Norwegian School of Economics

ESSAYS ON ENERGY MARKETS AND THE ENVIRONMENT

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Kyriaki Tselika

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Introduction

«Η φύσις μηδέν μήτε ατελές ποιεί μήτε μάτην»
"Nature does nothing in vain or without purpose"
Aristotle, 384-322 BC

The world's increasing need for energy has created many environmental challenges such as greenhouse gas emissions and climate change. In this context, the energy sector, which has a significant impact on the environment, can play a crucial role in the transition to a greener future. The energy markets are among the most complex and dynamic sectors worldwide. With multiple stakeholders involved, such as producers, consumers, policy makers and governments, the energy sector both influences and can be influenced by economic, political and social developments. Therefore, it is important to understand the interaction between the energy sector and the environment in order to optimize the production and consumption of energy and introduce efficient policies that promote environmental sustainability. The overall aim of this thesis is to explore these interactions and provide strategic recommendations for market participants such as investors and government.

The electricity sector is an important part of the global energy system and can cause negative environmental impacts. Although electricity consumption is not directly harmful to the environment, it has indirect negative impacts through generation and transmission which is responsible for a high share of greenhouse gas emissions (EIA, 2022). In recent years, electricity markets have undergone many changes to support the transition towards low-carbon societies. The deployment of renewable energy and flexible technologies have presented various challenges, but also opportunities for electricity markets, as they have to balance supply and demand while reducing emissions. Renewable energy sources, such as wind and solar power, have experienced substantial growth over the past few decades, and have become a key determinant in many electricity markets worldwide. Renewable energy production utilizes natural resources, such as wind or sunlight, to generate electricity with zero emissions, making them an attractive option for governments looking to reduce the environmental impact of electricity markets.

Despite being emission free, renewable energy poses several challenges in electricity markets. As it relies on natural resources, renewable energy production is intermittent, and can only produce electricity when these natural resources are available. For instance, electricity demand can be covered by solar power only when there is adequate sunlight. The integration of these variable sources into electricity markets can raise significant concerns regarding grid operation, security of supply and electricity prices. Research has indicated that increasing renewable energy in electricity markets can result in lower prices (Cludius et al., 2014; Csereklyei et al., 2019; Maciejowska, 2020) and also increased volatility (Kyritsis et al., 2017; Rintamäki et al., 2017), entailing higher uncertainty in electricity markets.

The electricity supply curve arises from the upward categorization of electricity generation technologies depending on their short-run marginal costs. Production plants with low marginal costs, such as nuclear power, are placed in the left part of the supply curve. On the contrary, high marginal cost plants, such as gas plants, are placed towards the right side of the supply curve, indicating that they will be active -dispatched - only when demand is high enough to justify higher prices. Renewable energy enters electricity markets as an almost zero marginal cost technology, hence, it is placed at the left of the electricity supply curve. Therefore, renewable energy shifts the electricity supply curve to the right replacing high marginal cost technologies. This shift results in a lower price equilibrium and is called the merit-order effect. This indicates that renewable energy generates a reshaped marginal cost structure in electricity markets (Ziel et al., 2015).

The dynamic nature of electricity markets, combined with the challenges stemming from the unique features of electricity and the intermittent nature of renewable energy sources, necessitates the use of a variety of econometric methods to analyze the available data and gain deeper insights into the relationships in electricity markets.

Paper 1 investigates the effect of renewable energy on the hourly distribution of electricity prices. Our paper introduces a novel approach to analyze the effect of renewable energy sources on electricity prices. This involves combining a panel framework, which can exploit the available hourly observations for electricity markets, with a quantile regression model that accounts for extreme observations. We argue that since the electricity price formation and renewable energy generation can show great variations during a day, using hourly observations could offer higher estimated accuracy. The results suggest that indeed hourly-related characteristics could impact the magnitude of the reduction in electricity prices caused by renewable energy, and using a panel framework rather than time-series methods could be a more efficient approach.

In order to encourage the expansion of renewable energy in electricity markets, governments have applied various support schemes. These support schemes can include feed-in tariffs, tendering, green certificates, subsidies, etc, and seek to stimulate zero-carbon supply by reducing the costs of renewable investors and generators and allow them to be competitive against conventional producers. Additionally, many countries have mandated a percentage of electricity to be produced by renewable energy with a goal of generating 100% electricity by low-carbon technologies in the future. After a decade of applying support policies for renewables, some countries consider to reduce their financial support or even cease them (IEA, 2021). Therefore, we are curious whether increasing renewable energy in electricity markets could affect their unit revenues and market value, and whether governments should consider providing financial incentives to renewable energy stakeholders.

Paper 2 explores the economic sustainability of renewable energy in the German wholesale electricity market, focusing on the cannibalization and cross-cannibalization effects of wind and solar power. These effects describe how an increase in wind or solar can decrease the revenue and market value of renewables. To explore the effects of cannibalization and cross-cannibalization in electricity markets, we analyze the entire distribution of wind and solar unit revenue and market value using a quantile regression approach. This enables us to identify potential variations in the strength of these effects across different parts of the revenue and value distribution, and assess their impact on market uncertainty. We conclude that increasing wind and solar power could result in lower revenues and value for renewable sources, thereby reducing profits and increasing the risk for generators and investors in electricity markets. This effect is most pronounced when wind and solar generate low revenues and have low value in the market. We recommend that governments and other stakeholders consider such effects of cannibalization and cross-cannibalization in policy formulation and investment strategies to achieve the sustainability goals in the electricity sector.

Besides the support provided by governments for green projects, financial markets can also provide climate-aligned capital. Green finance becomes increasingly significant in enhancing the affordability of low-carbon projects. There are various financial assets for companies and individuals to support efforts mitigating climate change such as green bonds and clean energy stocks. Green bonds can provide a way to organizations and companies to allocate capital to climate aligned projects and business activities (ICMA, 2016). Green bonds can finance projects that focus on reducing emissions, expanding renewable energy capacity and increasing energy efficiency. For instance, green bonds can fund projects such as wind and solar plants, energy efficient buildings and electrification of transportation systems. Another way for individuals and organizations to support the transition towards low-carbon economies is investing in clean energy stocks.

Although every investment entails risk, diversifying investments across various assets, known as portfolio diversification, can mitigate risk and increase potential returns for investors. This principle applies to green assets as well. Thus, investors who aim to align their investments with supporting a sustainable future while also maximizing returns, should consider investing in a diversified portfolio consisting of various green assets such as clean energy stocks, green bonds and other environmentally friendly investments. Consequently, it is crucial to explore the relationships between green assets to identify opportunities for diversification that can enhance climate-aligned capital and benefit investors.

Paper 3 investigates the connectedness between green bonds, clean energy stocks and carbon prices in both the time and frequency domain. We apply a novel framework by Baruník and Křehlík (2018) and analyze the total and directional spillovers in a comprehensive green financial system. This approach allows us to estimate the short-term and long-term return spillovers and provide recommendations for various types of investors. Our findings indicate that there are diversification opportunities both in the short-term and long-term in a fully green financial system.

