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Do uncertainty indicators affect realized green bond volatility?

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ABSTRACT:

Growing awareness for climate and environment related problems during the last decade has been creating a positive trend for socially responsible investing. This has led to an increasing demand for alternative investment possibilities among market participants. One these new sustainable investing instruments are the so-called green bonds. A green bond is, by definition, a fixed-income instrument established to raise money for environmentally friendly project.

This thesis explores the relationship between various uncertainty indices and green bond market volatility. These uncertainty meters include the implied stock market volatility index (VIX), the implied oil market volatility index (OVX), the global economic policy uncertainty index (GEPU), the geopolitical risk index (GPR) and lastly the daily infectious disease equity market volatility tracker (EMVID).

More specifically, this study concentrates on how changes in monthly denoted uncertainty variables influence the daily computed range-based realized volatility of two different green bond ETFs. Green bond data series used are from the iShares USD Green Bond ETF (BGRN) and the VanEck Green Bond ETF (GRNB). Data period for this study is between 3.12.2018 and 28.2.2023.

In order to capture this relationship from two different data intervals, this study is using the mixed-data-sampling (MIDAS) framework for regression modeling. Range-based realized volatilities for the green bond ETFs are computed using two different methods.

The findings in this study indicate that there is statistically significant positive relationship between changes in implied oil market volatility and the green bond market risk measured by range-based realized volatility. This study also finds evidence indicating that the green bond market volatility does not seem to significantly react to changes in macroeconomic conditions or stock market volatility.

KEYWORDS: Volatility, MIDAS, Green Bond, VIX, OVX, EMVID, GEPU, GPR

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TIIVISTELMÄ:

Viimeisen vuosikymmenen aikana lisääntynyt tietoisuus ilmaston lämpenemisestä ja ympäristöön vaikuttavista tekijöistä on luonut positiivisen trendin sosiaalisesti vastuullisen sijoittamisen ympärille. Tämä on johtanut markkinoilla kasvavaan kysyntään vaihtoehtoisia sijoitusmahdollisuuksia kohtaan. Yksi näistä uusista instrumenteista on vihreä joukkovelkakirjalaina eli green bond. Vihreällä joukkovelkakirjalainalla tarkoitetaan kiinteätuottoista arvopaperia, joka on luotu tietyn ympäristöystävällisen projektin rahoittamiseksi.

Tämä tutkielma perehtyy useiden eri epävarmuusindeksien ja vihreiden joukkovelkakirjamarkkinoiden väliseen yhteyteen. Tutkielmassa käytetyt epävarmuusmittarit ovat osakemarkkinoiden implisiittistä volatiliteettiä kuvaava indeksi VIX, öljymarkkinoiden implisiittistä volatiliteettiä kuvaava indeksi OVX, globaalin talouspolitiikan epävarmuutta kuvaava indeksi GEPU, geopoliittista riskiä kuvaava indeksi GPR sekä infektiotaudeista johtuvaa osakemarkkinoiden volatiliteettiä seuraava indeksi EMVID.

Tämä tutkielma keskittyy erityisesti siihen miten valituissa kuukausittain noteeratuissa epävarmuusindekseissä tapahtuvat muutokset vaikuttavat päivittäin noteerattujen vihreiden joukkovelkakirjamarkkinoiden realisoituneeseen volatiliteettiin. Vihreää joukkovelkakirjamarkkinaa kuvaavat tässä tutkimuksessa iShares USD Green Bond ETF (BGRN) ja sekä VanEck Green Bond ETF (GRNB). Tutkimuksessa käytetty data alkaa 3.12.2018 ja päättyy 28.2.2023

Tässä tutkielmassa regressioiden mallintamiseen käytetään MIDAS-viitekehystä (Mixed-data sampling) kahdessa eri intervallissa noteerattujen aikasarjojen välisten yhteyksien havaitsemiseksi. Lisäksi vihreiden joukkovelkakirjamarkkinoiden realisoituneen volatiliteetin laskemiseksi käytetään kahta eri laskentatapaa.

Tämän tutkielman tulokset osoittavat, että öljymarkkinoiden implisiittisen volatiliteetin muutosten ja vihreiden joukkovelkakirjamarkkinoiden välillä on tilastollisesti merkittävä positiivinen yhteys. Lisäksi tutkielma löytää merkkejä, että vihreiden joukkovelkakirjamarkkinoiden volatiliteetti ei näyttäisi ainakaan tilastollisesti merkittävällä tavalla reagoivan makrotaloudellisiin muutoksiin tai muutoksiin osakemarkkinoiden volatiliteetissä.

AVAINSANAT: Volatility, MIDAS, Green Bond, VIX, OVX, EMVID, GEPU, GPR

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Abbreviations

ADF	Augmented Dickey-Fuller
CBOE	The Chicago Board Options Exchange
BGRN	The iShares USD Green Bond ETF
EMVID	Daily Infectious Disease Equity Market Volatility Tracker
EPU	Economic Policy Uncertainty
ETF	Exchange Traded Fund
GDP	Gross domestic product
GEPU	Global Economic Policy Uncertainty
GPR	Geopolitical Risk Index
GRNB	The VanEck Green Bond ETF
GVZ	The CBOE Gold ETF Volatility Index
HF	High frequency
IMF	International Monetary Fund
LF	Low frequency
MIDAS	Mixed-data sampling
OVX	CBOE Crude oil ETF implied volatility index
PV	Present value
RV	Realized volatility
RVP	Realized volatility using the Parkinson method
RVRS	Realized volatility using Rogers-Satchell method
US	United States
VIX	CBOE Implied volatility index

1 Introduction

Green bonds are a form of fixed-income securities which are created for specifically mitigating the climate change. The bonds are primarily issued by corporate, government, and supranational entities (e.g., European Investment Bank, the World Bank etc.). The market for green bonds is relatively new as the first bonds were released in 2007. The first multilateral development institution to issue a climate-awareness bond was the European Investment Bank (EIB). The bond issued in 2007 was worth USD 1 billion. However, the fixed-income securities have experienced a strong market growth following their release. The green bond market has quickly caught the attention of environmentally conscious investors since the bonds are established to finance environmentally friendly projects covering for example alternative energy, energy efficiency, low-carbon transport, sustainable water, and waste and pollution projects. This success has led to several international exchanges to establish green bond market segments which importantly reinforces the reputation, liquidity and transparency throughout the market. (Tang and Zhang, 2018), (Reboredo, 2018), (Banga, 2019)

While especially the study by Reboredo (2018) has attracted growing interest among scholars and practitioners, it also leaves room for additional work on at least two paths. First path is an investigation into volatility connectedness between regular bond market and green bond markets. This can be seen interesting front to explore as the green bonds, like all fixed income assets, bear the credit risk of their issuers despite that they are separated from conventional bonds by the nature in which their proceeds can be used.

Second path left open by Reboredo (2018) is the extension of the empirical analysis to include also other valuable assets such as gold and crude oil and their implied volatility indices GVZ and OVX respectively as well as the US implied volatility index (VIX). All of these are considered widely to be valuable in hedging against financial asset. (Basher and Sadorsky, 2016) (Ahmad et al., 2018).

