Green Investments Under Uncertainty
- A cross-quantilogram approach

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Abstract

In this study, we analyze the quantile dependence for green bond returns and renewable energy stock returns with three major asset classes: corporate bonds, stocks and oil. Furthermore, we control the dependence structure for technology, uncertainties as well as lag structures and time-varying effects. We apply the cross-quantilogram developed by Han et al. (2016) that allows us to study the dependence structures between two time series in arbitrary quantiles. The results led us to three key findings: 1) The returns of the green bond market are tail-dependent on the returns of both long and short-term maturities for the corporate bond market but are not dependent on the stock market nor the oil market. The tail-dependence indicates that while investors may hold green bonds due to moral incentives, it is not enough during times of turbulence. Further, the dependence structures are short-lived. 2) The renewable energy market is dependent on oil returns of similar quantiles, suggesting that renewable energy substitutes oil when oil prices increase. However, renewable energy does not influence the oil market, indicating that oil is not a substitutional energy source for renewable energy driven firms. Renewable energy stocks are further highly dependent on the returns of the general stock market but are not influenced by the returns on the corporate bond market. 3) The dependence of both renewable energy and green bonds with the asset markets are time-varying. Our overall results obtained by this paper provides information that could help facilitate new investment allocations towards green investments. Further, the results may have immediate and important implications for investors. For those in the corporate bond market, adding green bonds does not add diversification benefits during turbulence. Similarly, renewable energy stock does not add diversification benefits to investors in the oil or stock market.

Key words: Green bonds, Renewable energy, Cross-quantilogram, Tail-dependence, Uncertainty
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Best regards,

Elsa Boyer de la Giroday and David Stenvall
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APPENDIX 68
1. Introduction

In the last decades, concerns regarding climate change has increased and embossed the agendas of policy makers. The UN Intergovernmental Panel on Climate Change (2018) expects global warming to reach 1.5°C above pre-industrial levels between 2030 and 2052, increasing climate risks and economic costs related to welfare and economic growth. As of recently, the Paris climate agreement sets the goal to keep the temperature rise below 2°C pre-industrial levels, while aiming for an increase below 1.5°C. This calls for a shift from high- to low carbon economies. In this context, the financial market plays a vital role in raising investment capital and relocating investments from carbon intensive investments to green alternatives. By analyzing dependence structures of green investments with major asset classes, we can provide new information on how green investments can add to investor portfolios contributing to this shift.

While green investments touch upon many areas, the most substantial is renewable energy, which is why policy makers and researchers in large have focused on this. The International Energy Agency (IEA, 2014) predicts a global need of 53 trillion USD in energy investments by 2035 to have a 50 percent chance of keeping the rise of the temperature below 2°C.

**Figure 1**: Total investments in renewable energy between 2004 and 2017

![Figure 1](image-url)

*Fig. 1. Source: Attributed from Frankfurt School-UNEP Centre/BNEF (2018).*

Figure 1 depicts total investments in renewable energy broke down into major sectors within renewable energy. Overall investments in these renewable energy sectors have increased with almost 500 percent between 2004 and 2017, with some noticeable dips both during the financial crisis in 2008 and the European debt crisis around 2012. Noteworthy is the 15 percent fall in total investments between 2015 and 2016 and that despite increased investment levels between 2016 and 2017, the growth rate of investments has decreased in recent years. A decrease in the growth rate of investments
while more funding is necessary underscores the importance of facilitating investment opportunities and channels of funding for companies in the renewable energy sector. Further obstacles for the renewable energy market are also emerging. The Paris climate agreement set expectations for investors regarding policy decisions in favor of green investments to dismantle investing barriers. However, the US election in 2016 resulted in favor of president Donald Trump, who declared his intentions of leaving the Paris climate agreement and develop the US coal industry (Trump, 2017). As the US stock market make up the largest volume of the global financial market, the US is a vital actor in reconstituting the financial market in favor of green investments. Hence, investors might be unsure of their expectations regarding coming policy implications, creating uncertainty that could hinder investment inflow towards the renewable energy sector.

While the growth rate of investments in renewable energy projects has diminished, a new instrument intended to solely finance projects with environmental or climate benefits, namely green bonds, has grown in recent years. Except for its green intentions the instrument works as a regular bond and can contribute reaching climate goals by shifting capital towards environmentally friendly alternatives. Although the first green bond was issued as early as 2007 by the European Investment Bank, the total issued amount has primary grown in recent years according to the Climate Bond Initiative (CBI, 2019). Figure 2 visualize the total amount of green bond issuance over time.

**Figure 2**: Total issuance of green bonds between 2012 and 2018

![Green Bond Issuance](image)

Fig. 2. *Source: Attributed from Climate Bond Initiative Green Bond Market Summary.*

Green bonds have sparked attention from both the private and public sector with issuance from a variety of different companies, municipalities, cities and countries. Even though the increase in recent years has been substantial, CBI (2019) reports a recent decrease in issuance growth. The funding type is also new and suffers from infant diseases. OECD (2015) points out that investors have limited information that affect their capability to analyze green bonds which hinder increased investment levels. Della Croce et al. (2011) report that while institutional investors are aware of the macroeconomic risks related to climate change, they are not confident in shifting their portfolio...
investments towards green alternatives. However, they might do so if they had more information and data on green investments.

Even though green investments are needed from an environmental perspective, they also need to be an attractive investment that benefit investors. While both bonds and stocks are typical securities in investor portfolios, they possess different characteristics that make them attractive for investors of different reasons. Although green investments by themselves may distinguish from other assets due to their green properties, different types of green securities might provide various diversification and hedging opportunities for investors. For these reasons, it is vital to gain information on how both green bonds and renewable energy stocks add to investor portfolios and interact with other asset classes. Despite the importance of this issue and the need for more information, previous literature mainly touch upon renewable energy investments and its mean dependence on other asset classes. The largest body of literature study the relationship between oil and renewable energy stock returns (Henrique and Sadorsky, 2008; Huang et al., 2011; Kumar et al., 2012; Sadorsky, 2012; Managi and Okimoto, 2013; Reboreda 2015). Another branch adds to the literature by studying renewable energy investments and its interactions with the stock market (Ahmad and Rais, 2018; Ivarsson Lundgren et al., 2018), interest rate (Bondia et al., 2016; Kocaarslan and Soytas; 2019) and carbon prices (Dutta, 2017; Ahmad et al., 2018). Even though there is plentiful of literature regarding renewable energy, only a few have focused on the green bond market in general and a single paper on how green bonds interact with other asset classes (Reboreda, 2018).

Further limitations with previous literature are the lack of studies regarding dependence structures during different market states. Numerous studies have shown that financial markets tend to move together during periods of financial turbulence, increasing spillovers between the markets. By only studying simple mean dependence, the co-movements during extreme turbulence are not incorporated in the analyzes and thus an incomplete picture of the dependence structures may emerge. Despite this, former literature on renewable energy investments mainly studies linear relationships and centers of distributions. Regarding studies of tail-dependence between renewable energy and other asset classes only a few exist. Reboreda (2015) and Reboreda and Ugolini (2018) uses copulas to investigate the dependence structure while Uddin et al. (2019) applies a cross-quantilogram approach. The literature on tail-dependence between green bonds and other assets are on the other hand close to non-existing. Only Reboredo (2018) has analyzed the tail-dependence of green bonds using multivariate copulas. However, the information that copulas can provide about tail-dependence is limited. For instance, you cannot capture correlation structures between assets in different market states, such as the correlation of lower quantiles for one asset with the normal state or upper quantiles for the other. Moreover, with copulas you cannot add longer lag structures without respecifying the model, increasing the risk of misspecification errors. Further, it does not allow for modelling partial dependence structures such as adding control variables.

Given the US election in combination with the Paris climate agreement and other recent events creating uncertainty for investors, it is also important to investigate how uncertainty affects green
investments. Research has shown that uncertainty can influence financial markets in a variety of ways, such as delaying investments, which could result in deprivation of necessary investments in green projects (Bloom, 2014). In addition, uncertainty on the financial markets can spillover to other markets. By controlling for different kinds of uncertainties it is possible to investigate the robustness of dependence structures and presence of systematic risk. Moreover, it will give investors additional information on the properties of green bonds and renewable energy stocks, such as their attractiveness during uncertain market periods. Furthermore, previous research has pointed to the high share of technology in renewable energy projects and therefore emphasized its importance for investors in the renewable energy market. Despite the importance of these topics, there are to our knowledge none controlling for neither uncertainty or technology on the green bond market and scarce research that touch upon the subject for the renewable energy market.

To achieve the goal of the Paris climate agreement and to shift the financial markets towards green investments, it is crucial to shed further light on the dependence structures of green bonds and renewable energy stocks. As pointed out, the research in this area is narrow and limited. The aim with this study is therefore to fill these research gaps by analyzing the quantile dependence for green bond returns and renewable energy stock returns with three major asset classes: corporate bonds, stocks and oil. To further analyze the dependence structure, we control for technology and different kinds of uncertainties. Our focus is on the following research questions:

- Is there any quantile dependence between renewable energy stocks or green bonds with major asset classes and how does the dependence structures change after including control variables and lags?
- If any dependence structures are found, what are the implications from an investor perspective?

To fulfill the aim of this paper we apply the cross-quantilogram method developed by Han et al. (2016). The cross-quantilogram allows us to study the dependence between two time series in different quantiles for both the dependent and independent variable. Further, the cross-quantilogram does not require any moment conditions, as mean or variance, to be calculated. By using this method, we can investigate the dependence structures in the full quantile-space and consider the full distributions. We also apply the partial cross-quantilogram which allows us to include both longer lag structures and control for partial dependence structures in the presence of technology return and uncertainty. To control for time-varying dependence structures we also present rolling sample estimations. Lastly, we calculate Sharpe ratios and perform EVT-GARCH-Copula based Value at Risk estimations of different portfolios to illustrate the risk and return of green investments.

Based on our results, we conclude the following: first, the returns of the green bond market are tail-dependent on the returns of the corporate bond market while there is no significant tail-dependence
between the green bond market and the stock or oil market. Second, the renewable energy market shows no clear pattern of dependence on the corporate bond market but is dependent on oil between similar quantiles, suggesting that renewable energy is an energy substitute to oil. Renewable energy is also highly dependent on the general stock market. Further, the dependence of both renewable energy and green bonds on the asset markets are time-varying. Finally, and maybe most importantly, the above results give investors important information on the characteristics of the green bonds and renewable energy market, dismantling barriers hindering investment growth.

Our contributions to the literature are multiple. To our knowledge, we are first to apply the cross-quantilogram to analyze the quantile dependence of green bonds with other assets classes, but also to control for uncertainties, lag structures and technology. Regarding the renewable energy market, we contribute by providing new information on the oil and renewable energy nexus by analyzing the quantile-dependence on a new time period. Moreover, we are the first to apply our method on renewable energy with both the corporate bond market as well as the US and European stock market. Further, we are first to compare the green bond and renewable energy market from an investor perspective, providing important information for portfolio risk management.

As follows, we present the theoretical framework in section 2. Thereafter, section 3 outlines the related literature. Section 4 consist of the methods used, followed by section 5 where we present our data and descriptive statistics including a variable analysis. Section 6 discloses the results and finally, we present conclusions and policy implications in section 7.
2. Theoretical framework

In this section, we review main theories that touch upon our area of research and basic theoretical linkages between different asset classes in terms of correlation. Firstly, we describe portfolio theory and how it relates to financial contagion and financialization. We then describe the theoretical linkages behind our control variables, uncertainty and technology. Thereafter, we outline behavioral finance and how it can affect the movements of green investments.

2.1 Portfolio theory, financial contagion and financialization

The rationality behind investing in renewable energy companies or green bonds can be found in modern portfolio theory. Markowitz (1952) laid a foundation for diversification and hedging with his pioneering work on this area. Markowitz (1952) states that no investment should be considered on its own but rather on how it adds to the portfolio risk and return. Combining assets with different fundamentals, investors can create portfolios on an efficient frontier, providing the maximum return for a given risk. Moreover, asset allocation, the ratio between broad asset classes such as stocks and bonds, is crucial for determining the portfolio risk and return (Bodie et al., 2014). As bonds generally are less volatile than stocks, they could be used to diversify stock portfolios. Furthermore, renewable energy investments or green bonds might have certain characteristics that distinguish them from other asset classes. This means that they could be used to further diversify portfolios in order to increase portfolio risk adjusted return. In other words, green investments could benefit investors in such way that their portfolio return increase in relation to their taken risk. Aside from diversification, investors can protect their investments by using hedging methods. One way to hedge an investment is to invest in assets that have negative correlations such that if one asset decreases in value the other would increase (Bodie et al., 2014). In the context of renewable energy stocks and green bonds, it might possibly be of use for hedging purposes depending on the components of the investor portfolios. If green investments have negative correlations with other assets during turbulence, then possible portfolio losses during economic downturns could be restricted. Therefore, investing in green bonds and renewable energy might not only provide important funding that would help reach future climate goals, but could also benefit investors. Moreover, correlations between assets can affect investment decisions and diversification possibilities as well as give investors desired information on possible future movements of assets.

Even though simple correlation or dependence measures traditionally have been used to gain information for hedging purposes, its effectiveness might shift during different market conditions. For example, market interconnectedness tends to strengthen and correlate more during turbulent market periods (Okimoto, 2008). The phenomenon of increased correlations and spillovers during turbulence is often called financial contagion. Expressed in other words, financial markets can be explained as asymmetric and tail-dependent. While financial contagion has been widely circumscribed there is no clear definition. For instance, Peng and Lon Ng (2012) describes financial contagion as “shocks or spillover effects transmitted across countries, especially during times of crisis”. Dornbusch et al. (2000) on the other hand defines it as “significant increase in cross-market
linkages after a shock to an individual country (or group of countries)”. There are several explanations to the transmission mechanisms behind the contagion effects between markets. One possible explanation is increased linkages due to deregulation and liberalization of the financial markets. As this has created investor opportunities to diversify portfolios in different markets, it has also impacted financial interdependence (Quinn and Voth, 2008). The transmission mechanisms might manifest itself in a variety of ways and are interconnected with investor behavior and risk aversion. During times of turbulence, investors tend to invest in low risk assets with high liquidity and quality creating co-movements between markets (Vayanos, 2004). These assets, often called “safe havens”, have traditionally been government bonds or gold¹, which are assets with low volatility and a stable value over time.

Aside from contagion, the development of the financial markets can create increased economic integration which in turn could affect co-movement between markets. After the dot com crisis, many institutions started to invest in commodity markets as it had been shown to have a negative relation to stock market returns. The investments were possible as new developments of commodity futures markets arose. When investments in commodity futures increased, so did the correlation between the stock and commodity markets (Tang and Xiong, 2012). The increased co-movement between assets over time that this example illustrates can be described by the term financialization. This also illustrates how the development of financial markets can influence dependence structures between markets, even those with different fundamentals. As positive correlations increase between markets it also becomes harder for investors to find investments that increase the portfolio risk return.