This thesis is comprised by the aforementioned three empirical papers that explore the interplay between energy markets and environmental sustainability. Through empirical analysis, its aim is to provide strategic guidance to investors, market participants, and governments. By employing empirical methods, the papers draw on real-world data to derive valuable insights that can support decision-making. The following paragraphs provide a full abstract for each of the empirical papers.

Paper 1. The impact of variable renewables on the distribution of hourly electricity prices and their variability: A panel approach.

This paper investigates the impact of intermittent renewable generation on the distribution of electricity prices and their variability in Denmark and Germany. We exploit hourly data from 2015 to 2020 and employ a novel panel quantile approach - the Quantiles via moments (MMQR) method. Previous research has mainly used aggregated-daily data and have applied a time-series setting. We argue that since the electricity price formation and renewable energy generation can show great variations during a day, a panel setting with 24 individual hours could offer higher accuracy. The combination of hourly specific effects and the quantile approach enable us to estimate the renewable sources effect on various price quantiles while controlling for market dynamics. In this way, we investigate extreme market cases accounting for the range and distribution of the electricity prices data. The results suggest that the merit-order effect occurs in both countries, with wind and solar generation having diverse effects on the electricity price distribution. Thus, policy makers should consider this diversifying effect to develop efficient renewable support schemes. We also explore non-linearities by including different demand levels in our model and investigate price variability. The outcomes indicate that wind generation increases (decreases) the occurrence of price fluctuations for low demand (high demand) in both countries. Meanwhile, in Germany, solar power stabilizes price fluctuations for high demand levels, stronger than wind. Market risk information could be useful for organizations in recognizing beneficial investment opportunities or hedging strategies. We finally aggregate the hourly observations into daily and compare the estimation outcomes. The results prompt us to believe that aggregated time-series tend to underestimate the RES impact on prices.

Paper 2. The cannibalization effect of intermittent renewables: The case of wind and solar power in Germany.

with Maria Tselika and Gunnar S. Eskeland

Over the past few decades, European states have applied various measures to expand the role of renewable energy in electricity generation. With the existing energy crisis, renewable energy sources are crucial to sustain a reliable energy system while reaching the EU sustainability goals. In this article, we explore the cannibalization and cross-cannibalization effect of renewable energy sources. The cannibalization (cross-cannibalization) effect describes how an increase in wind or solar power reduces its own (or each other's) unit revenues or market value in the electricity market. First, we construct two daily indices that present measures of the unit revenues and market value of wind and solar power. Subsequently, we employ a quantile regression model to analyze the cannibalization and cross-cannibalization effects at different levels of unit revenues and market values, while considering extreme market conditions. The results suggest that both wind and solar exhibit cannibalization and cross-cannibalization in certain parts of their distribution, predominantly in lower quantiles where the market values of wind and solar are low. We also find that cannibalization is more pronounced for higher levels of wind and solar penetration, and consumption. Additionally, we observe that solar power can raise the market value of wind in some cases, particularly for upper wind value quantiles, highlighting a complementary relationship between the two sources. To ensure the economic sustainability of renewable energy in electricity markets, governments should consider the cannibalization and cross-cannibalization impacts in policy-making regarding renewable energy. Market participants can also make better-informed investment plans and decisions by identifying cannibalization and assessing its impact on profitability and risk.

Paper 3. Connectedness between green bonds, clean energy markets and carbon quota prices: Time and frequency dynamics.

with Ingrid Emilie Flessum Ringstad

We investigate the time and frequency dynamics of connectedness among green assets such as green bonds, clean energy markets, and carbon prices. Using daily price data, we explore return spillovers across these green financial markets by applying the novel framework on time and frequency dynamics proposed by **?**. This allows us to identify the direction of spillovers among our variables, and decompose the connectedness to differentiate between short-term and long-term return spillovers. Our results indicate that green bonds and carbon prices act as net receivers of shocks, but mainly in the short-term. Also, we observe a low level of connectedness among our clean energy markets across both low and high frequency bands, even during times of economic or political crisis. Additionally, there are periods in which connectedness between the clean energy assets is driven by the long-term. In periods of economic and political stability, carbon prices may also provide an interesting diversifying tool for short-term investors. Our results should be of interest for investors and portfolio managers who focus on green financial markets, by strengthening the notion that green financial markets can offer diversification opportunities, for both short-term and long-term investors. This paper is the first to use this framework to investigate systematic risks within green financial markets.

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The impact of variable renewables on the distribution of hourly electricity prices and their variability: A panel approach

Kyriaki Tselika*

Abstract

This paper investigates the impact of intermittent renewable generation on the distribution of electricity prices and their variability in Denmark and Germany. We exploit hourly data from 2015 to 2020 and employ a novel panel quantile approach - the Quantiles via moments (MMQR) method. We argue that since the electricity price formation and renewable energy generation can show great variations during a day, a panel setting with 24 individual hours could offer higher accuracy. Therefore, we apply a panel approach that accounts for both the time and cross-sectional dimension of electricity prices. The panel allows us to control for time-invariant (hourly-specific) characteristics and can reveal hidden market dynamics that exist during a day. The combination of hourly specific effects and the quantile approach enable us to estimate the renewable sources effect on various price quantiles while controlling for market dynamics. In this way, we investigate extreme market cases accounting for the range and distribution of the electricity prices data. The results suggest that the merit-order effect occurs in both countries, with wind and solar generation having diverse effects on the electricity price distribution. Thus, policy makers should consider this diversifying effect to develop efficient renewable support schemes. We also explore non-linearities by including different demand levels in our model and investigate price variability. The outcomes indicate that wind generation increases (decreases) the occurrence of price fluctuations for low demand (high demand) in both countries. Meanwhile, in Germany, solar power stabilizes price fluctuations for high demand levels, stronger than wind. Market risk information could be useful for organizations in recognizing beneficial investment opportunities or hedging strategies. We finally aggregate the hourly observations into daily and compare the estimation outcomes. The results prompt us to believe that aggregated time-series tend to underestimate the RES impact on prices. In conclusion, hourly-related features seem to affect the merit-order effect and its robustness, and a panel approach should be considered when investigating electricity markets.

JEL Classification: C22, C51, C52, Q21, Q41

Keywords: Electricity prices, Panel quantile regression, Renewable sources, Merit-order effect, Price variability

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1 Introduction

Over the last decades, European (EU) initiatives encourage sustainable practices aiming at a climate-neutral continent by 2050. Electricity markets have been accentuated by these efforts and initiatives. Structural and operational changes, such as market integration, intend to reform electricity markets and improve their resilience. Electricity is sold in power exchange markets such as the European Energy Exchange (EEX). These markets include various economic characteristics that originate from the microstructure of power systems.

Technological improvement has triggered new objectives and regulations in the EU energy sector, which has encouraged the continuous growth of renewable energy sources (RES). Wind and solar energy– two rapidly developed renewable energy sources - play a key part in the energy sector transformation towards the new green era. The current EU climate action plan focuses on market decarbonization promoting a 55% greenhouse gas emissions reduction by 2030 (European Commission, 2019). In addition, the new Green Deal introduced goals regarding RES penetration to reduce emissions further, and initiate alternative flexible electricity usage. The new EU target for RES is set to 32% by 2030.