As stated, the growing popularity in green bonds as an environmental-related investment has not been matched in academic literature with abundancy. There still remains unanswered questions regarding the relationship between green bonds and other financial markets such as commodity markets. Investigations into these relationships are especially useful for those investors and risk managers who might be keen on understanding the dynamic dependencies between green bonds and other valuable assets such as gold, crude oil and fear indices for diversification, hedging effectiveness, and asset allocation purposes.

1.1 Purpose of the study

The motivation for this study rises from the ever-growing awareness of climate change related issues as well as from the trending nature of both ESG and socially responsible investing. These things combined have created, among investors, an increased demand for alternative investment possibilities and research into these alternatives. This study aims to research and analyze the relationship between green bond volatility and various uncertainty indicators. More precisely, the goal of this study is to examine how different uncertainty and fear indicators affect the range-based realized volatility in the green bond market. This thesis aims to find answers as to how changes in implied volatility indices from stock and oil markets influence the range-based realized volatility of the green bond market. Furthermore, the purpose is also to include changes in macroeconomic fear indices such as EMVID, GEPU, GPR in the study.

1.2 Hypothesis development

As mentioned before, the study aims to shed light into the relationship between uncertainty indices, implied oil and stock market volatility and realized volatility in the green bond market. The null hypothesis states that there exists no relationship between these variables. Therefore, the hypotheses of the study are as follows:

H1: VIX has a positive impact on the realized green bond volatility

H2: OVX has a positive impact on the realized green bond volatility

H3: GPR has a positive impact on the realized green bond volatility

H4: GEPU has a positive impact on the realized green bond volatility

H5: EMVID has a positive impact on the realized green bond volatility

1.3 Contribution

The intended contribution of this study is to show how changes in uncertainty and fear indices impact the green bond market uncertainty measured by realized volatility. The study also uniquely uses the MIDAS framework to capture linkages between daily computed realized volatility in the green bond market and monthly changes in different uncertainty indices. This study will be limited to the chosen data and the limited time period.

1.4 Structure of the study

The remaining structure of the study will be divided into six sections. The first part will go over previously existing literature on the subject. Second part covers the theoretical framework in which the study is conducted by explaining the characteristics of volatility, implied volatility and bonds. Third part covers the methodology used. The fourth part will go over and describe the planned data used for the regressions. Fifth part goes over the preliminary results of the analysis and the last part concludes the findings of the thesis with possible new research proposals that rise.

2 Empirical literature

This chapter briefly summarizes the pre-existing literature. As the green bond research is relatively young and the theme still constantly growing, the focus will be on the most recent studies and their implications.

Tang and Zhang (2018) explore the market response for green bond issuance. They find that the market response for issuing a green bond tends to affect the issuers' stock price positively. This might be one of the motivations behind the rise in popularity of the green bonds. Moreover Baulkaran (2019) explores stock market reactions for announcements regarding green bond issuance by publicly traded companies. He finds that significant cumulative abnormal positive returns follow the announcements. However, the study also shows that these abnormal returns are positively linked to a number of firm specific metrics such as Tobin's Q, firm size and asset growth whereas operating cash flow has a negative relationship with the returns. Tang and Zhang (2020) find that the positive market reaction is in part likely due to increased media coverage surrounding a green bond issuance which in turn leads to an increase in the investor base.

Zerbib (2019) focuses on the yields of green bonds compared to equivalent non-green bonds. The study highlights the presence of green bond premium which can be described a result of pro-environmental preferences. However later Hyun et al. (2020) show that at least on average green bonds do not include either yield premium or discount.

The seminal work regarding green bonds was conducted by Reboredo (2018). His study explores the relationship between green bonds and financial markets as well as treasury and corporate bond markets. The findings indicate that green bonds show ability to hedge both stock and energy markets. On the other hand, the study highlights inability to hedge treasury and corporate markets. In other words, the study highlights that green bonds tend to move more in line with conventional corporate and treasury fixed-income markets whereas the linkage with financial markets like energy and stock is very weak even in the presence of large price changes in these markets.

More recently Dutta et al. (2021) study the interactions between climate bonds and both stock and commodity markets during the COVID-19 outbreak. More precisely their paper investigates the time varying correlations between and green bonds and both markets respectively. They show that climate bonds show negative correlation with the S&P 500 whereas the correlation with both commodity markets is observed to be positive. This is mainly consistent with the findings of Robredo (2018) in showing that climate bonds tend to share the same characteristics with conventional bonds regarding their relation to the financial markets.

A market’s sensitivity to volatility of other markets has been thoroughly researched in the past. For example, according to Liu et al. (2013) the implied oil volatility index (OVX) is affected by volatility in other markets such as stock and gold. Moreover, this relationship is stronger in the presence of global economic instability. Dutta (2017) states that renewable energy markets are highly sensitive to crude oil implied volatility measured by the OVX. Dutta (2018) continues this and states that the OVX also has an effect and a relationship with the stock market in the US. This prevalence of volatility spillover raises questions on the relationship between the green bond market volatility and uncertainty in other markets.

In his paper Pham (2016) analyzes the volatility behavior of the green bond market using data from the S&P green bond indices. His findings indicate the presence of volatility clustering inside each individual green bond index. Furthermore, the study highlights volatility spillover between conventional and green bond markets. More recently Broadstock and Cheng (2019) explore the volatility spillovers between green bond market and conventional bond market. They find that the relationship between the two markets is increasingly affected by macroeconomic conditions such as policy uncertainty.

3 Theoretical framework

This chapter describes the theoretical framework behind the study. Both volatility and bonds are explained briefly. First section covers the definition of volatility followed by implied volatility. Second part goes through basic bond definition followed by bond pricing.

3.1 Volatility

Volatility, by definition, is the standard deviation of the return provided by a market variable in question such as equity or a commodity like gold or oil per unit of time when the return is expressed using continuous compounding. Volatility is usually denoted by σ. The intended use of volatility determines the unit of time used for calculation. For example, in risk management the unit of time is usually one day so that volatility is the standard deviation of continuously compounded return per day whereas in option pricing the standard is to use yearly returns continuously compounded daily. (Hull 2018: 213, 215)

In equation 1, we define the value of a variable, e.g., a stock or commodity, S_i at the end of the day *i*. For day *i*, the continuously compounded return of the variable in question per day is as follows (Hull, 2018: 214).

$$ln \frac{S_i}{S_{i-1}}. \tag{1}$$

Furthermore, this is also close to,

$$\frac{(S_i - S_{i-1})}{S_{i-1}}. \tag{2}$$

Therefore, we can say that daily volatility of a variable can alternatively be described as the proportional change in the variable during the day. Most commonly this is the definition of volatility used by people in risk management (Hull 2018: 214).

