green bonds are quite novel as an asset class the volatilities might affect them differently or as earlier study relating to stock-bond volatility relation from Young & Johnson (2004) who find the contrary indicating that it is risky to assume that trends in market volatility are same or universal across the securities markets in developed countries. In addition, study results from Reboredo (2018) confirm that the large price swings in the energy and stock markets have negligible impact on the green bond prices and thus show consistency with the contrary expectations of an inverse relationship between green bond returns and volatilities in the energy and stock markets.

The next chapter will draw a conclusion for the study of this thesis. Finally, the results are briefly analyzed and suggestions on a possible future research are also presented.

8. CONCLUSIONS

This thesis examines how uncertainties from various financial markets, such as crude oil, energy sector and stock market, affect the performance of green bond market, and provides further analysis on the suggestion of studying the relationship between green bond market and different financial markets from the prior study by Pham (2016). Also, this study aims to extend the research from Reboredo (2018) on the linkage between the green bonds and co-movements of the financial markets. More specifically, the goal of this research is to study the connection between the green bond's returns and different volatilities of the financial markets by the linear regression model, as known as the ordinary least squares. Since most of the green bond indices were computed starting from 2014, the sample period of this study begins from October 2014 to January 2020.

First, uncertainties in the energy and stock markets show to have a positive impact on green bond's returns when the volatilities of those markets are separately taken into consideration. In contrast, the relationship between green bond's performance and crude oil is however the contrary and it appears that the crude oil volatility has no significant effect on the returns of the green bond.

Second, when considering two or more volatility indexes simultaneously, the stock market uncertainty, VIX, appears to have the most significant effect on the performance of the green bond market. Interestingly, the coefficient of the crude oil volatility shows an estimate of a negative sign which is barely statistically significant at 10% level. This result suggests that the US VIX has a signaling effect on OVX and possibly indicating that the uncertainty could flow from the stock market to the crude oil market volatility. These findings seem to be consistent with the previous studies from Liu et al. (2013), Maghyereh et al. (2016), and Dutta (2018) where the US VIX shows to have an impact on volatility of crude oil and the causality running from the US VIX to the OVX. Thus, the total return of a green bond seems to depend on the crude oil price fluctuations since the results indicate a negative relationship between the green bond performance and the crude oil volatility. However, the dependence can be seen as quite weak in terms of low statistical significance level. Moreover, an interesting finding suggests that volatility of energy market has an impact on the green bond performance when only OVX is taken into account but not the with VIX. This result could possibly indicate that since both VIX and VXXLE highly co-move together, the relationship between them becomes insignificant but turns out to be significant with OVX in terms of lower co-movement between VXXLE and OVX.

Overall, the empirical findings show that majority of the alternative hypotheses are supported and the stock market volatility has the most dominant role when other implied volatility indices such as crude oil and energy market are considered contemporaneously. In addition, the VIX is highly statistically significant and has an impact on the green bond returns (ranging between 0.4% and 0.5%). However, the positive impact on green bond return is quite small and slightly close to zero which could ultimately suggest a weak effect on the total return of green bonds. This finding is consistent with the study from Reboredo (2018) where the results show that the green bond markets weakly co-move with the stock and energy commodity markets. Furthermore, the values of R-squared are low in all seven models used in the regression analysis of this thesis. This could suggest that the volatility in fixed-income market might explain better the impact on returns of green bonds. For instance, Reboredo (2018) finds that the green bond markets and the fixed-income markets are strongly dependent in terms of high correlation between green bond market returns and fixed-income markets. More specifically, the green bond and fixed-income markets closely co-move both under normal market circumstances and market times of experiencing upward or downward swings. However, the results show low linear dependence between the green bond market returns and stock and energy commodity markets. Therefore, this could explain the reason behind the insignificant results obtained when considering the volatility index of energy sector (VXXLE) simultaneously with the crude oil and stock market volatility indices.