In this article, we use a novel methodology to model power systems and show how the impact of renewable sources on electricity prices vary across their distribution depending on market dynamics. We focus on Denmark and Germany, which are appealing cases due to their high renewable penetration and distinct power features. Furthermore, investigating these two countries can allow us to compare our results with previous literature. The main advantage of using a quantile regression model is its ability to examine the relationship between electricity prices and RES across the entire price distribution. Therefore, the quantile approach allows us to understand the RES role on power market inefficiencies, such as extreme prices, and recognize market systems and regulatory frameworks that can reduce uncertainty and promote long-term flexibility. Bunn et al. (2016) highlight the advantages of using quantile regression to explore power prices, characterizing it as a semi-parametric method that allows the inclusion of fundamental variables. They also state that it could be used as an alternative methodology to regime-switching models. Furthermore, quantile regression does not assume a parametric distributional form for the error term (Davino et al., 2013) and allows the investigation of nonlinear relationships among variables. Overall, quantile regression could provide greater predictive accuracy and insights. It can, thus, be an important tool for market participants and stakeholders such as producers, regulators, etc., who should be able to model and gain information on the extremes of electricity prices in order to recognize market risks and adjust their actions.

The investigation of the effect of RES on electricity prices, through a quantile approach, is not a new research subject, but it has been quite spare. Nonetheless, our empirical findings contribute to the literature in various aspects. The main contribution is the use of the hourly data in a panel setting that accounts for time-invariant (or fixed) hourly effects. The high frequency of the data offers a wider information range that allows us to control for various market characteristics. Few studies employ hourly data with most not acknowledging and accounting for the hourly-specific effect. Second, the methodology allows us to investigate the price variability, approximated by the scale estimate. The method assumes that the scale function is linear which facilitates comparison with other methods. The scale parameter is a measure of dispersion (also called variability) and shows how spread is a distribution (Pham, 2006). Thus, the scale estimate provides information about the distributional heterogeneity of prices (Haylock, 2022) and is closely related to price variance. The MMQR approach estimates the parameter in the scale function, through which we approximate the effect on price variability. To the best of our knowledge, the electricity price variability effect has been studied only using aggregated-daily data. For instance, Maciejowska (2020) uses the Interquartile range - another measure of dispersion - based on the quantile estimates to investigate the variability effect of RES on electricity prices in Germany. Lastly, most studies apply linear quantile regression models while we incorporate non-linear effects in our approach. We would expect that the impact of renewable generation on electricity prices varies depending on the demand level. For instance, when the market struggles to accommodate the fluctuating supply by renewable generation due to lack of flexibility (storage capacity, etc.), we would anticipate the effect from RES intermittent generation to vary when demand is low (high) and renewable sources supply is high (low). Thus, we think it is important to incorporate the non linear effects by including different demand levels in our regressions.

It would be logical to wonder about our methodological approach and the reasons for choosing it over more established time-series methods. Electricity markets are characterized by distinct features that cause various methodological challenges for researchers. The need for a day-ahead market stems from electricity's poor storage capabilities, as well as supply and demand variability. To formulate an efficient econometric model, key electricity price dynamics should be considered. In the day-ahead market, the electricity prices are set the day prior to the delivery day. The market participants need to submit their bids before a specific time with delivery time the following day. Thus, the prices are set simultaneously for the 24 h of the following day. For instance, the bids to cover supply for hour 8 are submitted the same time as the bids to cover supply for hour 19. Therefore, the 24 determined prices correspond to the same set of information since they are determined at the exact same time. Therefore, treating day-ahead prices as a time-series could be misleading. Huisman et al. (2007) argued that day-ahead prices should be treated as a panel framework rather than a time-series. They showed that electricity prices mean-revert around a specific price level which differs over hours – especially between peak and off peak hours. Their results unveil that day-ahead electricity prices show cross-sectional correlation among hours, and one should consider day ahead electricity prices, in a panel framework, as the behavior of individuals (24 h) observed across time (time-series).

Previous research on the power sector has mainly used time-series models to investigate daily data or hours in isolation by choosing a representative hour based on group of hours that share similar characteristics (Hagfors et al., 2016b; Do et al., 2019; Keles et al., 2020). Some studies have focused on the daily average price of peak and off-peak hours examining the dynamics of the average price of a group of hours (Kyritsis et al., 2017; Maciejowska, 2020). All these studies ignore the cross-sectional information included in the electricity market microstructure and provide information about average or one-hour prices. Therefore, we deem important to consider these market microstructure characteristics and include the cross-sectional hourly effect in our research. But what advantages does the panel approach hold for the market? Our method suggests that group hours are heterogeneous. For instance, group hour 4 is very different than group hour 10. Time-series do not control for this heterogeneity and could obtain biased results. Hence, in a technical aspect, the panel framework allows us to control for time-invariant (group hours) characteristics. Panel data also give a large number of data points, increasing the degrees of freedom and improving the efficiency of the econometric estimates. They are also suited to study dynamic relationships based on inter-individual differences reducing the collinearity between current and former variables providing unrestricted time-adjustment estimates (Hsiao, 2007). Therefore, panels provide several methodological benefits in comparison to time-series or cross-sectional methods, providing greater predictive power and insights. The main methodological challenge for panel data with fixed effects is the incidental parameter problem. According to Nickell (1981) dynamic panel models with fixed effects are biased by $1/T$. In our case, the bias due to the dynamic formulation is expected to be small and we highly doubt it will affect the estimates since our time dimension - both in Denmark and Germany - can be considered large.

In our case, the group hours can hide a multitude of changes such as abrupt weather changes and policy implementations that panel can help us detect. Additionally, electricity price formation and risk vary highly during the day and renewable generation can be highly diverse among hours. Thus, many market agents are exposed to dynamics that depend on hourly variation. For instance, different production plants need more accurate tools to predict electricity price levels and fluctuations, as well as the effects on the market as a whole, in order to develop efficient bidding strategies. Another important example would be flexible storage facilities which need high predictive accuracy (hence less risk) to charge (discharge) when prices are low (high). If market agents realize higher gains, the market could benefit in the long-run by increased investments in new technologies (flexible systems, demand response technologies, etc.). Therefore, in this paper we revisit electricity markets to apply a highly realistic framework that accounts for important market features and can support market participants recognize profitable opportunities and adjust to market risks.

Explaining a little bit more on the methodological approach: the panel framework involves two dimensions; the individual and time element, which are the hours and days, respectively. We investigate various electricity price quantiles and how RES can impact them and model the electricity price distribution in two settings, accounting for different demand levels. The electricity price distribution is defined by quantiles, specifically $\tau = 0.1, .., 0.9$. Each electricity price quantile is estimated using a vector of exogenous variables, and various indicators to control for short-term dynamics and seasonal effects. The methodology allows us to investigate the RES impact on electricity price levels, but also the entire distribution, and account for hourly factors common across all hours and diverse between a specific hour. Finally, the price variability is evaluated through the scale estimate, which can provide crucial insights on market risk.