In risk management the focus is commonly on the variance rate rather than the volatility of the variable in question. Variance rate is the square of volatility, denoted as σ^2. The main difference is that while the standard deviation of the return in time *T* increases with the square root of time, the variance of this return however increases linearly with time. (Hull, 2018: 215)

3.1.1 Implied volatility

Implied volatility is seen as the market's opinion on the volatility of a specific security. For example, in options the basic valuation revolves around the Black-Scholes-Merton formula where the standard deviation is always an estimate. As the options always have a price in the actual market, the model can be calculated in a way that the presiding market price gives away the standard deviation implied by the Black-Scholes-Merton model. This standard deviation needed to make the option price follow the prementioned formula is in fact called the implied volatility. (Bodie et al. 2018: 741)

3.2 Bonds

The basic definition of a bond is that it is a security issued in connection with a borrowing arrangement. Issuer of the bond (borrower) sells a bond to the buyer (lender) for some predetermined amount of cash. The arrangement obligates the borrower to repay the lender with specified payments on specified dates. Bond payments are usually divided into two categories. Firstly, are the coupon rate payments which are the interest payments made for example semi-annually for the life of the bond. Secondly is the payment of the full value borrowed which is called par or face value. The par value of a bond is usually repaid at the maturity date of the bond. The coupon rate determines the annual interest payment on the borrowed capital denoted by par value of the bond. (Bodie et al. 2014: 446)

As a bond's coupon payments are occurring in the future, the lender has to take into account the time value of money which denotes that the value of cashflow today is different from the same amount received in the future. The calculated measure here is called present value which value is affected by market interest rate i.e., profit expectation in the market also known as the discount rate. The interest rate is separated into two different return components which are the nominal and the real rate of return. Nominal rate of return takes into account, besides the real interest rate, also the premium above it to compensate for inflation expectations. The real rate thus reflects the true cost and yield to both the borrower and lender respectively. Regarding the discount rate, market expectation is that no bond is risk free and so the rate always includes a risk premium related to bond specific risk factors. These risk factors include risks such as default or liquidity risk. (Bodie et at. 2014: 451-452)

3.2.1 Bond pricing

To put it in simple terms, the calculation of bond price could be done using one constant interest rate to discount cash flows of different maturities. It should be noted however that in reality the discount rate changes through time as the market expectations change. To be able to accurately value a debt investment instrument such as a bond, the future expected cash flows are all discounted by the appropriate discount rate on each point in time. By the definition explained before, the value of a bond revolves around both coupon payments and the payment of par value. This theoretical value can be denoted as the sum of discounted coupon payments and discounted par value as follows in equation 3 (Bodie et al. 2014: 452-453).

$$Bond\ value = \sum_{t=1}^{T} \frac{Coupon}{(1+r)^t} + \frac{Par\ value}{(1+r)^T} \tag{3}$$

where,

∑ = sum of coupon payments from time *t* to *T*

T = maturity date

r = interest rate

The first component to the right-hand side of the equation calculates the present value of coupon payments in different points in time. This is also called the annuity factor. The second component calculates the present value of initial par value received as the last payment at maturity. As so the price of a bond can also be denoted as (Bodie et al. 2014: 452-453):

$$\begin{aligned} Price &= Coupon \times \frac{1}{r}\left[1 - \frac{1}{(1-r)^T}\right] + Par\ value \times \frac{1}{(1+r)^T} \\ &= Coupon \times Annuity\ factor(r,T) + Par\ value \times PV\ factor(r,T) \end{aligned} \tag{4}$$

4 Methodology

This section first briefly describes the calculation basis of range-based realized volatility (RV), dependent on daily green bond ETF data. Secondly, we go over the basic characteristics of MIDAS framework and the construction of the model used in this study. All regressions are run in EViews.

4.1 Estimation of RV

Term of realized volatility (RV) was used for the first time by researchers Fung and Hsieh (1991). Realized volatility is defined as the sum of squared intraday returns calculated at short intervals. RV is defined as follows (Andersen and Bollerslev, 1998):

$$RV_t = \sum_{i=1}^{M} r_{i,t}^2,\ \ t = 1,2,\dots,T \tag{5}$$

$$r_{i,t} = 100 \times (\ln P_{i,t} - \ln P_{i-1,t}) \tag{6}$$

where *M* denotes the sampling frequency and $P_{i,t}$ stands for the closing price for period *i* on day *t*.

In this study we will be using the calculated range-based volatility which is superior at computing volatility compared to the simplified squared daily return model. The range-based volatility models take into account also the path of the underlying asset price inside the period of reference as well as appear to be less noisy than the traditional measure (Bakanova, 2010).

Following the work of Dutta (2017) instead of using the beforementioned traditional way of computing RV, we will be using the range-based models proposed by Parkinson (1980) and Rogers and Satchell (1991). These models are superior to the original as they take into account also the intraday movements by exploring high, low and opening prices.

The Parkinson (1980) model is denoted as follows:

$$RVP_t = \frac{1}{4ln2}[\ln H_t - \ln L_t]^2 \tag{7}$$

where H_t and L_t refer to the highest and lowest prices on a trading day *t*. We do however have to take into account that although the Parkinson model is theoretically efficient, it does assume a geometric Brownian motion with zero drift which means that in the presence of a non-zero drift, the model tends to overestimate the volatility (Dutta, 2017).

Second measure we incorporate is the later proposed model by Rogers and Satchell (1991) which does not assume the same geometric Brownian motion with zero drift that the first model does. According to Viteva et al., (2014) this estimator (RVRS) benefits greatly from the inclusion of opening and closing prices together with the high and low prices. This allows the model to capture any jumps during the non-trading times. The model is denoted as follows:

$$RVRS_t = \ln\left(\frac{H_t}{O_t}\right) ln\left(\frac{H_t}{C_t}\right) + ln\left(\frac{L_t}{O_t}\right) ln\left(\frac{L_t}{C_t}\right) \tag{8}$$

where O_t and C_t denote the opening and closing prices on a trading day *t*. It is worth noting that although the initial assumption is that the RVRS estimator is expected to be dominant over the Parkinson's estimator, this study will still be including the Parkinson model to work as a benchmark estimator.

To be able to examine the predictive power of the implied volatility and uncertainty indices in explaining the realized variance of Green Bond ETFs, we aim to estimate the following specification:

$$RV_{t+1} = \beta_0 + \beta_1 dUNC_t + \varepsilon_{t+1} \tag{9}$$

In Equation 9 RV_{t+1} denotes the computed realized volatility of a green bond ETF at time *t+1*, $\beta_1 dUNC_t$ denotes the the return of the benchmark uncertainty index to be tested at time t and ε_{t+1} is the error term. We will estimate the above model repeatedly for all the variables using both estimators of the range-based realized volatility. To test the effectiveness of our regressors in predicting future green bond ETF volatility we need to test our hypothesis $H_0 : \beta_1 = 0$ where if β_1 is statistically different from zero we note that the regressor index in question possesses influence over the green bond ETF volatility.