The green bonds are considered as new fixed-income financial instruments to fund renewable energy and energy efficient projects. Thus, more research is needed and further analysis for considering future research are suggested as follows. First, the explanatory power of the ordinary least squares is quite minor when using the volatility indexes of different financial markets. Thus, the future research could benefit in applying an alternative methodology as the regression model. Second, it would be interesting to study the causality in green bond-volatility relation, for instance, with the Granger causality test and the relationship between green bonds and volatility in the fixed-income market (e.g. with TYVIX and SRVIX if available) which could increase the explanatory power (R^2) of the OLS methodology. Third, an intriguing study relating to the tolerance of green bond's returns during times of high volatility such as market crashes in the global financial markets in order to evaluate the return-risk relation more specifically. Finally, a more deep and comprehensive analysis of the environmental impact of projects funded by green bonds would be important to be able to get the overall picture of the effects on the performance and returns of the new and growing green bond market.

LIST OF REFERENCES

Banga, J. (2019). The green bond market: a potential source of climate finance for developing countries. *Journal of Sustainable Finance & Investment*. 9:1, 17–32.

Baulkaran, V. (2019). Stock market reaction to green bond issuance. *Journal of Asset Management*. 20, 331–340.

Bauwens, L., Laurent, S., & Rombouts, J. V. (2006). Multivariate GARCH models: a survey. *Journal of Applied Econometrics*. 21:1, 79–109.

Bloomberg (2019). Bloomberg Barclays MSCI Green Bond Indices. *Bringing clarity to the green bond market through benchmark indices*. Available on the internet: https://www.msci.com/documents/1296102/11926825/Bloomberg+Barclays+MSCI+US+Green+Bond+Primer.pdf/bff9fd82-396d-ab79-3b7d-cfdecd5d3dea?t=1581430190070

Bloomberg (2017). Bloomberg Barclays MSCI Global Green Bond Index. Available on the internet: https://www.msci.com/documents/10199/242721/Barclays_MSCI_Green_Bond_Index.pdf

Bodie, Z., Kane, A., & Marcus, A. J. (2011). *Investments.* 11. edition. New York: McGraw-Hill/Irwin.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*. 31:3, 307–327.

Brealey, R. A., Myers, S. C., & Allen, F. (2016). *Principles of Corporate Finance*. 12. edition. New York, NY: McGraw-Hill International edition.

Brealey, R. A., Myers, S. C., & Allen, F. (2011). *Principles of Corporate Finance.* 10. edition. New York, NY: McGraw-Hill/Irwin.

Byrd, J., & Cooperman, E.S. (2018). Investors and Stranded Asset Risk: Evidence from Shareholder Responses to Carbon Capture and Sequestration (CCS) Events. *Journal of Sustainable Finance & Investment*. 8:2, 185–202.

Canina, L., & Figlewski, S. (1993). The informational content of implied volatility. *The Review of Financial Studies*. 6:3, 659–681.

Climate Bonds Initiative (2017). Bonds and climate change: state of the market. Available on the internet: https://www.climatebonds.net/files/files/CBI-SotM_2017-Bonds%26ClimateChange.pdf.

Connolly, R. A., Stivers, C., & Sun, L. (2007). Commonality in the time-variation of stock–stock and stock–bond return comovements. *Journal of Financial Markets*. 10:2, 192–218.

Daigler, R. T., Hibbert, A. M., & Pavlova, I. (2012). Examining the return–volatility relation for foreign exchange: evidence from the euro VIX. *Journal of Futures Markets*. 34:1, 74–92.

de La Grandville, O. (2001). *Bond pricing and portfolio analysis: Protecting investors in the long run*. MIT Press.

Dumas, B., Fleming, J., & Whaley, R. E. (1998). Implied volatility functions: Empirical tests. *The Journal of Finance*. 53:6, 2059–2106.

Dutta, A. (2018). Oil and energy sector stock markets: An analysis of implied volatility indexes. *Journal of Multinational Financial Management*. 44, 61–68.

Dutta, A. (2017). Energy sector uncertainty and clean energy stock returns: New evidence from crude oil volatility index. *Journal of Cleaner Production.* 164, 1156–1166.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*. 50:4, 987–1007.