2.2 Green investments, uncertainty and technology

In recent decades, a great amount of research has discussed uncertainty and how it affects the financial markets and the economy in general. Despite the attention, there is not a clear uniform concept of uncertainty and the transmission mechanism behind it (Bloom, 2014). Green investments might be affected by increased uncertainty in several ways. Starting from a firm perspective, Bloom (2014) points out that uncertainty negatively affect short-run growth by leading to reduced investments levels. For example, as uncertainty rises, companies may be cautious of investing decisions and therefore pause or stop projects. World Economic Forum (2019) points out that many green projects are still in the development stage and can therefore be seen as riskier. When uncertainty on the financial markets rises and the willingness to take on risk decreases, companies might choose not to invest in green projects. Additionally, green projects can also be affected from the consumer side. In uncertain periods, consumers oftentimes delay taking on expenses and demands increased risk premiums, leading to higher cost of finance and risk of firm default (Bloom, 2014). Given that uncertainty is interconnected with both investor behavior and financial linkages it can also contribute to financial contagion. Links between uncertainty and financial contagion comes from possible information asymmetries. If a country exhibits financial turbulence, investors in other

¹ The discussion regarding gold as safe haven are ongoing. Some authors, for instance Bekiros et al. (2017) argue that it may rather add diversification benefits than be a safe haven.
countries increasingly doubt accuracy of information and thereby the risk of similar turbulence in their own countries increases. In other words, as uncertainty rises the perception of margin of error from information increases (Kannan and Köhler-Geib, 2009). Further, a severe shock in one market can lead to increase risk premiums in other markets due to decreased risk willingness (Longstaff, 2010).

Moreover, affecting correlations between markets are the core fundamentals of assets and how investors view them. Regarding technology return, green investments and renewable energy heavily depend on technology developments affecting their fundamentals and how they could be viewed upon. For instance, Henrique and Sadorsky (2008) suggest that as renewable energy is dependent on the development of technology, investors view technology and renewable energy the same. In other words, investors in the technology sector might view renewable energy as one of many technology products to invest in. This implies that even though renewable energy intuitively would be an energy market investment, it might rather be a seen as technology investment.

2.3 Behavioral finance

Complicating the financial market, investors are affected by psychological bias. Traditionally, finance has assumed that investors act in their best interests through rational decisions (Nofsinger, 2002). However, while investors could benefit from portfolio theory, many rather act on morality, peer pressure and other biases. Today, it is well known in behavioral finance that investors are affected by the norms in their social environment regarding investment decisions (Nofsinger, 2002). Becker (1974) early on theorized on that philanthropic behavior can be motivated by a desire to avoid scorn or receive social praise. As green investments have grown in popularity, groups of investors may be inclined towards investing in these. Further, what norms value as good creates biases itself. For example, Baker and Nofsinger (2002) finds that investors often mix up what they consider good with being a good investment. Deepening the bias of norms is the state of cognitive dissonance. Shortly, this means that the brain struggles to handle opposite ideas. For example, an investor might avoid dealing with the potential conflict that could be “green companies are good (belief) but green companies are not good (investment)”.

The motivation behind investing in green assets may also come internally. This is because environmentally friendly portfolios are seldom on display for others to see, unlike an electric car that can show environmental responsibility. Etzioni (1988) theorize that investors struggle with internal conflicts between two economic motives, self-interest and morality. From this, Lewis and Mackenzie (2000) conclude that most investors find balance between self-interest and morality by investing in both what they consider moral as well as what they find serve their self-interest. Further, investors who would choose what they consider a moral portfolio over an immoral portfolio are less interested in profit maximizing (Rubaltelli et al., 2013). This can in turn affect the share of components in the portfolio. Dooren and Galema (2018) show that investors who partially but largely invest in socially responsible investments are especially affected by the disposition effect, selling winning stocks too early and holding losing stocks too long. Therefore, morally driven investors might not optimize
their portfolios in accordance to modern portfolio theory and in turn carry more risk than necessary. Taking a loss or carrying more risk due to morality without social pressure could be driven by self-signaling. Self-signaling can be a strong motivator to investors and can even cause subjects to expose themselves to pain (Quattrone and Tversky, 1984). Investing in green bonds might allow investors to strengthen their self-image as moral beings. Consider that an investor acts on their moral conscious adding green bonds or renewable energy stocks to their portfolio. This investor may be especially affected by morality and other biases, holding their green investments during turbulence which might possibly lead to that they are not as affected by economic downturns compared to other markets.
3. Literature review

In our field of study, it is evident that existing studies concerning the inter-linkage of green bonds with other assets are scarce. The main literature is focused on the mean-dependence of renewable energy stock prices with oil and technology. As of recently, another pile of literature adds factors such as carbon price, interest rates and uncertainty to further investigate the inter-linkage with renewable energy. The related literature on these three subjects are presented below.

3.1 Green bonds

Few scientific advancements have been done when it comes to green bonds, most likely due to the young nature of the asset class. The main literature on green bonds concern a yield comparison with conventional bonds (Barclays 2015; Bloomberg 2017; Climate Bonds Initiative, 2017; Zerbib, 2019). Hence, there exists only a scarce amount of studies on other aspects of green bonds. Pham (2016) for example, focus on the volatility behavior of the green bond market, using multivariate GARCH-models(1,1) further described as MGARCH-models. By using GARCH-models, volatility clusters can be considered, which are especially common in financial time series. The findings show that a shock in the conventional market spill over to the green bond market. In addition, Pham (2016) concludes that bonds labeled “green” experience larger volatility clustering than technically, but unlabeled, green bonds. Flaherty et al. (2017) use a panel data approach to determine the factors contributing to the price of green bonds. Their findings show that rising short-term interest rate of three months (3M) have negative effects on the price of green bonds. This holds for bonds issued by both government agencies and private companies, with larger effects on long-term bonds. Interestingly, Flaherty et al. (2017) find that VIX is a significant determiner of green bonds prices issued by government agencies, but not by private issuers. The authors argue that this may be due to the fact that investors tend to buy low risk assets such as government bonds when financial uncertainty increase.

The single study regarding green bonds that relate to our field of research is conducted by Reboredo (2018). In this study, Reboredo (2018) measures the dependence and price spillover of the green bond on the financial market. The dependence structure is measured using multivariate copulas. This method captures dependence in the tails of the distribution, i.e. dependence in extreme upwards and downwards market movements. The variables included in the study are green bonds, stock, treasury and corporate bond markets as well as energy markets. Reboredo (2018) concludes that green bonds exhibit both high integration and are significantly affected by price spillovers from the corporate and treasury bond markets. This implies that green bonds crash and booms with corporate and treasury bonds, making it a poor diversifier for investors in these markers. Reboredo (2018) further suggest that the symmetric tail-dependence indicate that the bond markets are substitutes. Moreover, his results suggest that the green bond market exhibits time-varying variations in the dependence structures. Besides the bond markets, Reboredo (2018) founds that the green bond market weakly

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2 See literature overview, table 4 in the appendix, for types of specification used.
co-moves with the stock and energy market. Extreme price changes in the stock and energy market, however, have almost no impact on the returns of the green bond market.

3.2 Oil, technology and renewable energy

Renewable energy and oil are to be considered as substitutional according Henrique and Sadorsky (2008), who suggest a positive relationship between oil prices and renewable energy companies. Hence, they argued that when the price of oil increases, so should the price of other energy sources. Further, Henrique and Sadorsky (2008) also proposed that technology firms and renewable energy companies might be seen as interchangeable to investors. Partly based on these arguments, a large body of previous literature using different methods, empirically studies the relationships between technology companies and oil prices with renewable energy stock prices. The results are not uniform and depends on which approach that is used to address the problem. When testing their hypothesis, Henrique and Sadorsky (2008) uses VAR-models and Granger causality tests to investigate the directionality between oil prices, technology and renewable energy stock prices during the time period of 2003-2007. They find causality running from oil and technology to renewable energy. The results are also supported by Kumar et al. (2012) and Bondia et al. (2016), though the latter only find short-run causality. From an investor perspective, these findings thereby imply that renewable energy stock is a poor diversifier for investors in the technology or oil market. In contrast, Huang et al. (2011), find Granger causality running from oil prices to renewable energy post 2006, using a sample period from 2001-2010. The authors conclude that the inter-linkage of oil and renewable energy becomes stronger after the Lebanon War, suggesting that the link becomes stronger as oil prices experience a higher level of volatility. Managi and Okimoto (2013), using a Markov-Switching VAR-model and impulse responses instead find a structural change in the relationship between oil prices and renewable energy stocks prices from 2007 and onwards. Similar to Huang et al. (2011), Managi and Okimoto (2013) argue that the results could be explained by the substitutional characteristics between oil and renewable energy following the sharp rise in oil prices during this period. Further, the authors hypothesize that the substitution effect can occur through technological innovation in the renewable energy sector.

Recently conducted studies concerning the relationship between fossil-fuel based energy and renewable energy stocks tries to capture the dependence structure between the variables using copulas and wavelets. By using copulas, the dependence structure on the average upper and lower tails can be retrieved, which represent extreme scenarios. Wavelets-analysis in turn, can be used to test for dynamic correlations over time and time-scales. The first study to apply copulas on oil, technology and renewable energy was conducted by Reboredo (2015). The results from this study show significant tail-dependence between oil prices and renewable energy stocks prices that are both time-varying and symmetric, meaning that oil and renewable energy stocks returns are dependent during volatile periods. This is in line with economic theory suggesting that market correlations increase during turbulence and again suggest that renewable energy and oil is a poor combination for investors looking to diversify. It also indicates that renewable energy is considered as an energy investment and could be a substitute to oil. Reboredo et al. (2017) studies non-linear causality
through a discrete wavelet approach. In contrast from the previous mentioned literature, their results suggest that the causality running from oil to renewable energy stocks is not consistent between different time frequencies. For an investor in the oil market, the results imply that there may be time horizons when renewable energy stock can be a diversifier. On the other hand, the authors also conclude that there is a stable non-linear causality running from renewable energy to oil.

Further, Uddin et al. (2019) investigate the quantile dependence between oil and renewable energy stocks using the newly developed cross-quantilogram method. This method allows for studying bivariate dependence between arbitrary quantiles of the included variables. Their results suggest that renewable energy is dependent on oil in similar quantiles but not between opposites. These results are in line with the findings of Huang et al. (2011) and Managi and Okimoto (2013), and further indicates that renewable energy may be a substitute to oil for energy-using firms. Moreover, the authors find that oil is tail-dependent on renewable energy, suggesting that they crash together during turbulence. As Uddin et al. (2019) also finds time-varying dependence structures, investors that want to keep both oil and renewable energy stocks in their portfolios would need to frequently rebalance.

3.3 Volatility modeling

Adding to the literature on oil, technology and renewable energy stock prices, a branch of studies focuses on the volatility dynamics of the relationships. Sadorsky (2012) use MGARCH(1,1) to analyze the volatility spillovers from oil prices, renewable energy stock prices and technology companies. The result of Sadorsky (2012) shows that renewable energy has a higher correlation with technology than with oil. Further, Ahmad (2017) use MGARCH(1,1)-models and a directional spillover approach developed by Diebold and Yilmaz (2012) to measure volatility and return spillovers between oil prices, technology stocks and renewable energy stocks. Ahmad (2017) using the directional spillover method, suggest that oil prices are the net receiver of both return and volatility spillovers, while the emitters are both renewable energy stocks and technology companies. Further, by using the MGARCH-models, Ahmad (2017) confirms the results. In addition, Pham (2018) use MGARCH(1,1)-models to investigate the volatility co-movements between stock prices of eleven different renewable energy sectors and oil prices. Her study shows correlations between oil and renewable energy stock prices but with time-varying effects over the sample period. Furthermore, the correlations also differ between the renewable energy-sectors. Lastly, Ahmad and Rais (2018) measures return and volatility spillover effects between the price of four energy indices (Brent, crude, heating oil and gasoline), technology and renewable investments stocks, using MGARCH(1,1) and the directional spillover method by Diebold and Yilmaz (2012). Their results suggest that there is limited dependence between the sub energy groups and renewable energy stocks. In addition, there are unilateral spillovers running from technology to renewable energy. Ferrer et al. (2018) using a return and volatility connectedness methodology find that oil prices are not a key driver of renewable energy stock prices. Therefore, they suggest that there has been a recent decoupling between renewable energy and fossil-based energy markets and that renewable energy stock rather is driven by other factors, such as technology innovation. Finally, a pairwise connectedness is found between
technology and renewable energy indicating that they are seen as interchangeable to investors, as supported by Henrique and Sadorsky (2008).

3.4 Dependence structures and macroeconomic variables

Another strand of literature adds the macroeconomic variables interest rates and carbon prices when analyzing the returns and volatility of renewable energy stock. Kumar et al. (2012), test for Granger causality using short-term interest rate (3M) and carbon prices in addition to oil, technology and renewable energy. They find causality running from oil, technology and interest rate to renewable energy. Carbon prices on the other hand, did not significantly influence renewable energy, which is also supported by Dutta (2017). Kumar et al. (2012) argue that this may be due to the low prices of carbon. Bondia et al. (2016) who instead use a non-linear Granger causality and interest rates (10Y) find short-run, but no long-run, bi-directional causality between interest rate and renewable energy. Further, they find causality running from technology to renewable energy. Kocaarslan and Soytas (2019) use oil, technology and interest rate (3M) and concludes that changes in oil prices, interest rates and technology stock prices affect renewable energy differently in the short and long-run. However, increased oil prices affect renewable energy asymmetrical in the long-run. Therefore, Kocaarslan and Soytas (2019) argue that increased investments in renewable energy in the short-run may be due to waves of speculations in combination with increased oil prices.

Moreover, Reboredo and Ugolini (2018) use a multivariate vine copula-model, capturing information by applying different copula models on the variables oil, gas, electricity, coal and renewable energy stock returns. The results suggest that oil and electricity prices were the main contributors to renewable energy stocks returns dynamics rather than the returns of the other energy classes. In addition, Reboredo and Ugolini (2018) concludes that extreme upward and downward movements in the energy price impact renewable energy stock returns in similar ways.