4.2 MIDAS framework

Because our data consists of both daily and monthly observations, we will be running our regression through the mixed-data sampling (MIDAS) framework proposed by Ghysels et al., (2002). Their model uses high frequency (HF) variables to explain the movements of low frequency (LF) variable. The simple MIDAS model is as follows:

$$\gamma_t = \beta_0 + \beta_1 B\left(L^{\frac{1}{m}};\ \theta\right) x_t^{(m)} + \varepsilon_t^{(m)} \tag{10}$$

for $t =, \ldots, T, where\ B\left(L^{\frac{1}{m}}; \theta\right) = \sum_{k=0}^{K} B(k;\theta) L^{k/m}$and $L^{1/m}$ is a lag operator such that $L^{1/m} x_t^{(m)} = x_{t-1/m}^{(m)}$; the lag coefficient in $B(k;\theta)$ of the corresponding lag operator $L^{k/m}$ are parameterized as a function of a small-dimensional vector of parameters θ (Ghysels et al., 2007).

However, because our study will be using LF (monthly) index data as our independent regressor to explain our HF (daily) data of green bond ETF realized volatility, we will be using the so-called reverse MIDAS (R-MIDAS) model proposed by Foroni et al. (2018). Their model is as follows:

$$x_t = \lambda_i (L^{k+1}) y_t + \delta_{1i} B_i(L, \theta_i) x_{t-\frac{1}{k}} + \varepsilon_t, \tag{11}$$

$$t = 0 + \frac{i}{k} + 1\frac{i}{k} + 2\frac{i}{k}, \ldots \tag{12}$$

$$i = 0, \ldots, k-1 \tag{13}$$

where $B_i(L, \theta_i)$ can be for example an exponential Almon lag polynomial but use of other types of polynomials are as valid as in standard MIDAS. Our data was run with the Almon lag polynomial and it is depicted by Foroni et al. (2018) as follows:

$$B_i(L, \theta_i) = \sum_{j=0}^{Q} b_i\,(j, \theta_i)L^j, \tag{14}$$

$$b_i(j, \theta_i) = \frac{\exp\,(\theta_{i1}j + \theta_{i2}j^2)}{\sum_{j=0}^{K} \exp\,(\theta_{i1}j + \theta_{i2}j^2)} \tag{15}$$

5 Data

The data consists of two different green bond ETFs as the dependent variables and five independent variables consisting of uncertainty indices. The ETF data consists of daily open, close, high and low values. The uncertainty indices are valued monthly.

The first ETF is the iShares USD Green Bond ETF (BGRN) which tracks the returns of, and index compiled out of investment grade U.S. dollar-denominated green bonds which are issued by both U.S. based and non-U.S. based issuers with the goal of funding environmental projects (iShares, 2023).

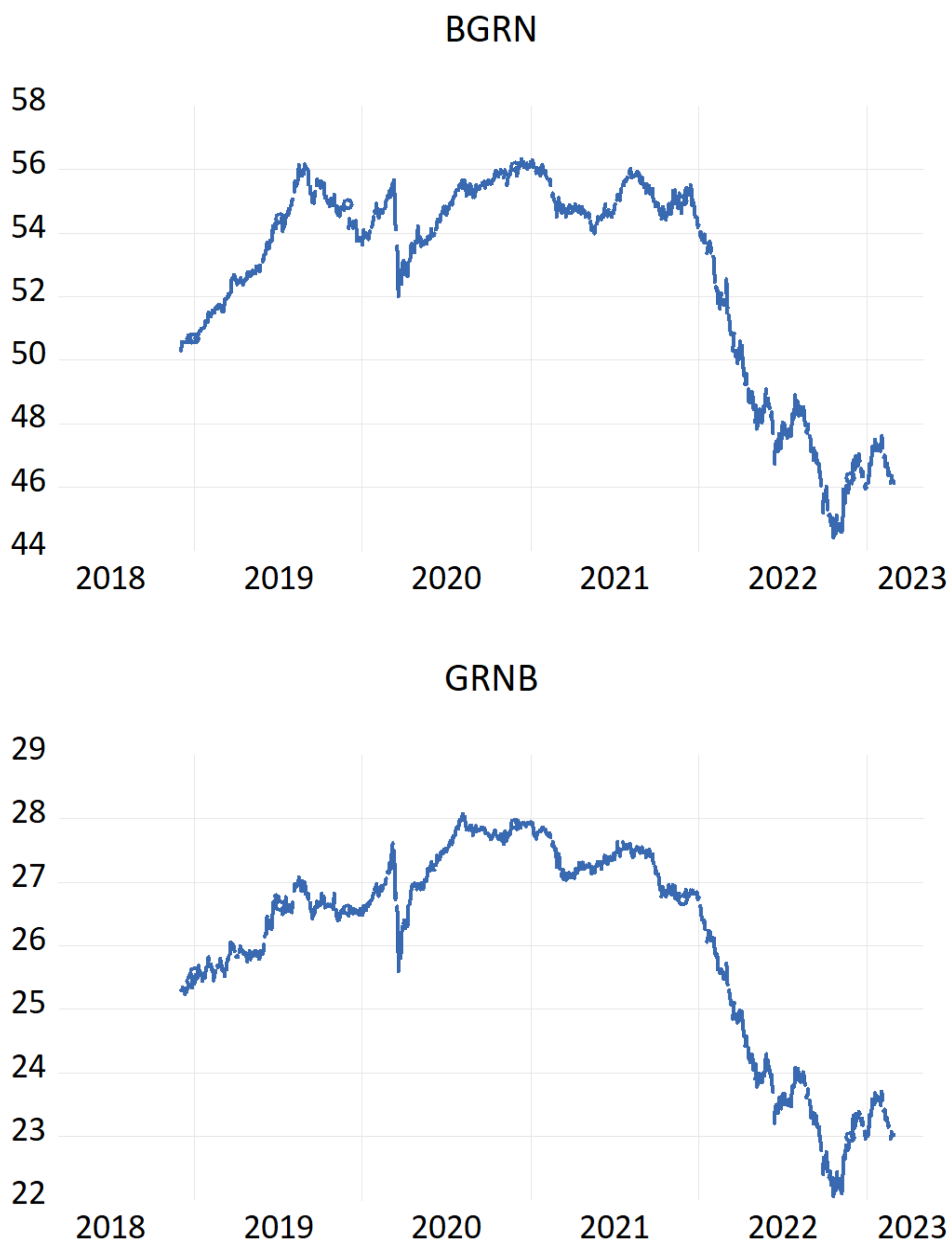
The second ETF is the VanEck Green Bond ETF (GRNB). This ETF has a goal of replicating, before fees and expenses, the price and yield performance of the S&P Green Bond U.S. Dollar Select Index (SPGRUSST) (VanEck, 2023).

Figure 1 shows the closing price of both the BGRN and GRNB through the time series between 3.12.2018 and 28.2.2023. The figures clearly show both the downfall due to COVID-19 pandemic in 2020 as well as the effect of growing tension in 2022 between Russia and the west which lead to the start of war in Ukraine. Data clearly shows that the effect of war in Ukraine to green bond prices greatly surpasses that of the COVID-19 pandemic. During COVID-19 green bond prices quickly recover from the initial fall but the ongoing war seems to have a more lasting downward impact on the market. At the same time the price of oil went up during the war which gives basis to a question of oil market hedging abilities regarding green bond returns.