2 Literature review

The adoption of RES and their inclusion in the electricity grid poses many new challenges. The intermittent nature of RES, which depend highly on geographical attributes and weather conditions, incite technical issues in the electricity grid. Variable RES generation does not follow electricity demand patterns, which can create imbalances in electricity markets. Moreover, new regulatory frameworks are bound to create new challenges for power systems. For instance, the EU directives promote the phasing out from coal and nuclear power in the following years, and countries are required to modify their energy policies and comply to the new regulations. The excess changes that power systems have undergone, and the new energy transition schemes, have profound consequences for electricity markets and their microstructure. Market inefficiencies have arisen in the form of extreme price fluctuations and spikes (see Hagfors et al., 2016) making it essential to explore electricity price dynamics.

A potential solution to market inefficiencies could be increased system flexibility, such as flexible consumption technologies. Real-option investments are needed to establish these flexible systems. Real options refer to tangible investment opportunities that are available to companies. Such investments in the power sector involve demand response systems, power storage systems and alternative fuel generation technologies. For instance, a demand-response system provides the opportunity to charge when RES supply is high and power demand low. On the other hand, the system can discharge when RES supply is low and power demand is high. In this way, power consumption is scaled up and down, depending on RES supply, making the power system more flexible and improving electricity supply security. However, real-option investments depend on long-term returns and investment risks, which are closely connected to power prices and their fluctuations (Black and Scholes, 1973; Cox et al., 1979). In particular, power storage companies could benefit from high electricity price variability by charging when prices are low and discharging when prices are high. It becomes obvious that RES penetration, electricity prices and real-option investments are strongly interconnected. Hence, it is important for market stability to explore how the structure and penetration of RES affect prices and, by extension, the value of real-option assets.

The effect of RES has attracted a lot of attention in the electricity market literature. The effect has been explored in numerous countries with different institutional settings (Gelabert et al., 2011; Clò and D'Adamo, 2015; Gullì and Balbo, 2015; de Lagarde and Lantz, 2018; Csereklyei et al., 2019; Prol et al., 2020; Marshman et al., 2020). Cludius et al. (2014), Paraschiv et al. (2014) and Würzburg et al. (2013) show that wind and solar power in Germany seem to relate negatively to electricity price levels, with their effect being independent on the market since solar is available during daylight while wind is generally higher during the night. Jónsson et al. (2010), focusing on the Scandinavian market of Denmark, employ a non-parametric approach to investigate the effect of wind energy forecasts on day-ahead prices. The results imply that higher wind penetration decreases electricity prices. On the other hand, Mauritzen (2013) applies a simple distributed lag model to explore the wind generation impact on trade, electricity prices and hydropower production in Denmark. He finds that Denmark stores excess wind power in hydro reservoirs in neighboring Norway and an extra unit of wind would result in a 5% reduction of prices in Denmark. Thus, it has been shown, that variable renewable sources reduce electricity price levels, which is called in the literature as the merit-order effect. The electricity supply curve shifts due to increased low-cost RES penetration in the market, which leads to decreased prices.

Renewable energy and its intermittent nature have changed another key feature of electricity prices, their variation. The early empirical studies concentrated on renewable sources and their effect on electricity prices but later extended to electricity price volatility. The important relation between renewable sources, the source type, and electricity price variability is empirically supported by a large body of the literature (Ketterer, 2014; Kyritsis et al., 2017; Rintamäki et al., 2017). Kyritsis et al. (2017) apply a GARCH-in-Mean model to explore the impact of wind and solar power on electricity price volatility in Germany. They show that an increase in wind generation will result in higher price volatility. In contrast, an increase in solar power is shown to reduce price volatility. The RES effect on electricity price volatility for two distinct cases – Denmark and Germany - was investigated by Rintamäki et al. (2017). The results illustrate how market dynamics play a central role in RES penetration and their impact on price volatility. They show that renewable energy reduces price volatility in Denmark due to its connection with other Scandinavian countries, that have hydro storage capacity. On the other hand, wind power production is shown to increase electricity price volatility in Germany due to its off-peak hours effect. Finally, solar power appears to decrease price volatility since it mainly contributes during peak hours.

The literature over the last years has used a wide range of dataset and established multiple settings to explore electricity prices. However, research has mainly focused on investigating daily electricity prices, ignoring the hourly-specific effect and the influence it has on power markets. Several papers have split daily electricity price data on peak-off peak[1] hours to stress out the diverse RES impact, within the day, on electricity prices and their movements (Paraschiv et al., 2014; Kyritsis et al., 2017; Rintamäki et al., 2017). Although the high dependence of RES on the hour within the day and its attributes have been highlighted, it has not been fully explored. Electricity produced by renewable sources is highly variable within a day due to the intermittent nature of renewables. In addition, different RES categories showcase different production patterns. For example, wind power is generally abundant during night hours while solar power is only available during sunlight hours. These market characteristics urge us to account for the hourly-specific effect and its embedded information on electricity prices.

Although the merit-order effect has been illustrated by multiple studies and settings, literature on the repercussions of RES on the shape of electricity price distributions has been spare (Hagfors et al., 2016a; Bunn et al., 2016; Sapio, 2019; Maciejowska, 2020; Sirin and Yilmaz, 2020; Apergis et al., 2019). Electricity prices are characterized by large fluctuations, spikes, and excess kurtosis, which have motivated studies regarding the tails of the electricity price distribution. Bunn et al. (2016) use quantile regression to evaluate the dependence of electricity price risks on fundamental market variables. More recently, Maciejowska (2020) employs a semi-parametric approach to

[1]Peak hours refer to the time period from 8 am to 8 pm while the rest refer to off-peak hours.

investigate the shape of the electricity price distribution. They examine the RES impact on the electricity price distribution and conclude that while wind has a stronger effect on lower quantiles, solar power's influence is intensified for upper price quantiles. Furthermore, they analyze the electricity price variability, through which they demonstrate the diverse RES impact dynamics. Lastly, Apergis et al. (2020) explore the tail dependence of electricity prices through copulas in the Australian market. They divide the chosen time frame into pre-during-post carbon tax periods and conclude that tail dependence highly differs between the investigated periods.

3 Data

The data employed concern the period from January 1, 2015 to November 30, 2020 for Denmark and January 6, 2015 to November 30, 2020 for Germany, providing a very rich dataset with 2154 and 2149 days, respectively. Thus, the entire dataset includes 51,696 h for Denmark and 51,576 h for Germany. Hourly data for electricity day ahead prices (€/MWh), forecasted loads, and forecasted wind power (GWh) in Denmark were obtained by Nordpool AS, the power market operator for the Nordic region. The hourly day-ahead prices, forecasted loads[2], wind and solar power forecasts in Germany were retrieved from EEX and the European Network of Transmission System Operators for Electricity[3] that collects and shares information from Transmission System Operators (TSO) around Europe. For an explanation of the electricity market in Europe, refer to Appendix A.

Table 1. Descriptive statistics.

Variable	Mean	Min	Max	St.dev.	Skewness	Kurtosis
Denmark						
Price	31.175	-58.8	200.04	15.04	0.345	4.99
Wind	1.316	0	4.503	0.963	0.673	2.468
Load	2.28	1.202	3.545	0.452	0.142	2.044
Germany						
Price	34.513	-130.09	200.04	16.465	-0.272	8.897
Wind	11.567	0.314	47.231	9.027	1.163	3.835
Solar	4.547	0	32.479	6.896	1.541	4.391
Load	54.855	28.824	75.912	9.499	-0.056	1.944

Table 1 presents the descriptive statistics for electricity prices, forecasted renewables and loads.