European Commission (2016). Study on the potential of green bond finance for resource- efficient investments.
Available on the internet: http://ec.europa.eu/environment/enveco/pdf/potential-green- bond.pdf.

German Development Institute (2016). Green Bonds: Taking Off the Rose-Coloured Glasses. Available on the internet:
https://www.die-gdi.de/uploads/media/BP__24.2016.korr_01.pdf.

Giot, P. (2005). Relationships between implied volatility indexes and stock index returns. *The Journal of Portfolio Management*. 31:3, 92–100.

Hachenberg, B., & Schiereck, D. (2018). Are green bonds priced differently from conventional bonds? *Journal of Asset Management*. 19:6, 371–383.

Hair, J.F., Black, W.C., Babin, B.J., & Anderson, R.E. (2014). *Multivariate Data Analysis: Pearson New International Edition.* 7. edition. Pearson Education Limited.

Hibbert, A. M., Daigler, R. T., & Dupoyet, B. (2008). A behavioral explanation for the negative asymmetric return–volatility relation. *Journal of Banking & Finance*. 32:10, 2254–2266.

Huang, T., Wu, F., Yu, J., & Zhang, B. (2015). International political risk and government bond pricing. *Journal of Banking & Finance*. 55, 393–405.

Hull, J. C. (2018). *Risk Management and Financial Institutions*. 5. edition. New Jersey: John Wiley & Sons Inc.

Hull J. C. (2015). *Options, Futures and Other Derivatives*. 9. press. New Jersey: Pearson Education Inc.

Johnson, R. R., & Young, P. J. (2002). Bond market volatility compared with stock market volatility: evidence from the UK. *Journal of Asset Management*. 3:2, 101–111.

Knüpfer, S. & Puttonen, V. (2014). *Moderni rahoitus*. 9. press. Helsinki: Alma Talent.

Liu, M. L., Ji, Q., & Fan, Y. (2013). How does oil market uncertainty interact with other markets? An empirical analysis of implied volatility index. *Energy*. 55, 860–868.

Maghyereh, A.I., Awartani, B., & Bouri, E. (2016). The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. *Energy Economics*. 57, 78–93.

MuniFin (2019). Green Bonds Impact Report. Available on the internet: https://www.kuntarahoitus.fi/app/uploads/sites/2/2020/03/2019-MuniFin-Green-Bonds-Impact-Report.pdf

Nikkinen, J., & Rothovius, T. (2019). Energy sector uncertainty decomposition: New approach based on implied volatilities. *Applied Energy*. 248,141–148.

Pham, L. (2016). Is it risky to go green? A volatility analysis of the green bond market. *Journal of Sustainable Finance & Investment*. 6:4, 263–291.

Reboredo, J.C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics.* 74, 38–50.

Reilly, F. K., Wright, D. J., & Chan, K. C. (2000). Bond market volatility compared to stock market volatility. *The Journal of Portfolio Management*. 27:1, 82–92.

Ruan, X., & Zhang, J. E. (2019). Moment spreads in the energy market. *Energy Economics*. 81, 598–609.

Schwert, G. W. (1990). Stock market volatility. *Financial Analysts Journal*. 46:3, 23–34.

Schwert, G. W. (1989). Why does stock market volatility change over time?. *The Journal of Finance*. 44:5, 1115–1153.

Simon, D. P. (2003). The Nasdaq volatility index during and after the bubble. *The Journal of Derivatives*. 11:2, 9–24.

Steeley, J. M. (2006). Volatility transmission between stock and bond markets. *Journal of International Financial Markets, Institutions and Money*. 16:1, 71–86.

Vo, M.T. (2011). Oil and stock market volatility: a multivariate stochastic volatility perspective. *Energy Economics.* 33, 956–965.

Whaley, R. E. (2013). Trading volatility: At what cost? *The Journal of Portfolio Management.* 40:1, 95–108.

Whaley, R. E. (2009). Understanding the VIX. *The Journal of Portfolio Management*. 35:3, 98–105.

Wooldridge, J. M. (2002). Introductory Econometrics: A Modern Approach. 2. edition. South-Western Publishing Co.