Uncertainty indices used are the CBOE (Chicago Board Options Exchange) Volatility index (VIX), the CBOE Crude Oil Volatility Index (OVX), the Global Economic Policy Uncertainty Index (GEPU), the Geopolitical Risk Index (GPR) and lastly the Daily Infectious Disease Equity Market Volatility Tracker (EMVID). (Economic Policy Uncertainty, 2023)

The VIX index originates from real-time prices of options on the American S&P 500 Index (SPX). VIX is aiming to reflect the investors' expectations of future (30-day) expected volatility in the stock market. The VIX Index is in a way a measure of market “fear” and is often used as the market's "fear gauge". VIX was introduced by the CBOE first time in 1993. (Saha et al., 2019)

Figure 1. Daily price for BGRN and GRNB from December 2018 to February 2023.



OVX is similar to VIX in that it is an estimate of expected 30-day volatility but differentiates from VIX in that it concentrates on the United States Oil Fund (USO) and more precisely options on the USO ETF. Both of these volatility indices are calculated by interpolating between two time-weighted sums of option mid-quote values. The OVX was published by the CBOE in 2007 (Chen et al., 2015).

GEPU, GPR and EMVID are all measures of policy-related economic uncertainty and extracted from policyuncertainty.com. Indices on the website are constructed to measure this uncertainty from three underlying components. Firstly, they use newspaper coverage denoted by index of search results on policy-related economic uncertainty in large newspapers. Second component follows the number of tax code provisions set to expire over the following 10 years as reported by the Congressional Budget Office (CBO). This second measure describes the uncertainty embedded in the path of federal tax code in the future. Third component aims to construct indices on policy-related macroeconomic variables by utilizing the dispersion between individual forecasters' predictions on future levels of the consumer price index (CPI) as well as federal, state and local expenditures. (Economic Policy Uncertainty, 2023)

GEPU was introduced by Davis (2016) and the index is constructed from GDP-weighted average of national EPU indices for 16 countries that account for two-thirds of the total global output value. The individual national indices are re-normalized to a mean of 100 from the first year 1997 and then the missing country values are regressed. Third step is the computing of the monthly GEPU index by using the GDP-weighted average of each of the 16 national EPU index values as denoted by the IMF's world economic outlook database (Davis, 2016).

GPR is introduced by Caldara & Iacoviello (2022) and uses the textual analysis-based approach by incorporating automated text-searches on the electronic archives of 10 major newspapers: the Chicago Tribune, the Daily Telegraph, the Financial Times, the Globe and Mail, the Guardian, the Los Angeles Times, the New York Times, USA Today, the Wall Street Journal, and the Washington Post.

The EMVID monthly index uses the newspaper method and is based on a textual analysis of four sets of terms as follows. E denotes economic, economy, and financial. M denotes “stock market”, equity, equities, and “Standard and Poor’s” V denotes volatility, volatile, uncertain, uncertainty, risk, and risky. Lastly ID denotes epidemic, pandemic, virus, flu, disease, coronavirus, MERS, SARS, Ebola, H5N1, H1N1, and then obtaining daily counts of newspaper articles that contain at least one term in each of E, M, V, and ID across approximately 3000 US newspapers. (Bouri et al. 2020)

Figure 2. illustrates the movements of each of the uncertainty indices from December 2018 all the way through to December 2022. From the graph we can see the impact of both COVID-19 epidemy in the early 2020 and Russia attacking Ukraine in early 2022 and the buildup before the attack. Uncertainty indices monthly returns are displayed in Figure 3.

Figure 2. Uncertainty indices monthly value 12/2018-12/2022

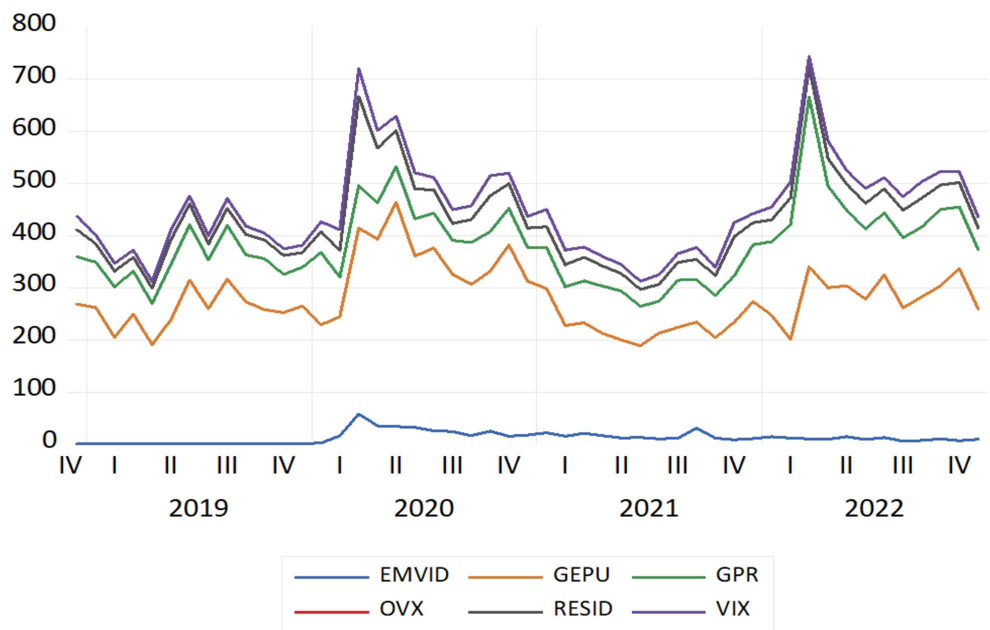


Figure 3. Uncertainty indices monthly returns

The calculated realized volatilities for both bond ETFs are illustrated in figures 4 through 7. Both calculation methods are used and as stated under methodology the graphic seems to support the notion that the RVP model slightly overestimates realized volatility compared to the RVRS. This notion seems to be true for both BGRN and GRNB data.

Figure 4. RVP for BGRN from December 2018 to February 2023.

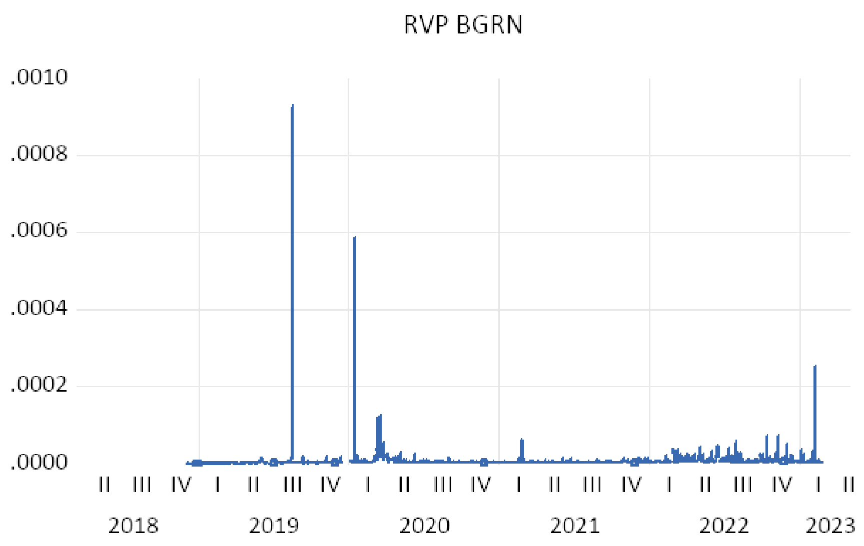


Figure 5. RVRS for BGRN from December 2018 to February 2023.