[2]There were 48 hourly observations of forecasted loads in Germany missing, for which we used realized values.
[3]https://transparency.entsoe.eu/

In both countries, the per hour distribution of prices is leptokurtic, indicating the asymmetric effect of extreme prices for their distribution. In the German market, the kurtosis level is much higher than in the Danish case. We use the Pesaran (2015) CD statistic to test for cross-sectional dependence and second-generation unit root tests to examine the stationarity of the panel. Since our panel is balanced and long, in terms of time, we apply Breitung and Das (2005) panel unit root test which indicates that the series are stationary, and we can proceed with the analysis without further modifications to the data. The cross-sectional dependence and unit-root results are available in Appendix B.

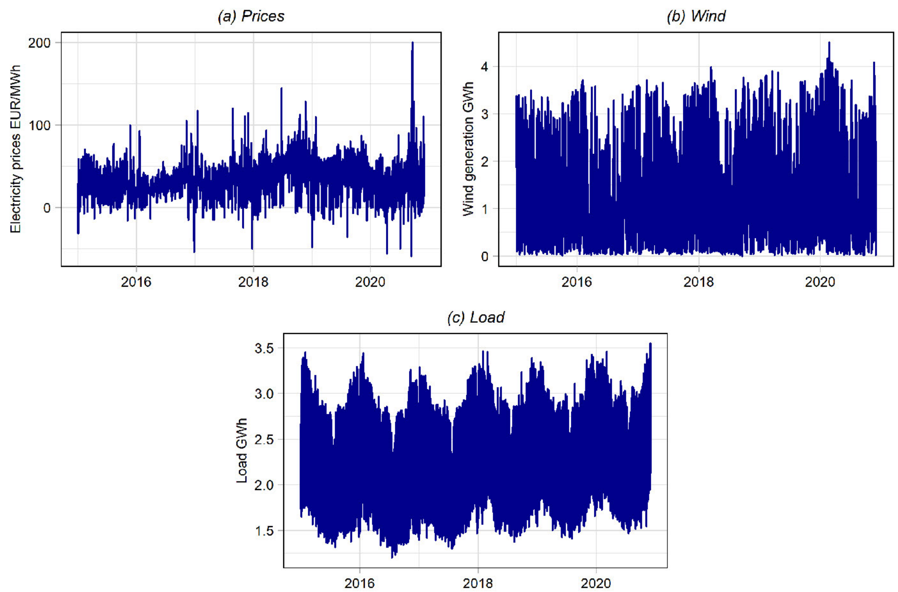

Figure 1. Fundamental variables in Denmark.

Another important illustration is the time-series evolution of electricity prices, RES and loads during the examined period. Figs. 1 and 2 demonstrate the underlying variables in Denmark and Germany. The fact that electricity prices show great fluctuations that contain extreme positive and negative values is apparent and in line with the kurtosis of the distribution. It is also evident in the figures that wind and solar generation vary widely throughout the year. This is mainly attributed to their dependence on weather conditions and hourly sunlight. Forecasted wind, solar and load follow a strong yearly seasonal pattern. While load and wind generation have higher values in winter and lower values in the summer, solar generation peaks during summer periods.

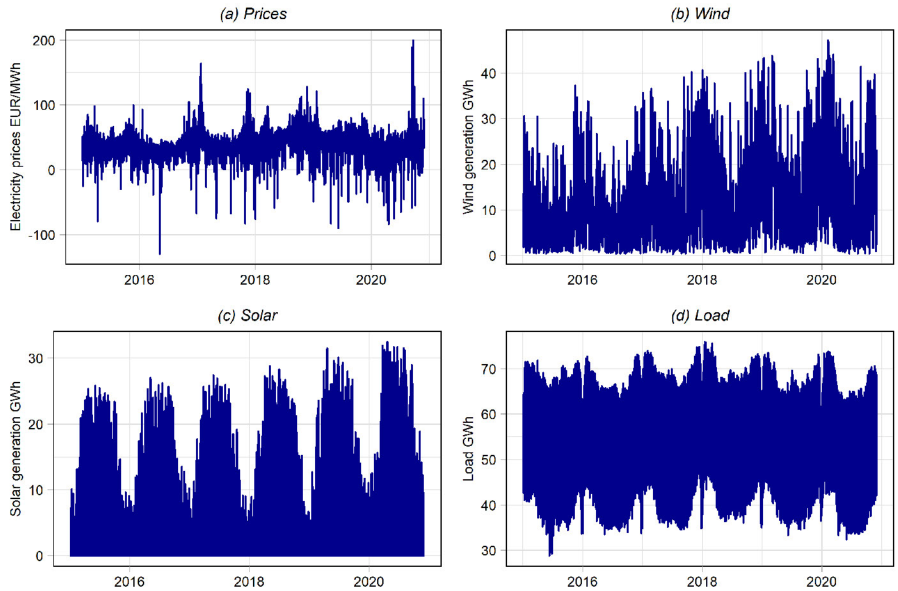

Figure 2. Fundamental variables in Germany.

Lastly, in Fig.3, we demonstrate individual boxplots for three electricity price levels (low, intermediate, and high) categorized by the hours of the day. The figures indicate that the electricity price distributions vary greatly, in both countries, during a day. We also notice that Denmark shows a lower price variability than Germany. Denmark has established strong interconnections with other Scandinavian countries, which allows access to flexible storage systems, contributing to lower price fluctuations. Electricity prices exhibit extreme values, in both countries, for almost all hours, but in Germany we observe a higher frequency of negative electricity spikes. This shows how diverse electricity markets are, even within Europe, and how important market integration can be to establish efficient electricity markets. Finally, Fig. 3 implies that the distribution of prices is linked to the hour itself. For instance, during the morning and afternoon hours, when industrial activities take place, higher electricity prices are observed. Therefore, it is obvious that the distributional effects of RES on electricity prices are linked to hourly-specific effects which our research accounts for.