3.5 The role of uncertainty in renewable energy pricing

Of value for this study, is the effect of uncertainty on green investments. Earlier research on the field is scarce but there are some studies conducted in recent years on renewable energy. Dutta (2017) use implied crude oil volatility (OVX), a proxy for oil price uncertainty, together with oil, carbon price and renewable energy stock returns. Dutta (2017) finds that oil price uncertainty runs to renewable energy and further concludes that renewable energy is immensely sensitive to oil price volatility. These results confirm economic theory that uncertainty can be highly contagious and spread between markets, in this case to the renewable energy market. Further, Ahmad et al. (2018) use MGARCH(1,1)-models to hedge renewable energy equities. The authors calculate hedging effectiveness by comparing different kinds of uncertainties: financial uncertainty (VIX) and oil price uncertainty (OVX), as well as four different kinds of asset classes: gold, bonds, carbon prices and oil. They find that VIX is most effective for hedging renewable energy equities, while bonds and carbon prices have low hedging effectiveness. Moreover, oil prices, OVX and VIX have a negative conditional correlation with renewable energy. In economic terms, this means that as oil prices, VIX and OVX increases, renewable energy stock prices decrease. Ivarsson Lundgren et al. (2018) apply
generalized vector autoregression method (GVAR) and both linear as well as non-linear Granger causalities to study the effect of uncertainty on renewable energy. As a proxy for uncertainty, they use three different indices financial uncertainty (VIX), economic policy uncertainty (EPU) and financial stress (FS). Other explanatory variables used are oil, exchange rate, interest rate (10Y) and stock market prices. The authors find multiple casualties run from renewable energy to the stock market, especially the European stock market, and argue that this may be due to the great use of renewable energy in Europe. Regarding the uncertainty variables, they find that all, but in particular FS, have directional impact onto renewable energy, concluding that uncertainty is reflected in the stock prices of renewable energy firms.

In summation, after reviewing the literature on renewable energy and green bond dependence structures we find that only one study has been done on green bond dependence with other assets. On the other hand, the nexus of renewable energy stock and oil has been thoroughly studied. However, while there are many contributions to the understanding of renewable energy, the previous literature in large focuses on mean dependence and therefore potentially overlook dependence structures in different market conditions.
4. Method

In this chapter we present the basic methodology framework that this paper relies on. Firstly, we present the unit-root tests, followed by a mathematical representation and motivation of the cross-quantilogram. Lastly, we present how we estimate portfolio risk and return using Sharpe ratios and Value at Risk.

4.1 Unit-root tests

Economic time series do in general suffer from time-varying mean and variance, so called non-stationarity. The non-stationarity might in turn be due to unit-roots or deterministic trends. Modelling series that contain unit-roots may lead to “spurious” results i.e. misleading evidence, and can often be solved by differencing the variables. We test the stationarity assumption by conducting unit-root tests developed by Dickey-Fuller (1979) and Phillips-Perron (1988). The augmented version of the Dickey-Fuller test (ADF) can be specified as equation (1), where $\Delta$ is the first difference estimator and $\theta$ is a coefficient.

$$\Delta y_t = \delta y_{t-1} + \sum_{i=1}^{k} \theta \Delta y_{t-i} + \epsilon_t$$

(1)

The inclusion of the lagged values of $\Delta y_t$ on the right side of the equation is the so called “augmentation”. The augmentation is added to correct for non-white noise residuals which is a requirement for the test to show trustworthy results. The ADF-test is then conducted by testing for the hypothesis that $\delta = 0$. If we can reject the hypothesis, the series has a unit-root. If the series steadily increase over time or has a clear starting level, we can conduct the test by including a deterministic trend ($\bar{\epsilon}$) or a constant ($\alpha$) in the procedure. The specification is then given by equation (2).

$$\Delta y_t = \alpha + \beta \bar{\epsilon} + \delta y_{t-1} + \sum_{i=1}^{k} \theta \Delta y_{t-i} + \epsilon_t$$

(2)

Regarding the Phillips-Perron (PP) test, it is conducted like the ADF test, but instead of including lags to correct for the non-white noise residuals it solves the problem by a non-parametric adjustment of the test-statistic.

4.2 Cross-quantilogram and recursive rolling sample estimations

In this study, we use the cross-quantilogram method developed by Han et al. (2016) to measure the dependence structures and directional predictability in quantiles between green investments and other asset classes. The cross-quantilogram is the bivariate version of the quantilogram developed by Linton and Whang (2007). The quantilogram was developed to test a stationary time series for dependence and directional predictability in different quantiles of the distribution. This is derived based on sample correlations by comparing the correlograms of so called “quantile hits” to pointwise confidence intervals. Han et al. (2016) extended the regular quantilogram by allowing for measurement of quantile dependence and directional predictability in a multivariate setting.
By using the cross-quantilogram, we can measure dependency in the full quantile-space and capture information of tail-dependence and contagion between markets. The ability to measure tail-dependence is essential as it give us information on the characteristics of green investments during different market states. A range of studies have shown that financial markets correlates more during times of crisis or in bad market states. This can have implications for portfolios as the dependence structures might change during different market conditions. While many methods, such as MGARCH-models, can be used to measure some type of correlation or dependence, they do not capture the full return distribution. By only focusing on the mean of the distribution investors miss out on information of how their portfolio components might behave during periods of abnormal returns.

Other possible methods to estimate dependence in other parts of the distribution are through extremograms, quantile-regressions or copulas. The extremogram developed by Davis and Mikosch (2009) is an extended version of the quantilogram and can like the cross-quantilogram be applied to bivariate time series. While the cross-quantilogram gives dependence estimates for the full quantile-space, the extremogram only focus on the extreme quantile-dependence. The quantile-regression in turn allows for regressing arbitrary quantiles of the dependent variables in a bivariate setting, but not with arbitrary quantiles of the independent variables. By using the quantile-regression we can therefore not tell if two time series are tail-dependent or not. Regarding copulas, it can measure general tail-dependency by upper and lower tail-coefficients. Even though the copula can be a good measure for tail-dependence in some cases, it does not fit our aim with this study. The difficulties of including longer lag structures along with the fact that it does not allow for partial dependence to be studied makes it inappropriate for this study. As we want to control the dependence structures both in different time perspectives and in presence of uncertainty and technology change, the cross-quantilogram is the fitting method as it permits lags and modelling partial dependence. Further advantages of the cross-quantilogram is that it does not require any moment conditions, as mean or variance to be calculated and it can capture correlation structures between assets in different market states, such as the correlation of lower quantiles for one asset with the normal state or upper quantiles for the other. It is also indifferent to variable transformations of the series like logarithmic transformations. The cross-quantilogram relies on the assumption of stationary time series. We test this using unit-root tests.

Given that the requirement of stationarity is fulfilled the cross-quantilogram can be applied. Below we present the mathematical foundations of the cross-quantilogram. Assume that $y_{1t}, y_{2t}, \ldots, y_{lt}$ where $y_{lt}$ are stationary time series with marginal distributions that has the quantiles $q_{lt}(\tau_t)$ where $\tau \in [0,1]$ and $\alpha < \tau < 1$ while $\tau_t$ is one conditional or unconditional quantile of $y_{lt}$. The quantilogram

---

1 The cross-quantilogram can be applied to a wide range of issues within economics and finance. Earlier studies have for instance used it to measure dependence on the stock market (Labidi et al., 2018), commodity markets (Jiang et al., 2016) and for analyzing dependence between oil and precious metals (Shahzad et al., 2018).
approach measures the serial dependence of two events \( \{ y_{1t} \leq q_1(\tau_1) \} \) and \( \{ y_{2t-k} \leq q_2(\tau_2) \} \) for any arbitrary pair of \( \tau_2 \) and in our case a positive integer \( k \) (lag) = 1, 2, ..., 22 (where 22 is one-month interval for daily data). This is called the quantile hit process and can be written as \( \{ 1[y_{it} \leq q_{it}(\cdot)] \} \). The cross-correlation of different quantile hits is then analyzed by the quantilogram approach, depicted in figure 3.

\[
\rho_{t}(k) = \frac{E[\psi_{t1}(y_{1t} - q_{1t}(\tau_1))\psi_{t2}(y_{2t-k} - q_{2t-k}(\tau_2))]}{\sqrt{E[\psi_{t1}^2(y_{1t} - q_{1t}(\tau_1))]}\sqrt{E[\psi_{t2}^2(y_{2t-k} - q_{2t-k}(\tau_2))]}},
\]

(3)

Where \( \psi_{t1}(y_{1t} - q_{1t}(\tau_1)) = 1[y_{it} \leq q_{it}(\tau_1)] - \tau_i \) so that the quantile hit process can be denoted as \( \psi_{t1} = 1[u < 0] - \alpha \). The higher the correlation coefficient \( \psi_{t} \) the higher the \( \rho_{t}(k) \). Assume, \( y_1 \) is a green bond index with the quantile \( q_1(0.05) \) at the time \( t \) and \( y_2 \) is a corporate bond index with \( q_2(0.05) \) at \( t - 1 \). If \( \rho_{t}(1) \neq 0 \) then there exist directional predictability from the corporate bond market to the green bond market in the 0.05 quantiles. This would imply tail-dependence between the markets. If instead \( \rho_{t}(1) = 0 \), no predictability exists. For the empirical estimations we firstly find the sample quantile \( \hat{q}_{it}(\tau_t) \) and from this we compute the sample counterpart of quantilogram that takes the following form:

\[
\hat{\rho}_{t}(k) = \frac{\sum_{t=k+1}^{T} \psi_{t1}(y_{1t} - \hat{q}_{1t}(\tau_1))\psi_{t2}(y_{2t-k} - \hat{q}_{2t-k}(\tau_2))}{\sqrt{\sum_{t=k+1}^{T} \psi_{t1}^2(y_{1t} - \hat{q}_{1t}(\tau_1))}\sqrt{\sum_{t=k+1}^{T} \psi_{t2}^2(y_{2t-k} - \hat{q}_{2t-k}(\tau_2))}},
\]

(4)

If there is no cross-dependence or directional spillover, then \( \hat{\rho}_{t}(k) \) will be zero. However, if \( \hat{\rho}_{t}(k) = 1 \) then there is most likely quantile dependence or directional spillovers. This is tested using the Box-Ljung significance test for autocorrelation so that:

\[
H_0: \hat{\rho}_{t}(1) = \ldots = \hat{\rho}_{t}(k) = 0
\]

(5)

\[
H_1: \hat{\rho}_{t}(k) \neq 0 \text{ for one or multiple } k
\]

The Box-Ljung test takes the form as presented in equation (6).

\[
\hat{Q}_{t}(p) = (T + 2) \sum_{k=1}^{p} \frac{\hat{\rho}_{t}^2(k)}{T-k}
\]

(6)

If \( \hat{\rho}_{t}(k) = 0 \) we reject \( H_1 \) and there is most likely no dependence. In addition, we incorporate the partial cross-quantilogram to introduce our control variables. The partial cross-quantilogram again measure the dependency between the two events \( \{ y_{1t} \leq q_1(\tau_1) \} \) and \( \{ y_{2t-k} \leq q_2(\tau_2) \} \), while also controlling for events between \( t \) and \( t - k \) and if there are state variables that exceed a given quantile. Our control variables are represented by the vector \( \mathbf{Z}_t = [\psi(y_{t3} - q_{3t}(\tau_3)), \ldots, \psi(y_{tn} - q_{nt}(\tau_n))]^{\top}. \) We assume a set of quantiles such that \( \tau = (\tau_1, \ldots, \tau_n)^{\top} \) and let \( h_t(\bar{\tau}) \) be a vector of
quantile hit processes so that \( h_t(\tau) = \psi_{z1}(\gamma_{1t} - q_{1t}(\tau_1)) \ldots, \psi_{zn}(\gamma_{nt} - q_{nt}(\tau_n)) \). The partial cross quantilogram is defined as equation (7), and can also be denoted as equation (8).

\[
\rho_{t|z} = -\frac{\rho_{zz}}{\sqrt{\rho_{z1}^2 \rho_{z2}^2}} \\
\rho_{t|z} = \delta \frac{\tau_1(1 - \tau_1)}{\tau_2(1 - \tau_2)}
\]

\( \delta \) is a scalar parameter. Therefore, testing \( \rho_{t|z} = 0 \) can be described as testing for predictability between two quantile hits, with respect to the chosen control variables \( z \). The sample performance of the Box-Ljung test statistics (1978) is based on stationary bootstrap procedures. The bootstrap procedure takes our data sample as proxy for the population and thereafter draws samples at random from it. The range of samples provides information of variability between them so that confidence intervals can be created, and hypothesis testing can be performed. To perform the cross-quantilogram we are bound to make assumptions that may affect the results. Firstly, the robustness of the results varies with the number of iterations. With few iterations, the results may change if the simulations are redone. To control for this, we perform 500 iterations which gives us results that are consistent over time and therefore robust. Secondly, the choice of significance level may impact the trustworthiness of our dependence structures. A higher level would increase the error marginal while a lower level would risk rejecting correct null hypothesis. We conduct our study based on a five percent significance level which is chosen based on econometric standard.

The cross-quantilogram output is presented as heatmaps and rolling windows for different assets to make the results easy to interpret. The X- and Y-axis represent eleven different quantiles ranging from \( q = (0.05, 0.1, 0.2, \ldots, 0.95) \). In total, the heatmaps consists of 1z1 squares representing different quantile combinations of the variables of interest. The results are presented with a lag length of one.\(^4\) The upper and lower quantiles are often denoted as the “tails” of the distributions representing abnormal market conditions. The lower quantiles e.g. 0.05 displays market conditions under stress while normal market conditions are presented by the 0.5 quantiles. Very good market conditions are on the other hand represented in the upper quantiles such as 0.95. The heatmaps are presented based on a color scale, indicating correlations between -1 (dark blue) to 1 (dark red). No correlation (green) is set for zero. Green therefore indicates when the cross-quantile correlation does not have any predictability of quantile dependency or directional spillovers.

To measure time-varying characteristics of our dependence structures in the lower, middle and upper quantiles we investigate the structures by applying recursive rolling windows estimations. The width of the rolling sample window is 252 days, representing one trading year, and advances daily. In other

\(^4\) The data has been tested with the lag lengths 1, 2, 5 and 22. One lag represent a one day lag, five lags represents one week, and 22 lags represent one month. Due to restricted space we only present lag one in the results which in general is the time period where the dependence is the strongest. Lag five can further be found in the appendix and lag two and 22 are available on demand. We restrict our method applications to lag 22 as dependency beyond one month is unlikely to be observed based on our results.
words, the estimation procedure starts by estimating the first rolling window and thereafter redo the procedure adding one day to the window for every new estimation. This procedure persists to the full sample. The dependence change over time is presented as the blue line. The output includes confidence intervals, presented as red lines.

4.3 Portfolio estimations

To illustrate the risk and return associated with investing in green bonds and renewable energy stocks, we construct different portfolios combinations and calculate the Sharpe ratio and Value at Risk (VaR) for these portfolios.