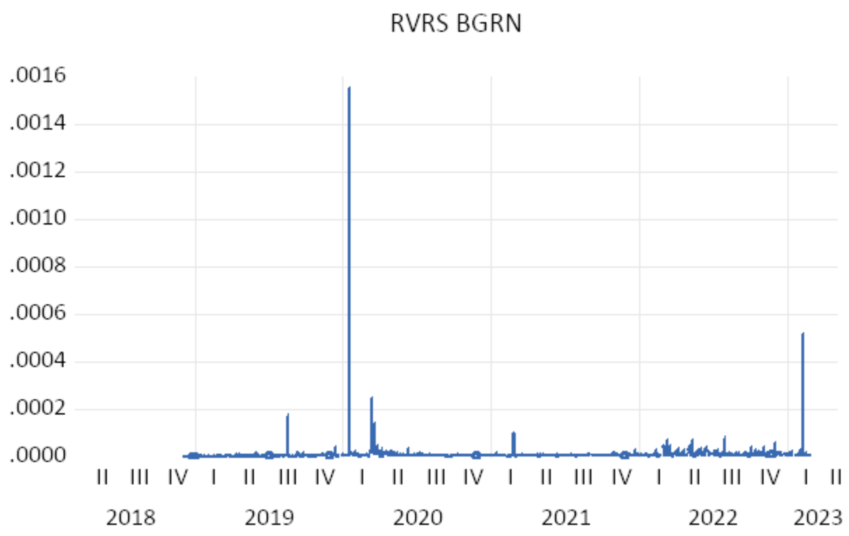


Figure 6. RVP for GRNB from December 2018 to February 2023.

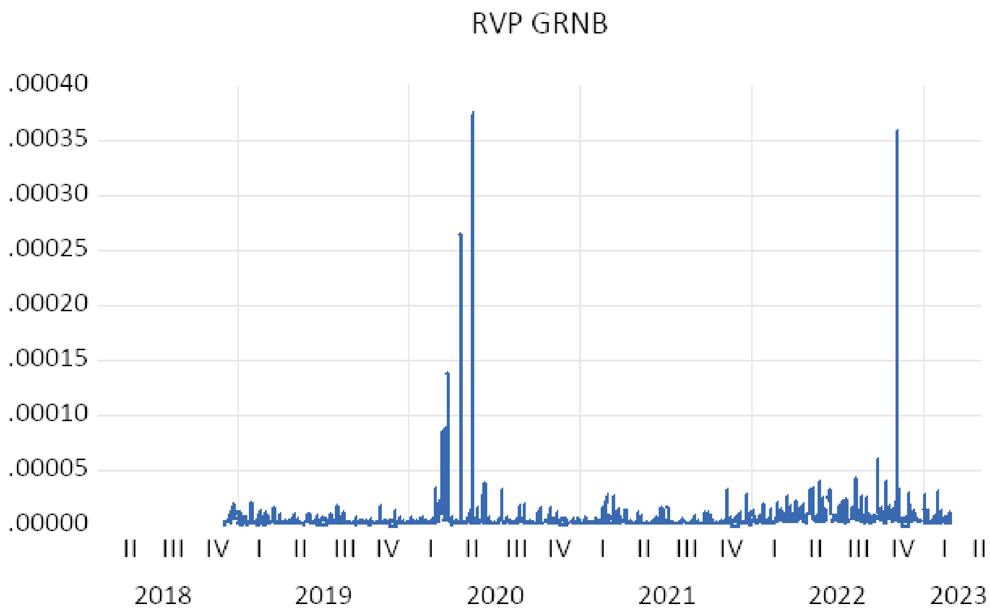
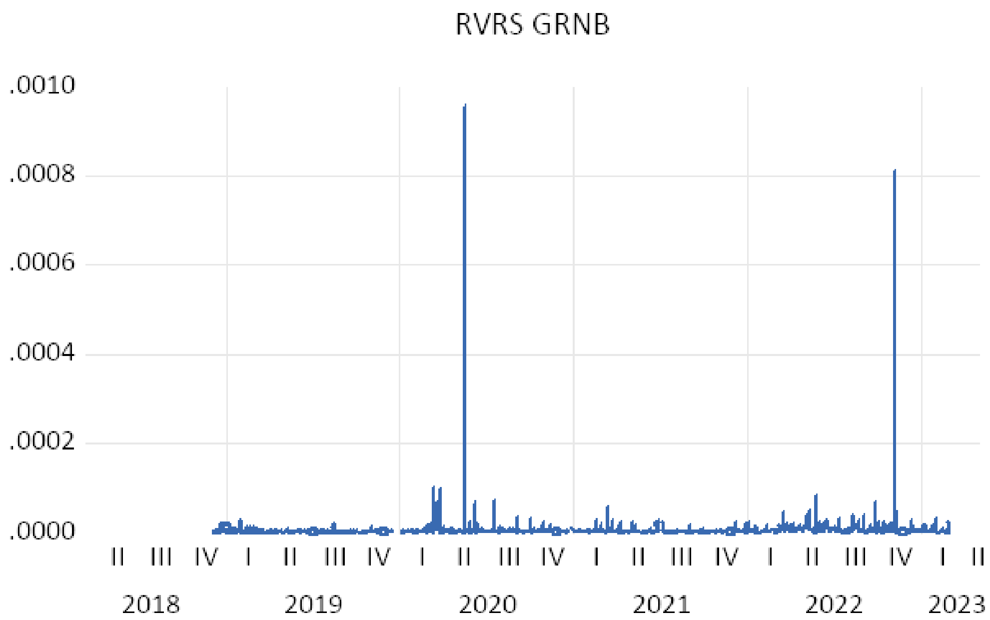


Figure 7. RVRS for GRNB from December 2018 to February 2023.



The descriptive statistics for RV calculations are presented in table 1. All the series show positive skewness. Kurtosis is also over 3 so the computed values are not normally distributed.

Table 1. Descriptive statistics for RV calculations.