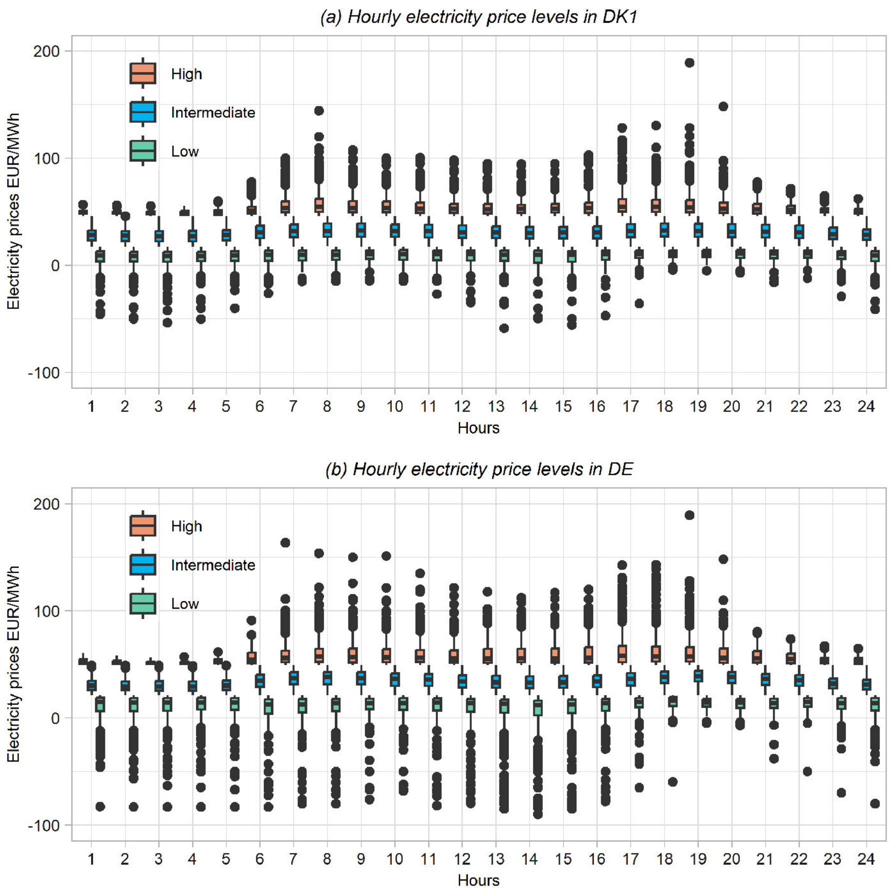

Figure 3. Boxplots of three electricity price levels (low, intermediate, and high) for each hour of the day in a) Denmark, and b) Germany. The price levels have been obtained by the unconditional quantile distribution of the prices with thresholds $\tau_L = 0.15$ and $\tau_H = 0.85$.

4 Methodology

Quantile regression was introduced by Koenker and Bassett Jr (1978) and has been applied in various economic applications. It is used to estimate the predictive value of independent variables on the quantiles of the dependent variable and is especially robust to outliers. In this empirical investigation, a novel approach by Machado and Silva (2019), called Method of Moments Quantile Regression (MMQR), is employed. The MMQR method is particularly relevant when individual effects or endogenous variables are recognized in a panel. Machado and Silva (2019) have established an estimator that combines the location-scale functions and estimates the conditional quantile functions. Additionally, the MMQR does not allow the quantile estimates to cross which is an important condition in empirical research (He, 1997; Chernozhukov et al., 2010). Finally, the MMQR estimator allows the hourly-specific effects to impact the entire electricity price distribution. As an initial point of analysis, a linear specification for exploring the RES effect on the electricity price distribution is explored. Then, we further include non-linearities in the model to assess the stability of the variables across different demand levels. Taking into consideration the link between electricity prices and demand, we examine the RES effect on the shape of the electricity price distribution conditional on three demand levels.

As previously discussed, the panel framework in electricity market research was initially proposed by Huisman et al. (2007). They highlighted the need to consider the market microstructure characteristics in electricity research and include the cross-sectional hourly effect. More recently, the individual-specific effects were incorporated in their research by Keppler et al. (2016). They investigate the RES and market coupling impact on electricity price spreads between Germany and France. They showed that the hourly-specific effect can be deemed extremely important when exploring interconnections between markets since transmission capacities can be rather diverse across the hours of a day, and congestion can prevent market integration.

In addition, by using daily data, we can overlook valuable information regarding important time variation. Therefore, a panel framework would be an appropriate setting for investigating the various links between electricity prices and fundamental variables. In the panel setting we establish a common dynamic across all hours and a varying factor for each hour. A panel framework for electricity prices has been established by previous research (Huisman et al., 2007; Karakatsani and Bunn, 2008; Peña, 2012; Keppler et al., 2016; Pham, 2019) but to the best of our knowledge has not been applied in a quantile scope.

The conditional quantile estimation of the location-scale is described as follows:

$$Q(\tau)_p = (\alpha_i + \delta_i q(\tau)) + \beta^L L_{it} + \beta^W W_{it} + \beta^S S_{it} + \theta_1 P_{i,t-1} + \theta_2 P_{i,t-7} + \phi C_{it} + Z'_{it}\gamma q(\tau), \quad \tau \in (0,1) \tag{1}$$

With $\Pr\{\delta_i + Z'_{it}\gamma > 0\} = 1$. Z is a k-vector of known differentiable (with probability 1) transformations of the components of X with element l given by $Z_l = \Xi_l(X), l = 1, \ldots, k$. We denote i the hour group and t the day, with $i = 1, \ldots, 24$ and T with $t = 1, \ldots, T$.

Eq.1 connects the th electricity price quantile with the vector of independent variables. The scalar coefficient $a_i(\tau) \equiv \alpha_i + \delta_i q(\tau)$ is called the quantile-τ fixed effect for individual i. We denote L_it the forecasted load, S_it he forecasted solar power generation, W_it the forecasted wind generation[4] and C_it a set of binary indicators to consider the effect of weekends, holidays, and seasonal parameters. We also use lagged prices to control for short-term price dynamics. According to Nickell (1981) dynamic models with fixed effects are biased by 1/T. Hence, the

[4]We assume that wind and solar generation are exogenous in our model since they are dispatched with regulatory priority and their production depends on weather conditions. For more information see Mauritzen (2013).

bias due to the dynamic formulation is expected to be small and we highly doubt it will affect the estimates since our time dimension - both in Denmark and Germany - can be considered large. Lastly, in the case of Denmark, solar power is minimal, hence only wind generation is accounted for, regarding this empirical analysis.

The scale parameter is a measure of dispersion (also called variability) and shows how spread is a distribution (Pham, 2006). For instance, for the normal distribution, the scale parameter corresponds to the standard deviation. According to Koenker and Zhao (1996), the scale is closely related to price variance, but provides a more natural dispersion concept. In our case, the scale effect measures how much the distribution will contract closer or expand away from the conditional mean. Thus, it can provide information about the distributional heterogeneity of prices (Haylock, 2022). The MMQR approach estimates an auxiliary regression to obtain the scale coefficients, through which we approximate the effect on price variability. Machado and Silva (2019) interpret a positive (negative) scale estimate of an independent variable, as the increase (decrease) in the dispersion of the observed dependent variable. Thus, this specification and estimation of the scale function can provide information on how the regressors affect elements of the conditional distribution that we are interested in, not focusing only its central tendency. Maciejowska (2020) used the Interquartile range – another measure of dispersion – to evaluate the effect of RES on the variability of electricity prices. There are some studies in other fields that interpret the scale estimate from the MMQR approach in a similar manner as us (Ike et al., 2020; Polemis, 2020; Haylock, 2022). Henceforth, the term price variability used in the rest of the paper refers to the scale coefficients drawn by the model.

Electricity consumption and renewable sources are often shown to have a reverse effect on price levels; load often increases prices while renewable sources reduce them. Ketterer (2014) showed that wind and solar share; the forecasted wind/solar generation divided by the forecasted load, has a negative impact on electricity prices. In addition, Maciejowska (2020) demonstrated the diverse effect of RES on electricity prices depending on demand levels. High interaction between load and renewable generation would be expected with the possibility of the demand effect overriding the RES price reduction. Thus, we could expect a higher predictive power of the model by including the interaction between the renewable generation and different demand levels.