Sharpe ratio measures the risk adjusted return of a portfolio which simply is the excess return of a single asset or portfolio divided by its corresponding standard deviation. This can be expressed as equation (9), where \( R_p \) is the portfolio return, \( R_f \) is the risk-free rate and the \( \sigma_p \) is the portfolio standard deviation.

\[
SR = \frac{R_p - R_f}{\sigma_p}
\]  

(9)

By further calculating portfolio VaR we can estimate potential portfolio losses for a specified investment horizon at a certain confidence level. Following Karmakar (2017), portfolio VaR can be expressed as:

\[
VaR^\alpha = F^{-1} (1-\alpha)
\]

(10)

If the confidence level is denoted as \( \alpha \) and \( (1-\alpha) = q \), the portfolio VaR is the \( q \)th quantile of a distribution \( F \) for a continuous random variable \( X \). Further, the inverse distribution function or quantile function, is expressed as \( F^{-1} \). If VaR result in a potential portfolio loss of five percent with a confidence level of 95 percent, we can expect to lose five percent of the portfolio value during one day out of 20. Similarly, VaR with 99 percent confidence level show the worst expected loss for one day out of 100. To give a fair representation of the risk associated with our portfolios we account for clustering volatility, fat tails and the correlations between the assets in the portfolios by fitting an EVT-GARCH-Copula to our data before estimating the VaR.

The extreme value theory (EVT) are applied to account for extreme events and consider the tail-risks associated with our portfolios. To apply the EVT there are two main approaches, the block maxima and Peak over Threshold (POT) method. The block maxima however are not optimal when dealing with financial data (Karmakar, 2017). We therefore use the latter method when calculating VaR. Using POT, we define thresholds of the distribution to which the observations exceeding the threshold are separated. These observations can then be approximated by the Generalized Pareto distribution (GPD).

To consider volatility clustering, which is common in financial time series, we fit a GARCH-process to our data. The GARCH-process was first proposed by Bollerslev (1986) and can be denoted
generally as GARCH(p,q), where p is the lag length of the error term \( \epsilon_t \) and q is lag length of the variance \( h_t \). A simple GARCH(1,1) is denoted below:

\[
\begin{align*}
\gamma_t &= \beta x_t + \epsilon_t \\
\epsilon_t &\sim D(0, h_t) \\
\theta_t &= \varphi + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \theta_{t-1}
\end{align*}
\]

Equation 10 and 11 expresses the mean- and variance equations. The combinational use of EVT and GARCH-models to estimate VaR is proposed by McNeil and Frey (2000) as a solution to the fact that EVT requires independent and identically distributed (i.i.d) data. This is uncommon for financial time series as they often experience volatility clustering. However, standardized residuals filtered by the GARCH-model can, as pointed out by McNeil and Frey (2000), approximately exhibit both i.i.d residuals and heavy tails to which we can apply the EVT.

To further consider the dependence between variables in the portfolio, we fit a copula to the data as it is often used to describe dependence between random variables. Even though copulas do not fit our aim when studying the quantile dependence, it still can be useful for modelling dependence in a portfolio as a base for VaR-estimations. A copula can be defined as a multivariate cumulative distribution function (CDF). Based on the findings of Sklar (1959) a multivariate joint distribution can be described by its univariate marginal distributions and a copula function. If we denote two random variables as \( X_1 \) and \( X_2 \), which in our case would be the return series of different indices, with their marginal CDFs \( F_{X_1}(x_1) = P(X_1 \leq x_1) \) and \( F_{X_2}(x_2) = P(X_2 \leq x_2) \). The copula function links the marginal distributions into a joint distribution function, as denoted in equation (13) where \( C \) is the copula function:

\[
C(x_1, x_2) = P(X_1 \leq x_1, X_2 \leq x_2)
\]

The full step-by-step process to calculating the VaR of a portfolio is as follows. Firstly, we fit a GARCH-process to our return data of the separate series and filter out the residuals. After that, we standardize the residuals with their conditional standard deviation and check the i.i.d properties by autocorrelation functions. Our next step is to model the marginal distributions based on the standardized residuals. We thereafter divide the distributions of the series into three separate segments. The Gaussian kernel is then applied on the interior parts and the EVT (POT-method) on the tails, with the Gaussian kernel being a non-parametric way to estimate the empirical CDFs of each series. Based on the previous steps, we fit and estimate parameters for a student-t copula on our series after first transforming the standardized residuals to a uniform distribution from the estimated empirical CDFs. By using the dependence structures from the copula, we use Monte Carlo to simulate returns for each index after first simulating corresponding standardized residuals. We thereafter transform the simulated logarithmic returns to arithmetic returns, define equally weighted portfolios, and convert them back to logarithmic returns. Having constructed the desirable return series based on the EVT-GARCH-Copula, we can finally calculate VaR for our portfolios.
5. Data and preliminary analysis

In this paper we analyze the dependence structures between renewable energy and green bonds with different asset classes. Renewable energy plays a vital role in shifting economies from carbon dependence and to reach climate goals. Further, green bonds have experienced fast growth in recent years, ensuring that projects that will help this shift can be financed. Both bonds and stocks are typical securities in investor portfolios as they possess different characteristics that make them attractive for investors. Therefore, renewable energy stocks and green bonds might provide different diversification and hedging opportunities for investors. By considering both renewable energy stocks and green bonds we are able to provide more information of how green investments adds to portfolios and to other assets classes.

We consider three different indices for green bonds and renewable energy stock returns respectively. In addition, asset markets are represented with indices for stocks, oil and the corporate bond market. We control for uncertainty on the financial market and the oil market as well as technology. The sample consist of daily data that ranges from October 2014 to November 2018, summing up to 1032 observations. The green bond indices are newly developed, hence, they only go back a few years. However, this starting date allows us to better capture recent events such as the Paris climate agreement, the US election and the OPEC oil glut, that in many ways concerns climate related issues. While daily frequency may suffer from noise, we argue that it fits our study as weekly or monthly data would result in few observations that could lead to misleading correlations. Further, as green bonds are less likely to have large daily movements, we can capture even small changes in return using daily data. Moreover, the large use of daily data in previous studies validates the use of it in this study. All indices are denoted in US dollar (USD) as we strive for unity between the indices and as USD can be considered a world currency. All data, except the green bond data, are collected from Thomas Reuters Datastream. As some holidays are not common across the indices, Datastream posts values from the previous business days on holidays, even though the market is closed. As this could bias our results, we clean for US holidays throughout the sample. Although some information may be lost, we can afford this given our large sample size.

Regarding green bonds, we use different indices to capture various aspects of the market, each with different compositions. The included indices are Barclays MSCI World Green Bond Index (MGB), S&P Dow Jones Green Bond Index and (DGB) and Solactive Green Bond Index (SOLAC). All of the green bond indices are retrieved from Bloomberg. These indices have been previously used by Reboredo (2018) and are the main green bond indices available. In MGB, securities must follow at least one of five defined environmental categories to be classified as a green bond. The categories, created by MSCI ESG Research are aligned with the Green Bond Principles (GBP) and are the following: alternative energy, energy efficiency, pollution prevention and control, sustainable waste, green buildings or climate adaptation. The index includes corporate, government-related, treasury

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5 The cross-quantilogram estimations were also estimated without cleaning the data but the results have close to no differences.
and securitized bonds. On the other hand, DGB base their criteria for inclusion on definitions made by the Climate Bonds Initiative (CBI). This index allows for corporate, government and multilateral bonds. Regarding SOLAC, the criteria of inclusion are as DGB based on CBI and allow for similar bonds. All indices are market-value weighted. In contrast to SOLAC, the former two indices allow for bonds issued in other currencies than USD. More information regarding the indices can be found in GBP-SBP (2018).

Due to the large size of the renewable energy market we include three indices aiming to capture different parts of the market. Firstly, we include a proxy for clean energy, the Wilderhill clean energy index (ECO), which is widely used in previous literature. This index selects clean energy companies that are reviewed based on their exposure to or development of clean energy. Generally, companies included focuses on technology for renewable energy. Secondly, we use the Wilderhill New Energy Global Innovation or (NEX). This index is comprised of companies that develop innovative technologies, mainly within wind, biomass and biofuels, small-scale hydro, geothermal and marine. Lastly, the S&P 500 global clean energy index (SPCE) is included and it is comprised of companies that focus on clean energy related business.

The choice of asset classes is based on previous studies, connections to renewable energy and green bonds as well as being regular investments in a typical investor portfolio. The asset classes used are the stock market, the oil market and the corporate bond market. Representing the stock market, we use the indices for S&P 500 (SPX) and STOXX 600 (STOXX). SPX consist of the largest 500 companies in the US with the IT-sector representing the greatest share. STOXX consist of large, mid and small companies in Europe, where the largest share of the underlying stocks is placed in Great Britain and in the Health Care sector. Further of interest is oil, that often is recognized as closely related to the renewable energy market. Given that green bonds also could finance energy related projects there might be a connection between green bonds and oil as well. We use the NYMEX WTI crude oil futures continuous contracts index (OIL) to represent the global oil market\(^6\). The future contracts are continuous as the current future rolls over to nearest future contract at the start of each month. By using continuous contracts, we solve the problem with price differences and gaps in the series arising from time premiums of overlapping contract months. To measure dependence between green investments and the bond market we use the corporate bond market as this is the main market for private investors. As the US market is the largest bond market in terms of volume, we include the S&P 500 1-5 Year Investment Grade Corporate Bond Index (CBS) and S&P 500 5-7 Year Investment Grade Corporate Bond Index (CB) as proxies for the corporate bond market. By including both short and long maturities we can capture different parts of the market.

Further we control for a set of uncertainties and technology returns. As Dutta (2017) and Ivarsson Lundgren et al. (2018) have shown, uncertainties can play a vital role in determining the relationship

\(^6\) In addition, we have used ICE Brent crude oil continuous contracts index representing oil to study if any differences occur compared to used WTI crude oil index (OIL). ICE Brent crude oil show almost identically estimation output with NYMEX which is why it is not presented in this paper but are available on demand.
between renewable energy investments and asset markets. Uncertainties can also contribute to contagion between markets during times of turbulence. We include uncertainties representing two different types of markets, the financial markets (VIX) and the oil market (OVX). VIX is a standard measure of financial uncertainty in financial literature. Regarding OVX, Dutta (2017) points out that oil price uncertainty can affect renewable energy more than the actual oil prices. Many energy driven firms are dependent on the price of oil and price uncertainty can affect the real economy. Uncertainties of the oil price may affect the willingness to invest and may therefore carry information on the dependence structure with renewable energy stocks and green bonds. All of the uncertainty indices are created by the Chicago board Options Exchange (CBOE), who derive each index from the price of options from each market, representing the 30-day expected volatility. Lastly, we control for technology return as it plays a vital role within the renewable energy market developing new innovative and effective ways of sourcing energy and much of the green bond revenues are invested into technology dependent sectors. As technology has a strong connection to both renewable energy and green bonds, it might affect the dependence structure of green bonds and renewable energy with other markets. Representing technology, we use the NYSE Arca Tech 100 index (PSE).  

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7 We have also controlled for a wider measure of uncertainty for the general energy markets (VXXLE) as well as EURO/USD exchange rate uncertainty (EUVIX). The results are closely related to both OVX and VIX and therefore do not give us additional information on the characteristics of our variables. Of this reason, these are not presented in this paper but are available on demand.

8 We have also controlled for technology by using the conditional volatility of PSE to test the hypothesis that the volatility of PSE rather than the return may affect the dependence structures. The conditional volatility was derived from PSE return through a GARCH(1,1) process. The conditional volatility of PSE was then used as a control variable in our estimations using the partial cross-correlation quantile model. The estimation with the conditional volatility of PSE has shown only marginal effects on the output and are therefore not presented but are available on demand.
Table 1: Descriptive statistics of the indices’ return

<table>
<thead>
<tr>
<th></th>
<th>25th (％)</th>
<th>Mean (％)</th>
<th>75th (％)</th>
<th>Std. Dev. (％)</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>JB</th>
<th>ADF(c)</th>
<th>ADF (ct)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Green bonds</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOLAC</td>
<td>-0.131</td>
<td>0.010</td>
<td>0.160</td>
<td>0.275</td>
<td>-0.410</td>
<td>7.126</td>
<td>760.144**</td>
<td>-22.762(1)**</td>
<td>-12.807(1)**</td>
</tr>
<tr>
<td>DGB</td>
<td>-0.390</td>
<td>0.002</td>
<td>0.197</td>
<td>0.124</td>
<td>-0.179</td>
<td>4.407</td>
<td>90.366**</td>
<td>-31.170(1)**</td>
<td>-31.119(1)**</td>
</tr>
<tr>
<td>MGB</td>
<td>0.083</td>
<td>0.005</td>
<td>0.107</td>
<td>0.063</td>
<td>-0.323</td>
<td>4.389</td>
<td>100.664***</td>
<td>-31.190(1)**</td>
<td>-31.209(1)**</td>
</tr>
<tr>
<td><strong>Renewable energy</strong></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>ECO</td>
<td>-0.778</td>
<td>-0.055</td>
<td>0.866</td>
<td>1.406</td>
<td>-0.122</td>
<td>4.776</td>
<td>77.079***</td>
<td>-16.432(1)**</td>
<td>-14.415(1)**</td>
</tr>
<tr>
<td>NEX</td>
<td>-0.467</td>
<td>-0.021</td>
<td>0.490</td>
<td>0.410</td>
<td>-0.463</td>
<td>5.962</td>
<td>388.618***</td>
<td>-16.136(1)**</td>
<td>-15.148(1)**</td>
</tr>
<tr>
<td>SPCE</td>
<td>-0.602</td>
<td>-0.023</td>
<td>0.087</td>
<td>1.088</td>
<td>-0.279</td>
<td>5.508</td>
<td>234.271***</td>
<td>-16.670(1)**</td>
<td>-15.670(1)**</td>
</tr>
<tr>
<td><strong>Economic and financial variables</strong></td>
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<td></td>
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<tr>
<td>OIL</td>
<td>-4.419</td>
<td>-0.014</td>
<td>1.164</td>
<td>2.448</td>
<td>0.776</td>
<td>5.064</td>
<td>188.241***</td>
<td>-31.906(1)**</td>
<td>-24.086(1)**</td>
</tr>
<tr>
<td>SPX</td>
<td>-0.296</td>
<td>0.031</td>
<td>0.441</td>
<td>0.414</td>
<td>0.066</td>
<td>6.472</td>
<td>860.848***</td>
<td>-16.601(1)**</td>
<td>-16.631(1)**</td>
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<tr>
<td>STOXX</td>
<td>-0.469</td>
<td>-0.003</td>
<td>0.310</td>
<td>1.006</td>
<td>-0.857</td>
<td>12.108</td>
<td>3732.426***</td>
<td>-17.120(1)**</td>
<td>-17.112(1)**</td>
</tr>
<tr>
<td>CB</td>
<td>0.314</td>
<td>-0.005</td>
<td>0.111</td>
<td>0.189</td>
<td>0.131</td>
<td>3.941</td>
<td>41.374***</td>
<td>-14.374(1)**</td>
<td>-14.380(1)**</td>
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<tr>
<td>CBS</td>
<td>-0.058</td>
<td>-0.007</td>
<td>0.046</td>
<td>0.088</td>
<td>-0.038</td>
<td>4.735</td>
<td>59.126***</td>
<td>-14.399(1)**</td>
<td>-14.394(1)**</td>
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<tr>
<td>PSE</td>
<td>-0.467</td>
<td>0.049</td>
<td>0.490</td>
<td>0.976</td>
<td>-0.690</td>
<td>5.552</td>
<td>141.141***</td>
<td>-15.479(1)**</td>
<td>-15.475(1)**</td>
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<td><strong>Uncertainty variables</strong></td>
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</tr>
<tr>
<td>OXV</td>
<td>-0.603</td>
<td>0.031</td>
<td>0.584</td>
<td>4.406</td>
<td>0.061</td>
<td>4.610</td>
<td>114.777***</td>
<td>-10.819(1)**</td>
<td>-10.814(1)**</td>
</tr>
<tr>
<td>VIX</td>
<td>-2.461</td>
<td>0.064</td>
<td>2.697</td>
<td>8.406</td>
<td>1.938</td>
<td>12.094</td>
<td>199.120***</td>
<td>-14.242(1)**</td>
<td>-14.246(1)**</td>
</tr>
</tbody>
</table>

Table 1. Note: SOLAC, DGB and MGB represent the green bond market; ECO, NEX and SPCE represent the renewable energy market; OIL represents oil prices; SPX and STOXX represent stock market; CB and CBS represent corporate bonds; PSE represents technology; OXV and VIX represent uncertainty on the financial market and oil market respectively. JB is the Jarque-Bera test for normality. ADF(c) and ADF(ct) checks for unit root with a constant (c) and with a constant and trend (ct), see appendix table 5 for additional Phillips-Perron unit root tests. The parentheses represent the optimal lag length based on AIC. *, ** and *** indicates significance at 10%, 5% and 1%. 