ETF	Method	Mean	Std. Dev.	Skewness	Kurtosis
GRNB	RVP	0,00000569	0,0000196	14,520	249,323
GRNB	RVRS	0,00000641	0,0000393	21,494	489,694
BGRN	RVP	0,00000673	0,0000357	20,573	483,632
BGRN	RVRS	0,00000731	0,0000517	25,962	751,867

Table 2 presents the descriptive statistics for monthly returns on each of the uncertainty indices. The returns on all the indices show positive skewness except for GPR. Null hypotheses for all indices is that they are normally distributed. All the variables show kurtosis over 3 so the returns are not normally distributed, and the null hypotheses seem to be rejected. This is reinforced by the Jarque-Bera test results which show statistical significance for all but GEPU and VIX at 1% confidence level. Stationarity of these return series is supported by Augmented Dickey-Fuller test which show statistical significance also at 1% level. Passing the ADF test is important keeping in mind the stationarity requirement in time series data and regression analysis.

Table 2. Descriptive statistics for uncertainty.

Index	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF
EMVID	0.182355	8.993711	1.837793	12.40703	208.2542***	-8.725966***
GEPU	-0.371041	49.33674	0.574846	3.623796	3.493112	-9.636482***
GPR	0.474286	33.10189	-0.399674	8.852899	71.24474***	-6.947370***
OVX	-0.216531	23.09384	2.404810	17.04021	449.6974***	-8.184286***
VIX	-0.076531	7.676672	0.110996	3.653517	0.972578	-8.433704***

*** indicates statistical significance at 1% confidence level

Table 3 below illustrates descriptive statistics for daily green bond returns for both ETFs respectively. Null hypothesis for both bonds is that they are normally distributed. Both series show a kurtosis above 3 indicating non-normality. Moreover, the Jarque-Bera testing shows statistical significance at 1% confidence level. Both statistics lead to the null hypothesis being rejected. Augmented Dickey-Fuller stationarity test also shows statistical significance, so we conclude that both series are suitable to be used in our regression analysis. Both series also show slightly negative skewness.

Table 3. Descriptive statistics for green bond returns.

ETF	rBGRN	rGRNB
Mean	-0.005156	-0.004459
Std. Dev.	0.339838	0.313503
Skewness	-0.086568	-0.329415
Kurtosis	9.097124	6.399839
Jarque-Bera	1587.409***	511.6997***
ADF	-31.02155***	-30.52731***

*** indicates statistical significance at 1% confidence level.

6 Empirical results

This chapter describes the results of the regressions used in the empirical part of this study. The results are displayed in tables to increase readability as well as to test the hypotheses for this study.

Tables from 4 to 7 show results of our MIDAS-regression for both bonds and both methods of calculating the RV. Tables 4 and 5 show results using the Parkinson method (RVP) to calculate range-based realized volatility. Results for the Rogers-Satchell method (RVRS) are in tables 6 and 7.

In all the tables the regressions are run in EViews with MIDAS regression coupled with 3-degree Almon polynomial. Each of the regressions are run separately for both bonds and separately for all the variables. Tables 4 and 5 use the Parkinson realized volatilities as the dependent variable and each of the uncertainty meters as independent variables whereas tables 6 and 7 use the Rogers-Satchell method.

The MIDAS regression results for RVP indicate that for both green bond ETFs, the OVX has a statistically significant influence over realized volatility. However only the GRNB data shows significance for GEPU and EMVID at 1% confidence level while BGRN data shows significance merely at 5% level. Keeping in mind that the RVP method tends to overestimate volatility when presented with non-zero drift, these results are used only as a benchmark for the RVRS results.

Table 4. Regression results for GRNB RVP MIDAS PDL/Almon (polynomial degree: 3).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VIX	0,000000309	0,000000206	1,497181	0,1348
OVX	0,000000174	0,000000067	2,613586	0,0091***
GPR	0,000000044	0,000000046	0,958312	0,3382
GEPU	0,000000048	0,000000012	3,998963	0,0001***
EMVID	0,000000274	0,000000063	4,374849	0,0000***

*** and ** indicate statistical significance at 1% and 5% confidence level respectively.

Table 5. Regression results for BGRN RVP MIDAS PDL/Almon (polynomial degree: 3).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VIX	0,000000309	0,000000206	1,4972	0,1348
OVX	0,000000174	0,000000067	2,6136	0,0091***
GPR	0,000000044	0,000000046	0,9583	0,3382
GEPU	0,000000073	0,000000032	2,3002	0,0217**
EMVID	0,000000367	0,000000167	2,1984	0,0282**

*** and ** indicate statistical significance at 1% and 5% confidence level respectively.

The RVRS results for both green bond ETFs in tables 6 and 7 are consistent with earlier findings regarding the OVX using the Parkinson method. The statistical significance here is even stronger than in the previous regressions indicating that changes in oil market uncertainty influences the realized volatility in the green bond market. The results are also constant regarding the other macroeconomic uncertainty meters and VIX in so that other than OVX there seems to be no significant relationship between green bond volatility and other variables. These findings are consistent with the presumption of RVRS method being dominant over the RVP in calculating realized volatility.

These results are consistent with the hypothesis H2 and lead to the rejection of null hypothesis regarding the OVX having no impact on green bond volatility. However, the regression doesn't show unequivocal statistical evidence regarding the other hypotheses H1, H3, H4 and H5. There however exists weak signs between the green bond market volatility and the EMVID index at 5% confidence level so more research is needed on the subject. This could include a larger data set and more enhanced modeling of realized volatility.

Table 6. Regression results for GRNB RVRS MIDAS PDL/Almon (polynomial degree: 3).

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
VIX	0,000000469	0,000000292	1,6035	0,1093
OVX	0,000000268	0,000000093	2,8635	0,0043***
GPR	0,000000120	0,000000066	1,8348	0,0669
GEPU	0,000000045	0,000000045	1,0107	0,3125
EMVID	0,000000538	0,000000235	2,2895	0,0223**

*** and ** indicate statistical significance at 1% and 5% confidence level respectively.

Table 7. Regression results for BGRN RVRS MIDAS PDL/Almon (polynomial degree: 3).

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
VIX	0,000000469	0,000000292	1,6035	0,1093
OVX	0,000000268	0,000000093	2,8635	0,0043***
GPR	0,000000120	0,000000066	1,8348	0,0669
GEPU	0,000000045	0,000000045	1,0107	0,3125
EMVID	0,000000538	0,000000235	2,2895	0,0223**

*** and ** indicate statistical significance at 1% and 5% confidence level respectively.

The findings in this study are consistent with the findings of Robredo (2018) displaying little or no influence for stock market over the risk observed in green bond market in terms of volatility. This strengthens the conclusion made by Dutta et al (2021) that green bonds can be used for hedging financial market risk in the US.

Following the work of Pham (2016) these results also insinuate that there seems to in fact be a relationship between oil market volatility and the green bond market. This can be somewhat expected as the oil market might be seen by market participants as the opposite of the green bond market. However, in contradiction to Pham (2016), the results show that there seems to be little or no interaction between green bond market volatility and macroeconomic conditions such as policy uncertainty. However, these results differ over different RV methods so more research is needed.

7 Conclusions

This thesis examines how uncertainty indicators influence the green bond market. These indicators include both traditionally used indices such as the OVX for crude oil and VIX for stock market as well as macroeconomic uncertainty indicators describing geopolitical, economic policy and infectious disease related risks. The goal of this study, more specifically, is to show how changes in a range of different uncertainty indicators individually influence the range-based realized volatility witnessed in the green bond market.