The three demand levels were drawn by the unconditional distribution of loads. We include an indicator in our model: $D_{1it} = 1_{L_{it} \leq L(\tau_L)}$, $D_{2it} = 1_{L(\tau_L) < L_{it} < L(\tau_H)}$, and $D_{1it} = 1_{L_{it} \geq L(\tau_H)}$ where the demand quantile thresholds are $\tau_L = 0.15$ and $\tau_H = 0.85$. These thresholds were selected in a manner that allows the inclusion of a sufficient number of observations for the estimation. Furthermore, these thresholds allow us to explore the electricity price distribution in connection to the demand level extremes. We also used different demand thresholds to test the robustness of our results and did not find any qualitative deviations between them. The robustness checks can be found in Appendix F.

Eq. 1 then becomes:

$$Q_p(\tau) = (a_i+\delta_i q(\tau))+\sum_{m=1}^{3} \beta_m^L L_{mit}+\sum_{m=1}^{3} \beta_m^W W_{mit}+\sum_{m=1}^{3} \beta_m^S S_{mit}+\theta_1 P_{i,t-1}+\theta_2 P_{i,t-7}+\phi C_{it}+Z_{it}'\gamma q(\tau) \tag{2}$$

where $L_{mit} = D_{mit}L_{it}, W_{mit} = D_{mit}W_{it}$ and $S_{mit} = D_{mit}S_{it}$.

According to Angrist and Pischke (2009) bootstrapping standard errors can be useful in settings like quantile regression, that the asymptotic distributions are characterized by unknown densities. Thus, we use the bootstrap clustered by group standard errors to treat potential heteroskedasticity and serial correlation in the panel.

5 Results

5.1 Distributional effects of RES on electricity prices

The empirical estimates for model 1, eq. 1, are presented in Table 2. All coefficients for wind and solar are negative and significant for all price quantiles at 1% level. Thus, a unit increase in wind or solar will reduce electricity prices in all quantiles. The findings clearly reflect the merit-order effect that has been explored extensively in the literature (e.g., Mauritzen, 2013; Cludius et al., 2014).

Table 2. The estimates of baseline model 1.

Variables	Quantiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Denmark									
Wind	-6.159***	-5.935***	-5.782***	-5.653***	-5.534***	-5.409***	-5.273***	-5.110***	-4.848***
Load	3.756***	4.971***	5.803***	6.506***	7.154***	7.833***	8.571***	9.458***	10.88***
Observations	51,696	51,696	51,696	51,696	51,696	51,696	51,696	51,696	51,696
Germany									
Wind	-0.927***	-0.883***	-0.850***	-0.822 ***	-0.794***	-0.765***	-0.733***	-0.694 ***	-0.632***
Solar	-0.552***	-0.557***	-0.561***	-0.564***	-0.567***	-0.570***	-0.574***	-0.578***	-0.585***
Load	0.668***	0.697***	0.719***	0.738***	0.756***	0.775***	0.796***	0.822***	0.863***
Observations	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

The results imply that although, there is a global RES impact on electricity prices, this impact is heterogeneous depending on price levels and renewable energy source type. In both Denmark and Germany, the estimates show that wind reduces electricity prices more on lower quantiles than in upper ones. The reason behind this result lies in the relationship between electricity prices and market-specific characteristics. During off-peak hours, demand is low and electricity prices are sometimes pressed down to zero or even below zero. The system inflexibility pressures conventional power plants to bid in negative prices when it is cost efficient, in short-time segments, than shutting down. An increase in wind production could further stress baseload producers to shut down, establishing a more prominent effect of wind during these times. It is evident that while the direction of the wind coefficients is similar in both countries, the magnitudes are different since they have diverse power production systems such as generation mixes, and renewable production capacities.

Focusing on Germany, solar has a slightly weaker effect on low prices than on high ones. Thus, solar generation seems to reduce the occurrence of extreme positive electricity prices and could be used as a tool to improve system balance. The market involves intense competition when demand is high resulting in high-cost technologies setting electricity prices. However, solar generation is mainly available during high demand hours and can be a setting price technology during these periods. This results in solar having a stronger impact on electricity prices than other energy sources at these times. We also notice that wind overpowers solar for all electricity price quantiles. The underlying reason behind this could be that wind capacity and availability is more extensive than solar power. Additionally, the load seems, as expected, to increase electricity prices in all quantiles with a higher impact on upper quantiles.

Table 3 presents the model estimates for electricity price averages and variability. While load increases electricity prices average, renewable sources seem to reduce it. All the estimates are statistically significant at 1% level except the scale estimate for solar in Germany which is not significant. The wind coefficients suggest that an increase in forecasted wind will give a rise to price variability in Denmark and Germany. This result is in accordance with previous research for Germany, but not for Denmark. We would expect wind to reduce price variability in Denmark (Rintamäki et al., 2017) since they are well-connected to neighboring countries such as Norway and Sweden, which grants Denmark access to flexible systems (hydro-reservoir) with high storage opportunities. Hence, one would expect that excess electricity from wind would be transferred to Norway and stored in its hydro-reservoirs, reducing the pressure in the market, and flatten the impact of wind. Instead, we notice that wind power increases price variability disregarding the favorable power market structure in Denmark. The positive wind estimates could be connected to the fact that wind exhibits a stronger impact on low price quantiles. An increase in forecasted wind could reduce already low prices further, displacing conventional energy producers and rendering the market inefficient even if they have access to hydro systems. We will further investigate this result in the following section where non-linearities are included in the model.

Table 3. Baseline model 1 location and scale estimates.

Baseline model (1)	Location	Scale
Denmark		
Wind	-5.515***	0.429***
Load	7.251***	2.334***
Germany		
Wind	-0.785***	0.096***
Solar	-0.568***	-0.011
Load	0.762***	0.063***

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

On the other hand, Germany has limited access to flexible systems and the concentration of wind generation in the North (Paraschiv et al., 2014) often challenges the power system causing greater price fluctuations. In the case of solar power in Germany, the scale estimate is negative, which indicates that an increase in forecasted solar could result in lower electricity price variability. This could relate to the fact that solar has a more intense effect on upper electricity price quantiles. The solar scale coefficient, though negative, does not seem to hold statistical significance. Model 2 (eq. 2) could reveal more information about the relationship between solar power and price variability. Finally, load exhibits a significant positive impact on electricity price variability in both countries.

5.2 Distributional effects of RES on electricity prices conditional on demand

Analyzing first the Danish distributional effect of wind, conditional on demand, the results of model 2 (Table 4) suggest that wind more strongly impacts upper price quantiles when demand is high and lower price quantiles for low and intermediate demand. Overall, the effect is more prominent for high demand levels and all the results are statistically significant at 1% level. This result is in line with our analysis in the previous section and provide a detailed illustration of the market effects. In higher demand quantiles, high-cost marginal technologies will bid more intensely in the market and increase competition. Thus, an increase in the forecasted wind will induce a sharp price dampening effect during these periods. The forecasted load estimates, contrarily, have a positive sign in all price quantiles which indicates that a rise in forecasted consumption will increase electricity prices.

Table 4. The estimates of the demand level model 2.