Table 1 depicts the descriptive statistics from the logarithmic returns for all indices. Given that the presented data is daily the mean of each index is as expected close to zero. Noticeable are the negative coefficients of the renewable energy mean stocks returns indicating negative returns during the sample period. Further and not unexpected, the renewable energy stocks return, and the oil returns have the largest standard deviations, indicating more volatile market conditions than for the bond markets. The oil return also shows large differences between its 25th and 75th quantiles. The green bond market in general exhibits larger losses in the 25th quantile and higher return in the 75th quantile than the corporate bond market, which also is in line with the higher standard deviation.

The skewness values for all variables largely deviates from zero, indicating skewed distributions. Further, all economic and financial indices have a negative skewness except of oil and the uncertainty indices, meaning that their normal distribution have a tail extended to the left. In contrast, oil and the uncertainty indices are skewed to the right. The kurtosis measures the fatness of the tails which can give us an estimate on the likelihood of extreme scenarios happening. All variables have kurtosis higher than three indicating leptokurtic distributions, which confirms deviation from the normal distribution and fatter tails. Noticeable, the kurtosis of VIX is the largest. Among the economic and financial variables, STOXX has the largest kurtosis. Again, the bond markets are among the variables with the lowest kurtosis as may be expected. Though interestingly, SOLAC is the exception with the second higher kurtosis after STOXX. Further, the Jarque-Bera (1980) test confirms the non-normality for all indices indicated from the kurtosis and skewness values. We also test for unit-roots using Augmented Dickey-Fuller test (1979). The tests may be sensible to the chosen lagged length. When conducting the ADF-test we therefore follow the AIC lag length criteria and chose the model with the lowest AIC-value. The parentheses in table 1 represent the optimal lag length based on AIC. The results from the ADF tests confirms stationarity for all indices.
Figure 3: Logarithmic returns

![Figure 3](image)

**Fig. 3.** Note: SOLAC, DGB and MGB represent the green bond market; ECO, NEX and SPCE represent the renewable energy market; OIL represent oil prices; SPX and STOXX represent the stock market; CB and CBS represent corporate bonds; PSE represent technology.

In figure 3 we show the return series for the indices. The three green bond markets as well as the renewable energy and oil market exhibit large variations in returns from 2014 and to the mid of 2015. This coincides with the OPEC oil glut that resulted in large oil price decreases. In recent years, the variation has been smaller with only temporary deviations during shorter time periods in the individual indices. The green bonds, DGB and MGB, show a noticeable downturn in November 2016, in the same period as the US election. However, the changes in daily return are overall small. During this time, the renewable energy returns seems to be rather stable but the changes in daily return are grander than those of green bonds. This is not surprising due to the more volatile
characteristics of stocks compared to bonds. Regarding the asset classes, STOXX have an extreme downturn the 24th of June 2016, followed by the Brexit referendum day June 23rd, 2016. STOXX reacts stronger than SPX, most likely as Brexit is more related to Europe than the US. Further, the corporate bond market exhibits small daily changes in return compared to the stock and oil market which again is not surprising due to the general low volatility of bonds.

Table 2: Unconditional correlation matrix

<table>
<thead>
<tr>
<th></th>
<th>SOLAC</th>
<th>DGB</th>
<th>MGB</th>
<th>ECO</th>
<th>NEX</th>
<th>SPCE</th>
<th>OIL</th>
<th>SPX</th>
<th>STOXX</th>
<th>CB</th>
<th>CBS</th>
<th>PSE</th>
<th>OVX</th>
<th>VIX</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOLAC</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>DGB</td>
<td>-0.307</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>MGB</td>
<td>0.374</td>
<td>0.344</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>ECO</td>
<td>-0.067</td>
<td>-0.042</td>
<td>-0.166</td>
<td>1</td>
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</tr>
<tr>
<td>NEX</td>
<td>-0.157</td>
<td>0.084</td>
<td>-0.163</td>
<td>0.761</td>
<td>1</td>
<td></td>
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<tr>
<td>SPCE</td>
<td>-0.314</td>
<td>0.083</td>
<td>-0.126</td>
<td>0.711</td>
<td>0.879</td>
<td>1</td>
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<tr>
<td>OIL</td>
<td>-0.154</td>
<td>0.030</td>
<td>-0.084</td>
<td>0.350</td>
<td>0.314</td>
<td>0.317</td>
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<tr>
<td>SPX</td>
<td>-0.049</td>
<td>-0.098</td>
<td>-0.180</td>
<td>0.704</td>
<td>0.641</td>
<td>0.963</td>
<td>0.277</td>
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<tr>
<td>STOXX</td>
<td>-0.341</td>
<td>0.223</td>
<td>-0.229</td>
<td>0.428</td>
<td>0.700</td>
<td>0.612</td>
<td>0.288</td>
<td>0.520</td>
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<tr>
<td>CB</td>
<td>0.235</td>
<td>0.490</td>
<td>0.764</td>
<td>-0.227</td>
<td>-0.108</td>
<td>-0.121</td>
<td>-0.571</td>
<td>-0.399</td>
<td>-0.173</td>
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<tr>
<td>CBS</td>
<td>0.264</td>
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<td>0.705</td>
<td>-0.227</td>
<td>-0.168</td>
<td>-0.110</td>
<td>-0.515</td>
<td>-0.296</td>
<td>-0.168</td>
<td>0.971</td>
<td>1</td>
<td></td>
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</tr>
<tr>
<td>PSE</td>
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<td>-0.068</td>
<td>-0.133</td>
<td>0.719</td>
<td>0.648</td>
<td>0.964</td>
<td>0.223</td>
<td>0.914</td>
<td>0.505</td>
<td>-0.163</td>
<td>-0.161</td>
<td>1</td>
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</tr>
<tr>
<td>OVX</td>
<td>0.061</td>
<td>0.010</td>
<td>0.091</td>
<td>-0.040</td>
<td>-0.333</td>
<td>-0.333</td>
<td>-0.403</td>
<td>-0.516</td>
<td>-0.287</td>
<td>0.085</td>
<td>0.169</td>
<td>-0.295</td>
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<tr>
<td>VIX</td>
<td>0.103</td>
<td>0.106</td>
<td>0.106</td>
<td>-0.069</td>
<td>-0.449</td>
<td>-0.459</td>
<td>-0.470</td>
<td>-0.335</td>
<td>-0.820</td>
<td>-0.446</td>
<td>0.370</td>
<td>0.238</td>
<td>-0.781</td>
<td>0.359</td>
</tr>
</tbody>
</table>

Table 2. Note: SOLAC, DGB and MGB represent the green bond market; ECO, NEX and SPCE represent the renewable energy market; OIL represents oil prices; SPX and STOXX represent the stock market; CB and CBS represent corporate bonds; PSE represent technology; OVX and VIX represent uncertainty on the financial market and oil market respectively. The unconditional correlation is the same as the Pearson correlation.

Table 2 shows the unconditional correlations of our included variables. From this table we observe that the green bond indices show high correlations with the corporate bond market. Interestingly, DGB and SOLAC have high negative correlations whereas the other green bond indices have strong positive correlations. Further, the returns of the green bond indices have negative or small positive correlations with the oil market, indicating that there might be diversification benefits of holding green bonds in combination with oil. Similar structures can be found between the green bond market and the stock market, with small and or negative correlations. The renewable energy stock indices highly correlate with each other as well as with both the oil and stock market. However, the renewable energy stock returns exhibit negative correlations with the corporate bond market, indicating diversification possibilities.
Figure 4: Historical prices of green bonds with the corporate bond, oil, and stock market

![Diagram](image)

**Fig. 4:** Note: Time series plot of MGB (left axis) in relation to CB, OIL, and SPX (right axis) respectively.

Figure 5: Historical prices of renewable energy with the corporate bond, oil, and stock market

![Diagram](image)

**Fig. 5:** Note: Time series plot of ECO (left axis) in relation to CB, OIL, and SPX (right axis) respectively.

Figure 4 gives an overview of the co-movements of the green bond market in relation to the included asset classes over time. As MGB co-moves closely with the other green bond indices (see figure 19 in appendix) we use it to represent the overall green bond market in figure 4. Firstly, the green bond market and the oil market show patterns of co-movements under certain time periods. However, the pattern is not consistent as the markets have a positive relationship in some periods and are seemingly inverse in others, indicating possible hedging opportunities. This is especially clear for the OPEC oil glut 2014 and the historically low oil prices of 2016. While oil uncertainty spiked, the return of green bonds increased. Generally, the green bond market has had strong returns after the Paris climate agreement at the end of 2015. However, the return fell at the end of 2016, around the same time as the US election. Secondly, the green bond market has large co-movements with both the bond market and the stock market, with some exceptions. Regarding the renewable energy market, it is represented by ECO in figure 5 as it closely co-moves with the other renewable energy indices (see figure 20 in appendix). Figure 5 indicates that the renewable energy market generally co-moves with both the oil and stock market, with only few exceptions. For oil, this might be explained by that low
oil prices did not give firms incentives to change to renewable energy, leading to lower returns for ECO. Interestingly, it seems like the green bond market and the renewable energy market do not co-move in similar ways to the other assets. The renewable energy market noticeable co-moves more with the other assets compared to green bonds.

**Figure 6:** Oil and financial uncertainty over time

![Graph showing oil and financial uncertainty over time](image)

*Fig. 6. Note: Time series plot of VIX (left axis) and OVX (right axis).*

Figure 6 depicts the uncertainty indices over time. From this figure we can observe that the Paris climate agreement did not lead to any larger uncertainty deviations. The US election in November 2016 however lead to spikes in both financial and oil uncertainty. Further, it seems like when investors worry about the oil price, uncertainty on the financial market also increase as many sectors use oil as an input. This is especially clear for when the OPEC oil glut began in 2014 due to advances in the US shale oil production. We observe similar correlations as the oil price reaches historic low during 2016, as the spike in oil uncertainty is followed by a similar spike in financial uncertainty.
6. Results and discussion

In this section we start by analyzing the results from the green bond estimations, including estimations with control variables as well as the rolling windows (figure 7 to 12). In a similar manner, we thereafter analyze the results regarding renewable energy stocks (figure 13 to 18). All the figures tied to the analyses of the cross-quantilogograms can be found at the end of this paper after conclusion and policy implications (figure 7 to 18). For cross-correlation heatmaps including lag five, see appendix figure 21 to 32. Finally, we present the risk and return measures for different green portfolio combinations.

6.1 Green bonds with major asset classes: cross-quantile dependence

Figure 7 displays the cross-quantile correlation spillovers from the asset markets to the green bond market. The vertical axis displays the green bond quantiles and the horizontal the asset market quantiles. We begin by looking at the corporate bond market for both long and short-term maturities, CB and CBS. If we observe the influence of CB on the green bond market (MGB) in the 0.05 quantile respectively, there is strong positive correlation. This indicates that when both the corporate bond market (CB) and green bond market (MGB) have abnormally low return, the corporate bond market (CB) affects the green bond market (MGB). In other words, if the corporate bond market (CB) have extreme negative return, the green bond market (MGB) will follow suit. This implies tail-dependence between the markets. Generally, this pattern is persistent for both long and short-term maturities of the corporate bond market and their influence on the green bond market (MGB and DGB) in the lower quantiles of the distribution. Unlike DGB and MGB, SOLAC does not have any clear pattern of dependence with the corporate bond market. While we do not see any obvious explanation to this, it might be due to differences in the composition of the indices. Even if SOLAC and DGB follow the same criteria based on the definitions made by CBI, the criteria are wide enough for inclusion differences to occur. Moreover, there are technical differences between the indices that could create differences in their characteristics. However, both long and short-term maturities of the corporate bond market have a persistent pattern of influence on the other two green bond indices, DGB and MGB.

Given that both long and short-term maturities of the corporate bond market show similar dependence structures with MGB and DGB, it may imply that actors with different time perspectives in their investments behave homogenous to the green bond market in bearish times. Green projects are in many cases in the development phase, and could possibly be considered as risky by investors, affecting the willingness to hold them during times of turbulence. On the other hand, investors may view the risks of green bonds and corporate bonds as similar during downturns due to general risk aversion in turbulence. Even if investors would consider holding green bonds as a moral act or to self-signal morality, the result suggest that they are in large affected by turbulence such that moral considerations are set aside. Our results further indicate that green bonds and corporate bonds crash rather than boom together, making green bonds a poor hedge to investors in the corporate bond market and can further not be seen as a safe haven. However, while we can observe tail-
dependence, there is little to no dependence in the middle to upper quantiles. Therefore, normal to higher parts of the green bonds return distribution might be driven by exogenous factors such as the uniqueness of green projects. These findings are, excluding SOLAC, somewhat persistent with Reboredo (2018) who finds that green bonds are strongly dependent on the corporate bond market in lower quantiles. However, Reboredo (2018) also finds tail-dependence in the upper quantiles of green bonds and corporate bonds which stands in contrast to our results. While we include the US corporate bond market, Reboredo (2018) uses the Global Aggregate Corporate Bond Index. As the global corporate bond index captures the European market it might explain the differences found. Green bond issuance in Europe started as early as 2007 and therefore the market for green bonds have had more time to establish in Europe. Therefore, investors in the European corporate bond market might also be more prone to view green bonds and corporate bonds as substitutes, creating correlations in more quantiles.