Young, P. J. & Johnson, R. R. (2004). Bond market volatility vs. stock market volatility: the Swiss experience. *Financial Markets and Portfolio Management*. 18:1, 8–23.

APPENDICES

APPENDIX 1. Unit root test results.

Variable	ADF
MSCI_GB	-38.5891***
VIX	-37.9684***
VXXLE	-37.964***
OVX	-38.1841***

Notes: This table presents the t-values of test statistic for ADF tests. The null hypothesis of ADF test is that the data have a unit root.
*** denote rejection of the null hypothesis at the 1% significance level. Thus, the variables show to be significantly stationary.

APPENDIX 2. VIF values for regression model 1 & 2.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		MSCI_GB	
VXXLE	0.000003	1.000029	1.000000
Constant	0.00000000782	1.000029	-
Observations	1384	1384	1384

Notes: MSCI is a dependent variable whereas VXXLE is an independent variable, respectively.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		MSCI_GB	
VIX	0.00000191	1.001367	1.000000
Constant	0.00000000777	1.001367	-
Observations	1384	1384	1384

Notes: MSCI_GB is a dependent variable whereas VIX is an independent variable, respectively.

APPENDIX 3. VIF values for regression model 3.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		MSCI_GB	
OVX	0.00000352	1.000496	1.000000
Constant	0.00000000787	1.000496	-
Observations	1384	1384	1384

Notes: MSCI_GB is a dependent variable whereas OVX is an independent variable, respectively.

APPENDIX 4. VIF values for regression model 4.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		MSCI_GB	
VIX	0.00000296	1.551467	1.549188
VXXLE	0.00000425	1.550082	1.549188
Constant	0.00000000777	1.004872	-
Observations	1384	1384	1384

Notes: MSCI_GB is a dependent variable whereas VIX and VXXLE are the independent variables, respectively.

APPENDIX 5. VIF values for regression model 5.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		MSCI_GB	
VIX	0.00000217	1.137587	1.135964
OVX	0.00000394	1.136173	1.135964
Constant	0.00000000776	1.001429	-
Observations	1384	1384	1384

Notes: MSCI_GB is a dependent variable whereas VIX and OVX are the independent variables, respectively.

APPENDIX 6. VIF values for regression model 6.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		MSCI_GB	
VXXLE	0.00000396	1.315547	1.315448
OVX	0.00000452	1.316115	1.315448
Constant	0.0000000078	1.001020	-
Observations	1384	1384	1384

Notes: MSCI_GB is a dependent variable whereas VXXLE and OVX are the independent variables, respectively.

APPENDIX 7. VIF values for regression model 7.

	Coefficient Variance	Uncentered VIF	Centered VIF
Variable		MSCI_GB	
VIX	0.00000296	1.560846	1.558164
VXXLE	0.00000480	1.747738	1.746133
OVX	0.00000444	1.289962	1.28949
Constant	0.00000000775	1.007277	-
Observations	1384	1384	1384

Notes: MSCI_GB is a dependent variable whereas VIX, VXXLE, and OVX are the independent variables, respectively.

APPENDIX 8. Residual test results of serial correlation and heteroskedasticity (with 2 lags) for regression models 1–7.

Breusch-Godfrey Serial Correlation LM Test	M1	M2	M3	M4	M5	M6	M7
F-statistic	1.444429	1.405437	1.65694	1.584467	1.411481	1.626536	1.579631
Obs.*R^2	2.891179	2.813292	3.315523	3.173132	2.827409	3.257183	3.165759
Prob. F(2.1380)	0.2362	0.2456	0.1911	0.2054	0.2441	0.197	0.2064
Prob. $\chi^2(2)$	0.2356	0.245	0.1906	0.2046	0.2432	0.1962	0.2054

Notes: This table presents the test of Breusch-Godfrey for serial correlation. Under the null hypothesis there is no serial correlation. The values in both probabilities report that the null hypothesis is not rejected. Therefore, the regression models from 1 to 7 show that there is no serial correlation.