All of the conclusions made in this study are restricted to the models and time period in which the study has been conducted. The regression modeling is done using the MIDAS framework. More specifically, this study uses this mixed-data sampling framework to be able to capture any relation between monthly noted uncertainty indices data and daily noted green bond data. The sample period starts from December 2018 and ends in February 2023.

The results of this thesis indicate that changes in the crude oil market uncertainty seem to have a statistically significant positive impact on the experienced volatility in the green bond market. These results are significant at 1% confidence level. The results support the initial hypothesis of oil market volatility having a positive influence over the green bond volatility.

This study also shows that changes in the stock market uncertainty seem to have little or no effect to green bond volatility statistically. These findings are consistent with the findings by both Robredo (2018) and Dutta et al. (2021) which indicate the stock market playing little or no role in the experienced green bond volatility and the green bond suitability for hedging financial market returns respectively. These results also indicate that as uncertainty in the green bond market does not react to changes in stock market volatility, the green bond market could possibly be used to hedge the stock market in highly volatile times. This hedging ability might be an important implication for portfolio managers as well as institutional investors.

The study also finds weak positive linkage between the infectious disease-related uncertainty index EMVID and green bond volatility. This relationship is statistically relevant across our line of our regressions, but only holds a weak significance at 5% confidence level using the RVRS method for computing the realized volatility. The findings also indicate that the other tested macroeconomic uncertainty indices show no reputable statistically significant relationship with green bond volatility.

Overall, the results in this thesis show that there is a positive relationship between the oil market uncertainty and uncertainty experienced in the green bond market. The results also indicate a weak relation to changes macroeconomic conditions, but this cannot be definitely concluded from the data and needs more in-depth research into the subject.

As the research into the green bond-nexus is still at a very early stage, there is still much we don't fully understand regarding the green bond market and its relation to other financial markets as well as the impact of changes in macroeconomic conditions to green bond. Thus, research in the future could be directed towards a few different directions. Firstly, the findings of this study need to be robustly tested and confirmed with other models and a longer data period which also should include other green bond markets around the world. Secondly it would be interesting to see if the relationship between uncertainty indices and the green bond market volatility prevails in the presence of market shocks or at the time of an economic crisis.

References

Ahmad, W., Sadorsky, P., & Sharma, A. (2018). Optimal hedge ratios for clean energy equities. *Economic Modeling*, 78, 278-295.

Andersen, T.G., Bollerslev, T. (1998). Deutsche Mark-dollar volatility: intraday activity patterns, Macroeconomic announcements, and longer-run dependencies. *Journal of Finance*, 53, 219-265. https://doi.org/10.1111/0022-1082.85732

Chen, Y., He, K. & Yu, L. (2015). The Information Content of OVX for Crude Oil Returns Analysis and Risk Measurement: Evidence from the Kalman Filter Model. *Annals of Data Science*, 2, 471-487.

Bakanova, A. (2010) The information content of implied volatility in the crude oil market. *Working Paper*. University of Lugano Switzerland.

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.

Basher, S. A., & Sadorsky, P. (2016). Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. *Energy Economics*, 54, 235-247.

Baulkaran, V. (2019) Stock market reaction to green bond issuance. *Journal of Asset Management*, 20, 331-340. https://doi.org/10.1057/s41260-018-00105-1

Bodie, Z., Kane, A., Marcus, A. J. (2018). *Investments*. 10. edition. New York: McGraw-Hill Education.

Bouri, E., Demirer, R., Gupta, R., & Pierdzioch, C. (2020). Infectious Diseases, Market Uncertainty and Oil Market Volatility. Energies, 13:16, 4090. https://doi.org/10.3390/en13164090

Broadstock, D. C. & Cheng, L. T. (2019). Time-varying relation between black and green bond price benchmarks: Macroeconomic determinants for the first decade. *Finance Research Letters*, 29, 17-22. doi: 10.1016/j.frl.2019.02.006

Caldara, D. & Iacoviello, M. (2022). Measuring Geopolitical Risk. *American Economic Review*, 112:4, 1194-1225.

Davis, S. J. (2016) An index of global economic policy uncertainty. *NBER Working Papers, National Bureau of Economic Research, Inc*. http://www.nber.org/papers/w22740

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.

Dutta, A. (2017) Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index. Journal of Cleaner Production, 164, 1157-1166.

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., Bouri, E. & Noor, H. (2021) Climate bond, stock, gold, and oil markets: Dynamic correlations and hedging analyses during the COVID-19 outbreak. *Resources Policy*, 74, 102265. https://doi.org/10.1016/j.resourpol.2021.102265

Economic Policy Uncertainty. (2023). https://www.policyuncertainty.com/Policyuncertainty methodology

Febi, W., Schäfer, D., Stephan, A., & Sun, C. (2018). The impact of liquidity risk on the yield spread of green bonds. *Finance Research Letters*, 27, 53-59.

Foroni, C., Guérin, P. & Marcellino, M. (2018). Using low frequency information for predicting high frequency variables. *International Journal of Forecasting*, 34:4, 774-787.

Ghysels, E., Santa-Clara, P. & Valkanov, R. (2002). The MIDAS touch: mixed data sampling regression models. *Working paper*, *UNC and UCLA*.

Ghysels, E., Sinko, A. & Valkanov, R. (2007). Midas Regressions: Further Results and New Directions. *Econometric Review*, 26:1, 53-90. DOI: 10.1080/07474930600972467

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

Hyun, S., Park, D. & Tian, S. (2020). The price of going green: The role of greenness in green bond markets. *Accounting & Finance*, 60:1, 73-95. doi:10.1111/acfi.12515

iShares. (2023). https://www.ishares.com/us/products/305296/ishares-usd-green-bond-etf

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.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of Business*, 53:1, 61-65.

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.

Rogers, L., C., G., & Satchell, S., E. (1991. Estimating Variance From High, Low and Closing Prices. *Annals of Applied Probability*, 1:4, 504-512. doi: 10.1214/aoap/1177005835

Saha, A. Malkiel, B. G. & Rinaudo, A. (2019). Has the VIX index been manipulated? *Journal of Asset Management*, 20, 1-14.

Tang, D. Y., & Zhang, Y. (2018). Do shareholders benefit from green bonds?. *Journal of Corporate Finance*, 61. https://doi.org/10.1016/j.jcorpfin.2018.12.001

Tang, D. Y. & Zhang, Y. (2020). Do shareholders benefit from green bonds? *Journal of Corporate Finance*, 61. doi:10.1016/j.jcorpfin.2018.12.001

VanEck. (2023). https://www.vaneck.com/us/en/investments/green-bond-etf-grnb/

Viteva, s., Veld-Merkoulova, Y. V., Campbell, K. (2014) The Forecasting accuracy of implied volatility from ECX carbon options. *Energy Economics*, 45, 475-484. https://doi.org/10.1016/j.eneco.2014.08.005

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance*, 98, 39-60.