Also depicted by figure 7, is how the green bond market is influenced by the stock market. Overall, there is little to no dependence between European stock market (STOXX) and the green bond market. Interestingly, we could presume that green bonds would be more dependent on the European stock market, as Europe has been pioneers regarding issuance of green bonds. However, the US stock market (SPX) does have some influence on the returns of the green bond market, mainly when both SPX and green bonds are close to, but somewhat below normal returns. Reboredo (2018), who uses a world stock index (MSCI World), finds weak and time-varying correlations between the stock market and the green bond market. As our results are similar to those of Reboredo (2018) we extend on his research by finding clear differences in how STOXX and SPX influence green bonds. While Reboredo (2018) finds spillover effects using a world index, this index places more than 50 percent in the US stock market. Therefore, it could explain why the US stock market in our study give similar dependence structures as Reboredo (2018). Given that there is no dependence in up- or downturns and small dependence in the rest of the quantile-space, the green bond market can act as a good diversifier to the stock market in general, with some exceptions to the median values of SPX. This conclusion is especially relevant for investors in the European stock market. Our results further points to that investors on the stock market may not necessary be engaged in the green bond market.

Given that green bonds consist of many projects that are dependent on energy, particularly renewable energy projects, we might expect to find dependence between oil return and green bond return. This especially as renewable energy often has been concluded to be a substitute to oil. Despite this, our results show almost no dependency between the variables in any quantiles. Both SOLAC and MGB show no clear pattern of dependency on oil. DGB in turn only shows small positive correlations with oil when it is in its lowest quantiles and the oil returns is in the middle quantiles. In general, there is no clear dependence pattern between the two markets that could further indicate that green projects dependence on energy is considered by investors. As there is generally little dependence between the markets and none in the tails, this implies that the green bond market can be good diversifier for investors in the oil market. Our results of no tail-dependence are in line with
the findings of Reboredo (2018) that reaches the same conclusion but using the general energy market, including for example both the crude oil and natural gas market. However, Reboredo (2018) find weak co-movements during regular market conditions between the energy market with the green bond market, which is in contrast to our results that shows no pattern of such correlations. This suggests that other energy markets rather than the crude oil market in particular contribute to such dependence structures. While green bonds partially finance energy related projects, these energy projects are likely not enough to consider them as energy investments. The results also indicate that investors in the oil market in large do not invest in green bonds.

Moreover, we consider the reverse relationship in our estimations by studying the green bond return influence on the major asset market. In figure 8, SOLAC have positive influence on the returns of the corporate bond market (CB, CBS) when SOLAC is in its lower to middle quantiles and the corporate bond market is in similar quantiles. This indicates that when both SOLAC and the corporate bond market have bad performance, SOLAC will affect the corporate bond market return so that it further will perform badly. In other words, investors in both markets will likely sell their bonds when they do not perform as strong as normally. While the other green bond indices, DGB and MGB, does not show similar results, the results from SOLAC does however not stand in contrast to the others. In comparison with the spillovers from the other direction (figure 7), tail-dependence were found between the green bond and corporate bond market with the latter influencing the first. Our results from SOLAC shows similar patterns of dependence but with the green bond market instead influencing the corporate bond market. Further, looking at DGB and MGB, they have negative influence on the corporate bond market when they are in their upper quantiles and when both shorter and longer maturities of the corporate bond market are in their middle to lower quantiles. The results suggest that when DGB and MGB have abnormally positive returns, the corporate bond market will be affected negatively. Interpreted from an investor perspective, the negative correlations might implicate that investors sell of corporate bonds in favor of green bonds when the green bond market is booming, and the corporate bond market is crashing. Further comparing the results from figure 7, we cannot see indications of investors selling off green bonds when the corporate bond market is booming, and the green market is performing badly. This is interesting as these findings indicate that some moral aspect might be involved that hinders investors of selling green bonds in favor of corporate bonds. Such behavior could have implications for investors as it indicates that those in the green bond market might hold losers too long, being especially affected by the disposition effect in accordance to Dooren and Galema (2018). Overall, we only find tail-dependence from the corporate bond market to the green bond market and not the reverse, meaning that the corporate bond market leads the returns of the green bonds during turbulence in both markets. This might imply that the corporate bond market may react to information quicker than the green bond market.

In figure 8 we can also analyze the green bond market influence on the stock market. We observe that there is almost no directional spillover to the European market (STOXX) or the US market (SPX). However, DGB does have positive correlations with the US market when both are in their middle
quantiles, suggesting a dual relationship as the US market influence DGB in similar manners. The duality of their dependence structures could be due to that both indices are technology dependent, creating a linkage between them. As this relationship does not hold in the tails of the distribution and as the other indices has little or no correlations with the stock market, investors in the green bond market can still diversify their portfolio in turbulent times by investing in the stock market. The general lack of dependence from the green bond market to the stock market may stem from their different fundamentals from being different types of assets. Regarding spillovers to the oil market, the green bond market has little to no influence, making oil a good diversification tool for investors in the green bond market. As observed before, investors in the oil market are unlikely to be in the green bond market which the results from figure 8 further confirms.

6.2 Green bonds with major asset classes: partial dependence, lags and rolling sample

Figure 9 and 10 depict the partial dependence of green bonds and the asset markets after controlling for uncertainties and technology. The figure include technology return (PSE), financial uncertainty (VIX) and oil price uncertainty (OVX). As considered in the theoretical framework, uncertainties might affect investment flows and strengthen financial linkages between markets. Further, as the project financed through the green bond market could be technology dependent, technology might affect the dependence structures. Our estimations show that there are only marginal differences to the original estimations when including these control variables, indicating that they do not carry relevant information on the dependence of green bonds with other asset classes. Therefore, the dependence structure is most likely driven by non-diversifiable risk, also called systematic risk. These results can have economic implications as it means that we are not able to hedge our portfolios from systematic risk by considering PSE, VIX and OVX. Our results also suggest that the characteristics, or components, of the green bond market and asset market may be the driver of the dependence structures rather than technology and uncertainties. Flaherty et al. (2017) have shown that VIX might affect the price determination of green bonds when issued by government agencies. However, in contrast to Flaherty et al. (2017) our indices do not separate private from public issuers and our overall results suggest that the dependence structures are robust to technology (PSE) as well as uncertainty on the financial markets (VIX) and the oil market (OVX).

Figure 11 and 12 depict the rolling windows and show how correlations change over time as this cannot be captured in the cross-quantile correlations. In general, the estimations from the extreme quantiles show that the correlations from the asset markets to the green bond markets are time-varying. Even though the existence of correlations tends to be stable, the strength of it is not. These results are similar to those of Reboredo (2018) who also find correlations to be time-varying. Further, the correlation trend in the mean quantiles are more stable over time compared to the extreme quantiles with only minor changes in strength. One interesting finding is that the correlations are more volatile in the start of the time series. As the green bond market have expanded significantly only in recent years, this might have affected the stability of the market that in turn results in increasingly stable correlation structures. The results might therefore be explained by investors shifting the perception of risk related to the green bond market. Moreover, studies have shown that
correlations tend to increase during crisis periods. Even if our sample focuses on recent events, leaving out any large-scale crisis, we cannot see any changes in correlations due to environmentally related events, such as the US intended withdrawal from the Paris climate agreement. While this event can create uncertainty for investors in green financial markets, it is not necessarily perceived as a crisis.

With the cross-quantilogram we can analyze the dependence structures by including lag structures. The lag structure of the directional spillovers from the asset markets to the green bond market are depicted in figure 21 to 23 (appendix). From these figures, we note that the dependence reaches its peak and is gone by lag five. In other words, after a week there is no influence from the asset markets to the green bond market left. This indicates that investors react to new information on the corporate bond, oil and stock market quickly and homogeneously. Further, investors may react at the same time to new information as they have similar investing strategies. If we instead turn to the reverse dependence structure, the green bonds influence on the asset market including lag five (appendix figure 24 to 26). We observe that green bonds have close to no influence on the stock or oil market at the fifth lag. As green bonds did not show a clear pattern of influence on these market at the first lag, the short time of dependence is expected. Further, we observe that when green bonds are experiencing good market conditions, their negative directional spillover onto the corporate bond market lasts even after a week, indicating longer lasting influence from green bonds to corporate bonds. This means that investors in both the green bond market and the corporate bond market act heterogeneously to new information that concerns the green bond market. Therefore, investors may have different incentives behind investing in green bonds and as a result also react differently to new information.

6.3 Renewable energy with major asset classes: cross-quantile dependence

Figure 13 depicts the asset markets influence on the renewable energy market. The corporate bond market, both long and short-term maturities do not particularly have directional spillovers to the renewable energy market. While there are few studying the relationship of bonds and renewable energy, Ahmad et al. (2018) study hedging possibilities of renewable energy using bonds. They find that bonds are a poor hedge to renewable energy due to low hedge effectiveness. However, Ahmad et al. (2018) does not measure the effectiveness in the tails. Regardless, our results show similarities as there are few correlations between the markets and only weak negative correlations. The negative correlations tend to gather toward the upper left corner, indicating that renewable energy returns increase when the corporate bond market return decreases. While this indicates hedging opportunities, the correlations are weak, and the pattern is not consistent for all indices. One possible explanation might be that the investors in the corporate bond market are not necessary in the renewable energy market. The motivation behind purchasing corporate bonds could be that the investors on this market are risk averse and therefore avoid the general stock market, especially during turbulence.

Further on figure 13, we observe that the stock market has large influence on the returns of NEX and SPCE in the full quantile-space. Again, the directional spillovers are greater from the US market
(SPX) than the European market (STOXX). Moreover, the effects are strongest to NEX which could be explained by NEX consisting of companies that develops technologies used in renewable energy companies and that the US stock market mainly consist of technology companies. Henrique and Sadorsky (2008) suggest that renewable energy could be seen as technology product. The strong directional spillover effects may therefore be due to that both the stock market and the renewable energy market are dependent on technology. Moreover, investors might view the renewable energy market as just another type of stock, creating the close dependencies. While ECO is not as influenced by the stock market, there are quantile correlations that could indicate similar dependence structures.

Regarding the nexus of oil and renewable energy, the previous literature is not uniform on the direction of dependence. A number of studies indicate weak causality running from oil to clean energy (Henrique and Sadorsky, 2008; Kumar et al., 2012; Bondia et al. 2016), causality running in both directions (Reboredo et al., 2017) while Huang et al. (2011) and Managi and Okimoto (2013) suggest that causality from oil to renewable mainly holds during extreme changes in oil prices. Reboredo (2015) and Uddin et al. (2019) find tail-dependence between oil and renewable energy in both directions and proposes that they crash and boom together. In contrary to all above studies, Ferrer et al. (2018) suggest a recent decoupling between renewable energy and the oil market. Our results in turn suggest that the renewable energy returns, as depicted by figure 13, are dependent on oil. Even though ECO differs from NEX and SPCE, the pattern from the latter two are strong and consistent. Strong correlations reaching from the bottom left corner to the top right indicate that renewable energy both crashes and booms with the oil market, with the exceptions of the absolute lowest quantiles. Given that we have differences between the indices, earlier studies may have reached different conclusions based on the used index representing renewable energy. Moreover, the differences could come from differences in the construction of the indices, for example that ECO is mainly composed of US stock in contrast to NEX and SPCE. While Reboredo et al. (2017) and most of the previous literature analyzes the relationship using Granger non-causality tests, our cross-quantilogram tells us about the directional predictability in the same sense but for different quantiles. Our findings can therefore be comparable and in line with the findings of Henrique and Sadorsky (2008), Kumar et al. (2012) and Bondia et al. (2016). Further, while Ferrer et al. (2018) suggest a recent decoupling between fossil-based energy markets and renewable energy, our overall results show strong dependence structures. The difference between the results could be due to that Ferrer at al. (2018) exclusively use ECO representing the renewable energy market and that their methodology does not capture spillovers for different market states. Their longer time period could also have an impact on the differing results.

Furthermore, Henrique and Sadorsky (2008), Huang et al. (2011), Managi and Okimoto (2013) and Uddin et al. (2019) suggest that renewable energy could act as a substitute to oil when the oil prices increases. As our results show strong correlations stretched across the quantile-space indicating that when oil prices increase, energy-using companies instead turn to renewable energy as they become relatively cheaper. Moreover, the substitution effect could depict a general trend were firms change the source of energy towards more green alternatives. Again, ECO differs from the other indices,
maybe due to that it mainly consists of US stock. As the US has fewer climate policies than for example the EU, there are fewer firm incentives to switch from oil to clean energy sources, which might explain the differing results. In contrast to our results, Henrique and Sadorsky (2008) theorize that investors in the technology market consider renewable energy as a technology product to invest in. However, our results rather indicate that investors consider renewable energy to be an energy investment based on the high dependence structures with oil. Another explanation to our results might be that the strong dependence structures is a result of the recent decades of financialization of the commodity market. The strong dependence could therefore be due to general correlations between the commodity market and the stock market. Finally, our results can also have implications for investors in the oil market as it indicates that we cannot hedge or diversify by simply investing in the renewable energy market.

In the next figure, 14, we observe small tendencies of tail-dependence from renewable energy (ECO and NEX) to both long and short-term maturities of the corporate bonds market. This could imply that investors in the renewable energy market sell their corporate bonds with their renewable energy investments during times of turbulence. Given that renewable energy leads the returns on the corporate bond market, the former might react quicker to new information. However, the suggested tail-dependence is weak and not consistent for all indices, which further strengthen the argument of different investors. Overall, the results from the corporate bond market suggests that renewable energy could be a diversifier for investors in the market no matter the state of the market.

Regarding renewable energy and its influence on the stock market, we observe that all indices has a strong influence on the European stock market. These results are similar to Ivarsson Lundgren et al. (2018) who finds strong directional spillover effects from renewable energy to the stock market, mainly the European market. The directional spillover effects are stronger than those to the US stock market, possibly due to the European market being more invested in renewable energy. This further means that there are bi-directional spillover effects between the stock and renewable energy market. As mentioned before, this indicates that renewable energy could be viewed as just another stock by investors. Further, we observe tail-dependence between the renewable energy market and the stock market. This could have been expected from a theoretical standpoint, as both are in the stock market and investors therefore may have similar risk aversion towards these investments during turbulent times. Interestingly, we observe that renewable energy has negative influence on the US stock market when renewable energy is in its lower quantiles and the US stock market is in its upper quantiles. This might simply suggest that when renewable energy has abnormally bad returns, and the US stock market is in a bull state, investors move from renewable energy stock to the regular US stock market.