Heteroskedasticity Test: Breusch-Pagan-Godfrey	M1	M2	M3	M4	M5	M6	M7
F-statistic	0.068513	0.72608	0.217234	0.377708	1.050089	0.298044	0.92038
Obs.*R^2	0.068609	0.726749	0.217514	0.756642	2.101545	0.597124	2.763614
Scaled explained SS	0.1242	1.338833	0.390188	1.395389	3.865995	1.0807	5.089781
Prob. F(1,1382)	0.7936	0.3943	0.6412	0.6855	0.3502	0.7423	0.4302
Prob. $\chi^2(1)$	0.7934	0.3939	0.6409	0.685	0.3497	0.7419	0.4295
Prob. $\chi^2(1)$	0.7245	0.2472	0.5322	0.4977	0.1447	0.5825	0.1653

Notes: Notes: This table presents the test of Breusch-Pagan-Godfrey for heteroskedasticity. Under the null hypothesis there is no heteroskedasticity. The values in probabilities report that the null hypothesis is not rejected. Therefore, the regression models from 1 to 7 show that there is no heteroskedasticity.

APPENDIX 9. Residual test results of Ljung-Box for autocorrelation (adjusted for 3 AR terms).

Lag	AC	PAC	Q-Stat	Probability
1	0.005	0.005	0.0332	
2	0.006	0.006	0.0884	
3	0.007	0.007	0.1548	
4	-0.008	-0.008	0.2385	0.625
5	-0.035	-0.035	1.9374	0.38
6	0.001	0.001	1.9383	0.585
7	-0.016	-0.015	2.282	0.684
8	0.011	0.012	2.4517	0.784
9	-0.036	-0.036	4.216	0.647
10	-0.01	-0.011	4.3663	0.737
11	0.003	0.003	4.3807	0.821
12	0.049	0.049	7.698	0.565
13	-0.055	-0.055	11.876	0.293
14	0.029	0.026	13.047	0.29
15	-0.017	-0.018	13.462	0.336
16	0.019	0.02	13.956	0.377
17	-0.008	-0.006	14.039	0.447
18	0.018	0.014	14.475	0.49
19	0.04	0.042	16.763	0.401
20	0.033	0.029	18.25	0.373
21	-0.019	-0.013	18.741	0.408
22	0.018	0.013	19.18	0.445
23	0.005	0.007	19.209	0.508
24	-0.004	-0.003	19.227	0.571
25	-0.017	-0.009	19.644	0.605
26	0.011	0.005	19.81	0.653
27	0.01	0.017	19.949	0.7
28	-0.008	-0.01	20.046	0.744
29	0.034	0.041	21.651	0.708
30	0.011	0.005	21.833	0.746
31	0.015	0.015	22.167	0.774
32	-0.006	-0.006	22.214	0.811
33	-0.027	-0.023	23.219	0.806
34	0.018	0.017	23.7	0.823
35	0.005	0.008	23.737	0.854
36	0.002	0.004	23.743	0.882

Notes: This table presents the residual test of Ljung-Box for autocorrelation. The null hypothesis is that there is no autocorrelation. The probabilities show that the null hypothesis is not rejected and there is no autocorrelation.

APPENDIX 10. Residual test results of ARCH LM for testing the ARCH effect.

Heteroskedasticity Test: ARCH (with 1 lag)	
F-statistic	0.014842
Obs.*R^2	0.014864
Prob. F(1.1378)	0.9031
Prob. $\chi^2(1)$	0.903

Notes: This table presents the test of ARCH LM (with 1 lag) for testing the null hypothesis that there is no ARCH effect. The probabilities show that the null hypothesis is not rejected and thus there is no ARCH effect.

Heteroskedasticity Test: ARCH (with 3 lags)	
F-statistic	0.624307
Obs.*R^2	1.875815
Prob. F(3.1374)	0.5993
Prob. $\chi^2(3)$	0.5986

Notes: This table presents the test of ARCH LM (with 3 lags) for testing the null hypothesis that there is no ARCH effect. The probabilities show that the null hypothesis is not rejected and thus there is no ARCH effect.