Moreover, the renewable energy market has little influence on the returns of oil, indicating that the relationship is mainly unidirectional, from oil to renewable energy, for our time period. Our results are therefore in contrast to Reboredo et al. (2017) and Uddin et al. (2019) suggesting a bidirectional relationship. According to Uddin et al. (2019) renewable energy might especially influence oil return during extreme market conditions, suggesting tail-dependence between the assets. One explanation
behind our contrasting results may lie in the choice of time-period. Based on our theoretical framework we know that correlation tend to strengthen during turbulence. While our chosen time-period captures parts of the oil glut, both Reboredo et al. (2017) and Uddin et al. (2019) use time periods that spans over the financial crisis, which was an especially turbulent time for oil prices. In other words, since we do not include the financial crisis our largest negative daily oil return (lowest extreme quantile) may still be higher than the lowest return quantile of oil for previous studies. Another explanation related to the time period might be the increased focus on sustainability in recent years. If the renewable energy prices increase, it could be difficult for energy-using firms or investors to turn back to oil as they might want to signal environmental responsibility.

6.4 Renewable energy with major asset classes: partial dependence, lags and rolling sample

Regarding the partial cross-correlations, depicted in figure 15, we note that our control variables, technology (PSE) and financial uncertainty (VIX), carry information regarding the influence of the US stock market (SPX) on renewable energy (NEX). This could be due to that uncertainty increase contagion effects between the markets and therefore carry information on the dependence structures. Further, as the SPX and the renewable energy market both are technology dependent, technology could create a link between the markets affecting the dependence structures. NEX, as mentioned, mainly includes companies developing innovative technologies and SPX mainly consist of companies in the IT-sectors. Hence, the results are in line with previous literature that considers the role of technology regarding renewable energy (Kumar et al. 2012; Bondia et al. 2016; Ahmad and Rais, 2018; Kocaarslan and Soytas, 2019). Even though PSE and VIX carries some information, the dependence structures are still strong and covers the full quantile-space even after including control variables. This implies that VIX and PSE cannot be used for hedging the risk between the variables. Overall, aside from that PSE and VIX affects the NEX dependence on SPX, the inclusion of control variables, as depicted by figure 15 and 16, does not change the dependence structure of renewable energy and the asset markets. It might have been expected that OVX would carry information as Dutta (2017) finds that oil price uncertainty significantly affects renewable energy prices, more so than the actual oil prices. However, our results indicate that so is not the case. Note that the results do not exclude that oil price uncertainty affects renewable energy prices, only that it does not affect the dependence structure between oil and renewable energy. Further, similar to Uddin et al. (2019) including PSE as a control variable does not affect dependency between oil and renewable energy. Studying the reverse relationship, the control variables do not carry information on the dependence structure from the renewable energy markets to the corporate bond, stock or oil market.

Turning to the rolling window estimations as depicted in figure 17 and 18, our results generally show that the renewable energy market and the asset market have time-varying correlations, such that the strength of the correlations changes over time. Regarding renewable energy dependence on oil, the OPEC oil glut as well as the historic low prices of oil seem to increase the correlations in the mean of the distributions. This is similar to the results of Managi and Okimoto (2013) who finds a structural change in correlations between oil and renewable energy following sharp changes in oil prices. Our
findings further suggest that dramatic changes in oil prices increases its correlations with the renewal energy market.

Regarding how long-lived the influence of the stock and bond market on the renewable energy market is, we observe in figure 27 to 29 (appendix) that corporate bonds have a short-lived influence, that does not hold at lag five. As is little and weak dependence to begin with, this is not surprising. However, the stock and oil market does have some lasting directional spillovers onto the renewable energy market as there are some directional spillovers at lag five, after a week. Regarding the stock market, the influence on the renewable energy market is especially lasting for the upper and lower quantiles for both the stock and renewable energy market. This means that investors in both markets act heterogeneously, react differently, to new information on the stock and oil market. The general strong dependence on the stock market could explain the long-lasting lag structures. Further, investor herding mentality during especially strong or poor market conditions could affect the strength of the dependence structures. If we instead study the influence of renewable energy on the asset markets, depicted by figure 30 to 32 (appendix), it is short-lived for both the corporate bond and oil market. However, renewable energy does have lasting directional spillovers onto the stock market after a week, mainly in the lower quantiles of renewable energy.

6.5 Green bonds and renewable energy from an investor perspective

By comparing the dependence structures of green bonds and the major asset classes with the same structures for the renewable energy stocks we can extend our analyses. The renewable energy indices are based on stocks and also show high dependence with the stock market. Similarly, green bonds have high dependence on the bond market. Further, renewable energy seems to be closely interconnected with both stock and oil compared to green bonds. The high dependence on the stock market is not unexpected, as stock investments in general behave similar to each other. However, the interconnection with oil indicates that renewable energy stocks in large may be regarded as an energy investment. Despite that green bonds may finance energy investments, our results suggest that investor mainly regard them as a bond investment. Investors looking for diversification opportunities by investing in green alternatives could therefore use this information in their investment decisions. For example, investors with high exposure to the corporate bond market might be better off by investing in renewable energy stocks rather than in green bonds. Investors already in the energy market can instead diversify their portfolios by investing in green bonds.

As discussed throughout this paper, moral incentives and signaling might lead some towards green investments. In short, if investors are willing to hold green investments due to moral incentives, it may be less affected by turbulence than other assets. However, our results give mixed evidence regarding how the moral aspects of investing might affect investing behavior. For instance, even though investors might invest in green bonds during normal market circumstances, the tail-dependence on the corporate bond market indicates that they sell off their green bonds similar to corporate bonds when the times are worse. For renewable energy, the high dependence on both the stock- and oil markets suggest the same pattern during turbulence. Our results therefore point to
that the moral aspects do not overshadow general risk aversion during turbulence. However, some results still indicate that morals might play a role in determining investor behavior, but perhaps not during general turbulence, and maybe not for all types of assets. For instance, the unilateral relationship between oil and renewable energy stocks indicates that oil is substituted for renewable energy, but not the other way around. This means that those that hold renewable energy stocks are not likely to switch back to oil investments. Morality could therefore play a role when investors are deciding between alternatives in the energy market. Overall, it is easy to follow the moral path and invest green when times are good but when there is market turbulence, self-interest might overtake morals.

6.6 Risk and return of green portfolio combinations

The following section presents the risk adjusted portfolio performance and risk estimations for green portfolio combinations. This is measured by calculations of portfolio Sharpe ratios and VaR-estimations based on the EVT-GARCH-Copula approach described in the methodological section (4.3). These portfolios have been made by combinations of single indices representing the green bond and renewable energy market with the asset markets included in this study. To highlight benefits or downsides with investing green we also construct portfolios consisting exclusively of corporate bond- and renewable energy indices and compare them with both pure green portfolios and semi-green portfolios. All of the portfolios are equally weighted and held constant during the sample period. The constructed portfolios are not necessarily representative of the markets in general but rather for portfolios mirroring these indices. However, our estimations can still provide rough approximations of the risk related to investing in green assets, and further complement the cross-quantilogram estimations. For the green bond market, we restrict our analyzes and mainly use MGB as it closely co-moves with the green bond market as depicted in figure 19 (appendix). For the same reason we use ECO for the renewable energy market. Different combinations might yield different results, which is why these results are only valid for these exact indices combinations. The results are presented in table 3, where the Sharpe ratios are expressed on a yearly basis and the VaR with a monthly investment horizon.
First, we start by comparing the results from the sole corporate bond (CC) and green bond (GG) portfolios with the mixed portfolio (CG) of these assets classes. As depicted by table 3, the green and corporate bond portfolios all have negative mean Sharpe ratios. The negative ratios cannot be interpreted but are most likely due to a general downturn during our time period and rising risk-free rates. The portfolio performance during bull market (95th to 100th quantile) are positive and negative during bear markets (0 to 5th quantile) for all combinations. We note that the mixed portfolio (CG) have the highest risk adjusted return during bull markets. However, the VaR estimations indicate that the downside risk is also higher for this portfolio compared to its bond counterparts.

Regarding the renewable energy stock portfolios, it is clear that the pure renewable energy stock portfolio (RR) has performed worse than the portfolio consisting of general stocks (SS) and the mixed portfolio consisting of both renewable energy and general stocks (RS). Further, the mixed portfolio (RS) has lower risk adjusted return than the pure stock portfolio for our time period, which is a likely result of the general poor performance of renewable energy stocks. This is true during bull markets and for the general mean measure. Studying the potential portfolio losses estimated by VaR, at 95 percent and 99 percent the combination portfolio (RS) has the highest possible loss, followed by the solely renewable energy stock portfolio at 99 percent. For the 90 percent VaR renewable energy has a higher potential downside, followed by the combination portfolio. Overall, while green bonds and renewable energy have in this paper shown diversification possibilities with the other asset classes, they are not necessarily beneficial for investors to add to their portfolios. For the other portfolio combinations, during bull market the green bond and oil portfolio combination (GO) has the strongest performance though closely followed by the others. Not surprisingly, and likely due to their close dependence structures, the renewable energy stock and oil portfolio (RO) have the largest possible loss estimated by the VaR.
7. Conclusion and policy implications

In the last decades, concerns of climate change have embossed the agendas of policy makers. Shifting investments towards environmentally friendly alternatives is fundamental to reach climate goals and avoid significant economic costs to society. However, due to research gaps, investors lack important information on the fundamentals of renewable energy and green bonds, creating investment barriers and holding back growth within these areas. Previous studies have focused on mean-to-mean dependence and therefore given an incomplete picture of green investments. This study has aimed to fill these research gaps by analyzing the quantile dependence for green bond returns and renewable energy stock returns with three different asset classes; corporate bonds, stocks and oil. To fulfill the aim, we used the cross-quantilogram approach developed by Han et al. (2016). Further, we controlled our estimations for technology, different kinds of uncertainty and time-varying effects by applying partial-cross quantilogram estimations and rolling-window estimations.

Our results led us to three key findings: 1) The returns of the green bond market are unidirectional tail-dependent on the returns of the corporate bond market for both long and short maturities of corporate bonds but are not dependent on the stock or oil market. The tail-dependence indicates that while investor may hold green bonds due to moral incentives, it is not enough during times of turbulence. For these, the dependence structures are short-lived. 2) The renewable energy market is dependent on oil between similar quantiles, suggesting that renewable energy substitutes oil when oil prices increase. Some influence last even after a week, at the fifth lag. However, renewable energy does not influence the oil market, indicating that oil is not a substititional energy source for renewable energy driven firms. Renewable energy stocks are further highly dependent on the returns of the general stock market but are not influenced by the returns on the corporate bond market. 3) The dependence of both renewable energy and green bonds on the asset markets are time-varying in the extreme quantiles.

Our key findings presented in this study have important and immediate policy implications. Firstly, investors in the corporate bond market cannot hedge or diversify their portfolio during downturns by investing in green bonds. One explanation could be that investors are attracted by green bonds due to moral incentives, but that it is set aside during times of turbulence. Therefore, by obtaining green bonds as a supplement to corporate bonds, the risk return ratio of the portfolio will not necessary increase. On the other hand, investors on the stock or oil market have opportunities to diversify their portfolios by investing in green bonds because of weak dependence structures, both during booms and busts. Therefore, investors in these markets might decrease their risk in portfolios by investing in green bonds, making it an interesting investment not only from a moral standpoint. Regarding renewable energy stocks, it would add little diversification benefits for those in the oil market due to strong dependence structures.

The differences in dependence structures between renewable energy stocks and green bonds should be taken into consideration by policy makers. Governments pushing for raised capital towards green
alternatives need to be aware of the differences between the assets as well as the opportunities and risks as it carries to portfolios. While morals could be a strong force our results indicate that it is not enough for investors in turbulent times. Therefore, government policy would need to be focused on increasing investor incentives. Finally, potential investors should strongly consider the time-varying characteristics of green bonds and renewable energy dependence on the asset classes. As the dependence structure change over time and are also affected by market changes, the time-varying characteristics could be an obstacle due to the need of portfolio rebalancing.
Figure 7: Asset markets return to green bonds

Fig. 7. Note: Denotes the quantile cross-correlations in heatmaps. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level). In figure 7 the horizontal axis represents the green bond return quantiles and the vertical axis represents the economic and financial variables.
Figure 8: Green bond return to asset markets

Fig. 8. Note: Denotes the quantile cross-correlations in heatmaps. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5 % significance level).
**Figure 9:** Corporate bond and stock market return to green bonds with control variables

![Heatmaps of Corporate bond return spillover](image)

**Fig. 9.** Partial cross-correlation heatmaps of Corporate bond return spillover (horizontal axis) to Green bonds (vertical axis). The output has one lag.
Figure 9: Stock market and oil return to green bonds with control variables

Fig. 9. (Continues)
Figure 10: Green bond return to corporate bond and stock market with control variables

Fig. 10. Partial cross-correlation heatmaps.
Figure 10: Green bond return to corporate bond and stock market with control variables

Fig. 10. (Continues)
Figure 11: Rolling window asset market return to green bonds

Fig. 11. Note: Denotes the quantile cross-correlation rolling windows. The blue line represents the change in correlations and the red line represent confident intervals.
Figure 11: Rolling window asset market return to green bonds

Fig. 11. (Continues)
Fig. 12. Note: Denotes the quantile cross-correlation rolling windows. The blue line represents the change in correlations and the red line represents confident intervals.
Figure 12: Rolling window green bond return to asset markets

Fig. 12. (Continues)
Figure 13: Asset markets return to renewable energy

**Fig. 13.** Note: Denotes the quantile cross-correlations in heatmaps. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Fig. 14. Note: Denotes the quantile cross-correlations in heatmaps. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 15: Corporate bond and stock market return to renewable energy with control variables

Fig. 15. Partial cross-correlation heatmaps.
Figure 15: Stock market and oil return to renewable energy with control variables

Fig. 15. (Continues).
Figure 16: Renewable energy to corporate bond and stock market return with control variables

Fig. 16. Partial cross-correlation heatmaps.
Figure 16: Renewable energy to stock market and oil return with control variables

Fig. 16. (Continues).
Figure 17: Rolling window asset market return to renewable energy

Fig. 17. Note: Denotes the quantile cross-correlation rolling windows. The blue line represents the change in correlations and the red line represent confident intervals.
Figure 17: Rolling window asset market return to renewable energy
Figure 18: Rolling window renewable energy return to asset markets

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Fig. 18. Note: Denotes the quantile cross-correlation rolling windows. The blue line represents the change in correlations and the red line represent confident intervals.
Figure 18: Rolling window renewable energy return to asset markets
8. Reference list


APPENDIX

Table 4: Literature overview

<table>
<thead>
<tr>
<th>Article (year)</th>
<th>Period</th>
<th>Method</th>
<th>Variables</th>
<th>Directionality</th>
<th>Key findings</th>
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<tr>
<td>Hernández and Saldivery (2008)</td>
<td>2005-2007 (Weekly)</td>
<td>VAR, Granger Causality</td>
<td>Oil, Tech, Interest rate (rM) and renewable energy</td>
<td>Oil, Tech, Interest rate → renewable energy</td>
<td>A shock in tech affects renewable energy more than a shock in oil.</td>
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<td>Huang et al. (2011)</td>
<td>2004-2011 (Weekly)</td>
<td>VAR, Granger Causality</td>
<td>Oil, renewable energy</td>
<td>Oil, Tech, Interest rate → renewable energy</td>
<td>Oil has a significant impact on renewable energy only after the Middle East wars of 2006 and 2008.</td>
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<td>Kormel et al. (2009)</td>
<td>2004-2011 (Weekly)</td>
<td>VAR, Granger Causality</td>
<td>Oil, Tech, Interest rate (rM), Carbon price and renewable energy</td>
<td>Oil, Tech, Interest rates → renewable energy</td>
<td>There is a positive relationship due to increasing oil prices and substitution effects of alternate energy sources. Carbon prices are not significant, maybe due to its low prices.</td>
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<td>Saldivery (2011)</td>
<td>2005-2010 (Daily)</td>
<td>MGARCH, BSGARCH, DCC/GOARCH</td>
<td>Oil, Tech and renewable energy</td>
<td>Oil, Tech → renewable energy</td>
<td>The conditional correlation between tech and renewable energy are higher than between oil and renewable energy. Oil could be a useful hedge to renewable energy.</td>
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<td>Manghi and Oltmanns (2011)</td>
<td>2004-2011 (Weekly)</td>
<td>MSVAR</td>
<td>Oil, Tech, Interest rate (rM) and renewable energy</td>
<td>Oil, Tech → renewable energy</td>
<td>Noted structural market changes Nov and Dec 2007 affecting the relationship of oil and renewable energy. A surge in oil prices has been between implications for the market.</td>
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<td>Pham (2016)</td>
<td>2010-2018 (Daily)</td>
<td>Unit-Root Multivariate DCC/GARCH</td>
<td>Green Bonds and conventional Bonds</td>
<td>Green bond market → Oil and renewable energy</td>
<td>No volatility spillover in oil and renewable energy. A volatility spillover from the conventional bond market to the green bond market.</td>
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<td>Ahmad (2017)</td>
<td>2009-2015 (Daily)</td>
<td>DCC/CCC/BEKK/GARCH, VAR/MA/GARCH</td>
<td>Oil, Tech and renewable energy</td>
<td>Tech → renewable energy and Oil, Tech and renewable energy → Oil</td>
<td>Tech has significant returns and volatility spillover into renewable energy and oil. Tech and renewable energy are net emitters of spillovers, while oil is a net receiver.</td>
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<tr>
<td>Duan (2017)</td>
<td>2007-2018 (Daily)</td>
<td>Range-based realized volatility measure</td>
<td>Oil volatility, Oil, Carbon price and renewable energy</td>
<td>Oil volatility → renewable energy</td>
<td>Renewable energy is sensitive to oil volatility shocks. Oil volatility may contain information of historical volatility. Oil volatility have bigger effects than oil prices.</td>
</tr>
<tr>
<td>Flattery et al. (2017)</td>
<td>2015-2016 (Monthly)</td>
<td>Panel data regression, fixed effect model</td>
<td>Green bonds, VAR, Interest rates (rM) and US dollar futures index</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Koborodo et al. (2017)</td>
<td>2006-2012 (Daily)</td>
<td>Worden cointegration, linear/nonlinear Granger Causality</td>
<td>Oil, Tech innovation and renewable energy (global and sectoral)</td>
<td>Renewable energy → Oil</td>
<td>The dependence between oil and renewable energy is weak in the short run and stronger in the medium-long run. There is a non-linear causality from renewable energy to oil and mixed evidence of causality from oil to renewable energy.</td>
</tr>
<tr>
<td>Ahmad and Kazi (2018)</td>
<td>2006-2017 (Weekly)</td>
<td>Directional spillover, ADO/EGARCH</td>
<td>Tech, Islamic Market, sub-energy groups and renewable energy</td>
<td>Renewable energy → Oil</td>
<td>There is limited dependency between oil, sub energy groups and renewable energy. There are unidirectional spillovers running from technology to renewable energy.</td>
</tr>
<tr>
<td>Ahmad et al. (2018)</td>
<td>2008-2017 (Daily)</td>
<td>A/DCC/GMGARCH, Hedging ratios</td>
<td>Unemployment, bonds, Oil, Gold, Carbon prices and renewable energy stocks.</td>
<td>Tech → renewable energy</td>
<td>Hedging ratios varies over time. VAR is the most effective for hedging renewable energy stocks.</td>
</tr>
<tr>
<td>Ferret et al. (2018)</td>
<td>2006-2017 (Daily)</td>
<td>Spillover index, VAR</td>
<td>Real four factors, Tech, Bonds and renewable energy</td>
<td>Tech → renewable energy</td>
<td>The renewable energy sector decouples from the crude oil sector. There is lower volatility and returns connectedness in longer time periods. Oil and renewable energy do not compete on the same markets.</td>
</tr>
<tr>
<td>Tramon Lardner et al. (2018)</td>
<td>2004-2016 (Daily)</td>
<td>GVAR, linear and nonlinear Granger causality, spillover index</td>
<td>Oil, Exchange rate, Interest rate (rM), Unemployment, Stock market and renewable energy</td>
<td>Renewable energy → Stock market</td>
<td>The European market has a strong dependency on renewable energy. Uncertainties significantly impact renewable energy stock prices. Financial stress is the most influential of uncertainties.</td>
</tr>
<tr>
<td>Pham (2018)</td>
<td>2010-2018 (Daily)</td>
<td>A/DCC/GMGARCH</td>
<td>Oil and renewable energy (sectoral)</td>
<td>Oil, Tech → renewable energy</td>
<td>Suggests of spillovering correlations between oil and renewable energy. The correlations vary across different renewable sectors, such as, the hedging effect of oil vary differs sectors.</td>
</tr>
<tr>
<td>Koborodo and Upsilon (2018)</td>
<td>2006-2017 (Daily)</td>
<td>Multivariate Vine copula dependence</td>
<td>Oil, Energy prices and renewable energy</td>
<td>Oil, Energy prices → renewable energy</td>
<td>Oil and energy prices impact the dynamics of renewable energy stock returns. The price impact on renewable energy is symmetric, therefore extreme falls or spikes in energy prices similarly affect renewable energy.</td>
</tr>
<tr>
<td>Kovarán and Soysal (2019)</td>
<td>2004-2018 (Daily)</td>
<td>NARDL-model</td>
<td>Tech, Interest rate (rM), Oil and renewable energy</td>
<td>Oil, Tech → renewable energy</td>
<td>Renewable energy is affected asymmetrically and differently in the long and short-term. An increase in oil prices leads to an increase in renewable energy in the short run.</td>
</tr>
<tr>
<td>Arola (2019)</td>
<td>2010-2018 (Daily)</td>
<td>Matching method approach</td>
<td>c.g. Green Bonds</td>
<td>Oil → renewable energy</td>
<td>Green bonds have a significant but marginal positive compared to the conventional bond market.</td>
</tr>
<tr>
<td>Udine et al. (2019)</td>
<td>2010-2017 (Daily)</td>
<td>Crossquantileigram</td>
<td>Stocks, oil, gold, USD/EUR and renewable energy</td>
<td>Oil, Tech → renewable energy</td>
<td>Renewable energy is dependent on oil when it are in the same quantities and not in opposite quantities. Oil is tail dependent on renewable energy.</td>
</tr>
</tbody>
</table>

## Table 4: Indices overview

<table>
<thead>
<tr>
<th>Green bonds</th>
<th>Ref. name</th>
<th>Source</th>
<th>Weighting method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barclays MSCI World Green Bond Index</td>
<td>MGB</td>
<td>Bloomberg</td>
<td>Market-Value</td>
</tr>
<tr>
<td>S&amp;P Dow Jones Green Bond Index</td>
<td>DGB</td>
<td>Bloomberg</td>
<td>Market-Value</td>
</tr>
<tr>
<td>Solactive Green Bond Index</td>
<td>SOLAC</td>
<td>Bloomberg</td>
<td>Market-Value</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Corporate bonds</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P 500 5-7 Year Investment Grade Corporate Bond Index</td>
<td>CB</td>
<td>Thomas Reuter Datastream</td>
<td>Market-Value</td>
</tr>
<tr>
<td>S&amp;P 500 4-5 Year Investment Grade Corporate Bond Index</td>
<td>CBS</td>
<td>Thomas Reuter Datastream</td>
<td>Market-Value</td>
</tr>
</tbody>
</table>

### Renewable energy

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<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Wilderhill Clean Energy Index</td>
<td>ECO</td>
<td>Thomas Reuter Datastream</td>
<td>Equal-Dollar</td>
</tr>
<tr>
<td>Wilderhill New Energy Global Innovation</td>
<td>NEX</td>
<td>Thomas Reuter Datastream</td>
<td>Market-Value</td>
</tr>
<tr>
<td>S&amp;P 500 Global Clean Energy Index</td>
<td>SPCE</td>
<td>Thomas Reuter Datastream</td>
<td>Free-Float</td>
</tr>
</tbody>
</table>

### Economic and financial variables

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<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>S&amp;P 500 Index</td>
<td>SPX</td>
<td>Thomas Reuter Datastream</td>
<td>Market-Value</td>
</tr>
<tr>
<td>STOXX 600 Index</td>
<td>STOXX</td>
<td>Thomas Reuter Datastream</td>
<td>Free-Float</td>
</tr>
<tr>
<td>NYMEX Crude Oil Futures Continuous Contracts Index</td>
<td>OIL</td>
<td>Thomas Reuter Datastream</td>
<td>-</td>
</tr>
<tr>
<td>NYSE Arca Tech 100 index</td>
<td>PSE</td>
<td>Thomas Reuter Datastream</td>
<td>Price-Weighted</td>
</tr>
</tbody>
</table>

### Uncertainty variables

<table>
<thead>
<tr>
<th></th>
<th>Option Price Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Financial Market</td>
<td>VIX</td>
</tr>
<tr>
<td>Oil Market</td>
<td>OVX</td>
</tr>
</tbody>
</table>

Table 4 Note: Table of indices used with reference name, source and weighting method. MGB, DGB and SOLAC represent the green bond market; CB and CBS represent the corporate bond market; ECO, NEX and SPCE represent the renewable energy market; SPX and STOXX represent the stock market; OIL represents the oil market; PSE represent technology; VIX and OVX represent financial and oil price uncertainty respectively.

## Table 5: Philips-Perron (PP) unit-root tests

<table>
<thead>
<tr>
<th></th>
<th>PP(c)</th>
<th>PP(ct)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Green Bonds</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOLAC</td>
<td>-29.201***</td>
<td>-29.215***</td>
</tr>
<tr>
<td>DGB</td>
<td>-31.131***</td>
<td>-31.138***</td>
</tr>
<tr>
<td>MGB</td>
<td>-31.150***</td>
<td>-31.210***</td>
</tr>
<tr>
<td><strong>Renewable energy</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECO</td>
<td>-29.575***</td>
<td>-29.571***</td>
</tr>
<tr>
<td>NEX</td>
<td>-24.197***</td>
<td>-24.185***</td>
</tr>
<tr>
<td>SPCE</td>
<td>-25.168***</td>
<td>-25.354***</td>
</tr>
<tr>
<td><strong>Economic and financial variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OIL</td>
<td>-33.999***</td>
<td>-34.109***</td>
</tr>
<tr>
<td>SPX</td>
<td>-32.892***</td>
<td>-32.874***</td>
</tr>
<tr>
<td>STOXX</td>
<td>-31.103***</td>
<td>-31.086***</td>
</tr>
<tr>
<td>CB</td>
<td>-31.810***</td>
<td>-31.821***</td>
</tr>
<tr>
<td>CBS</td>
<td>-34.148***</td>
<td>-34.142***</td>
</tr>
<tr>
<td>PSE</td>
<td>-32.483***</td>
<td>-32.471***</td>
</tr>
<tr>
<td><strong>Uncertainty variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OVX</td>
<td>-32.281***</td>
<td>-32.289***</td>
</tr>
<tr>
<td>VIX</td>
<td>-34.942***</td>
<td>-34.935***</td>
</tr>
</tbody>
</table>

Table 5 Note: SOLAC, DGB and MGB represent the green bond market; ECO, NEX and SPCE represents the renewable energy market; OIL represents oil prices; SPX and STOXX represents and stock market; CB and CBS represent corporate bonds; PSE represent technology; OVX and VIX represents uncertainty on the financial market and oil market respectively. PP(c) and PP(ct) checks for unit-root with a constant (c) and with a constant and trend (ct). *, ** and *** indicates significance at 10%, 5% and 1%. 

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**Figure 19:** Normalized price of green bonds

![Graph showing normalized price of green bonds](image)

**Fig. 19.** Note: The green bond indices DGB, MGB and SOLAC have been normalized so that they share a unit index to be able to compare their co-movements.

**Fig. 20:** Normalized price of renewable energy stocks

![Graph showing normalized price of renewable energy stocks](image)

**Fig. 20.** Note: The renewable energy stock indices ECO, NEX and SPCE have been normalized so that they share a unit index to be able to compare their co-movements.
Figure 21: Corporate bond return spillover to green bonds

Fig. 21. Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 22: Stock market return spillover to green bonds

Fig. 22. Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 23: Oil return spillover to green bonds

Fig. 23. Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 24: Green bond return spillover to corporate bonds

Fig. 24. Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 25: Green bond return spillover to the stock market

**Fig. 25.** *Note:* Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 26: Green bond return spillover to oil

**Fig. 26.** Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5 % significance level).
**Figure 27.** Corporate bond return spillover to renewable energy

**Fig. 27.** Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5 % significance level).
Figure 28: Stock market return spillover to renewable energy

Fig. 28. Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 29: Oil return spillover to renewable energy

Fig. 29. Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 30: Renewable energy return spillover to corporate bonds

Fig. 30. Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 31: Renewable energy return spillover to the stock market

Fig. 31. Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).
Figure 32: Renewable energy return spillover to oil

**Fig. 32.** Note: Denotes the quantile cross-correlations in heatmap form. No predictable directionality is set to zero, the colored squares are regions where the Box-Ljung test statistics is statistically significant (5% significance level).