τ	Denmark			Germany					
	Wind			Wind			Solar		
	$\beta^W_{1,L}$	$\beta^W_{2,M}$	$\beta^W_{3,H}$	$\beta^W_{1,L}$	$\beta^W_{2,M}$	$\beta^W_{3,H}$	$\beta^S_{1,L}$	$\beta^S_{2,M}$	$\beta^S_{3,H}$
0.1	-6.944***	-6.284***	-5.283***	-1.387***	-0.952***	-0.606***	-0.623***	-0.595***	-0.329***
0.2	-6.209***	-5.964***	-5.723***	-1.259***	-0.892***	-0.657***	-0.622***	-0.581***	-0.415***
0.3	-5.699***	-5.742***	-6.028***	-1.164***	-0.848***	-0.695***	-0.620***	-0.570***	-0.478***
0.4	-5.274***	-5.557***	-6.283***	-1.083***	-0.810***	-0.727***	-0.619***	-0.561***	-0.532***
0.5	-4.884***	-5.388***	-6.516***	-1.005***	-0.773***	-0.759***	-0.618***	-0.552***	-0.584***
0.6	-4.478***	-5.211***	-6.759***	-0.924***	-0.735***	-0.791***	-0.617***	-0.543***	-0.638***
0.7	-4.044***	-5.022***	-7.019***	-0.832***	-0.692***	-0.828***	-0.616***	-0.532***	-0.700***
0.8	-3.522***	-4.795***	-7.331***	-0.725***	-0.642***	-0.871***	-0.615***	-0.520***	-0.771***
0.9	-2.682***	-4.43***	-7.834***	-0.551***	-0.561***	-0.940***	-0.613***	-0.501***	-0.887***
Obs	51,696	51,696	51,696	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Also in Germany, wind generation has a stronger price reducing effect on lower electricity price quantiles when demand is low than when it is high. In the intermediate demand level, the impact is diminishing from lower to upper price quantiles. On the other hand, solar forecasts follow a similar pattern to wind, but the magnitude of the estimates is different. What is noteworthy, is that in all three demand levels, wind estimates exceed solar estimates. The results suggest that both renewable sources impact similarly the median of electricity prices but not the tails of the distribution. Finally, forecasted loads increase electricity prices for all quantiles in all demand levels with the coefficients for the upper price - higher demand quantiles being the strongest.

Moving forward to the electricity prices average and variability estimates in Denmark (Table 5), the average electricity prices are shown to be reduced by forecasted wind for low, intermediate, and high demand levels. Wind significantly also impacts price variability for all demand levels. The wind estimates are positive for low and intermediate demand levels and negative for high demand. This ambiguous result indicates that price variability and wind generation depend strongly on electricity demand. Generally, during low electricity demand, wind power would suffice to cover electricity consumption, which combined with the renewable sources pressure on conventional power plants, could result in excess electricity supply in the market. Hence, an extra unit of forecasted wind could urge greater price fluctuations and marker uncertainty. On the contrary, when demand is high, the entrance of high-cost technologies in the market intensifies competition. During these times, an increase in wind power, a low-cost generator, would pull electricity prices down, reduce extreme fluctuations and enhance electricity security. The results also show that forecasted load increases electricity prices on average as well as their variability and may, thus, cause electricity price fluctuations including positive price spikes.

Table 5. Model 2 (conditional on demand) location and scale estimates.

Demand level	Model (2)	Location	Scale
Denmark			
Wind	W_L	-4.837***	1.392***
	W_M	-5.367***	0.605***
	W_H	-6.545***	-0.833***
Load	L_L	7.277***	1.671***
	L_M	7.481***	2.221***
	L_H	7.986***	3***
Germany			
Wind	W_L	-0.979***	0.266***
	W_M	-0.761***	0.124***
	W_H	-0.769***	-0.106***
Solar	S_L	-0.618***	0.003
	S_M	-0.549***	0.03*
	S_H	-0.602***	-0.177***
Load	L_L	0.817***	-0.026*
	L_M	0.763***	0.01
	L_H	0.767***	0.088***

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Wind and solar, carrying diverse characteristics, can influence differently electricity price variability in Germany. It is shown that both wind and solar increase price variability for low and intermediate loads. More importantly, the results indicate that when demand is high the negative relation between solar generation and price variability is stronger compared to the equivalent effect of wind power. Solar availability and generation capacity characteristics compared to wind production patterns could relate to this. Additionally, geographical characteristics may also contribute to this result especially when the results are used for comparative analysis. In Germany, energy consumption is mainly concentrated in the southern part while wind power is mostly produced in the northern part (Paraschiv et al., 2014). Thus, transmission constraints and congestion across the country, could prevent wind generation from covering electricity demand, allowing solar power to impact electricity prices during these times. The graphical representations of the results are available in Appendix D.

Although our results reflect the well-known merit order effect, our estimates diversify from previous research that uses individual hours or aggregate time-series methods. Focusing on the extensively researched case of the German electricity market, we can notice that empirical results have been underestimated or overestimated compared to our findings. Regarding the median of the electricity price distribution, a stronger effect of renewable sources on prices has been found in contrast to our results (Cludius et al., 2014). When individual hours are investigated an underestimation of the renewable sources effect for most hours in different quantiles has been revealed (Hagfors et al., 2016b; Do et al., 2019). On the other hand, Maciejowska (2020) has shown that solar power has a much stronger effect on upper price quantiles than in lower quantiles which is in contrast with our research findings. Specifically, we illustrate that considering the hourly-specific characteristics, the merit-order effect could be uniform for all price quantiles. This could be reasonable since solar power generation patterns reveal a great dependence on the hour of the day due to the sunlight. Thus, we consider the addition of the hourly fixed effects a potential to provide higher accuracy outcomes. In the next section, we clarify that our results differ from previous findings due to the time-invariant (hour-specific) characteristic, rather than the high frequency of the data.

Research to date has measured price variability in various ways, using different frequencies, and reaching diverse findings (for instance Ketterer, 2014; Rintamäki et al., 2017; Maciejowska, 2020). Therefore, even if our measure of variability differs greatly from previous studies, we still think it is important to highlight the differences in our results, and the potential implications for electricity research. Kyritsis et al. (2017) has shown that solar has a significant negative impact on price variability in Germany, considering daily aggregated data, but no significant effect in off-peak hours. On the other hand, we illustrate that solar has no significant relationship with the electricity price variability. Furthermore, we show that solar generation reduces price variability only when demand is high, while Maciejowska (2020) demonstrates that solar has a stronger negative and statistically important impact when demand is intermediate. These differences could provide crucial evidence on the dependence of solar generation on the hour of the day and its characteristics. In the case of Denmark, Rintamäki et al. (2017) have presented, using daily data, that wind power decreases price volatility in Denmark while we have revealed the opposite effect. Therefore, the diverse results steer us to think that the cross-sectional dimension plays an important role in RES and electricity research and should be considered in future research. In the following section we directly analyze the results between the panel and time series approach and describe the benefits of our chosen method.

6 Daily time-series vs hourly panel data

A large portion of the literature has employed aggregated daily (time-series) data to investigate the RES effect on electricity price distributions. In this paper we use high-frequency data that allow us to control for hourly-specific effects which could impact the research outcomes. We would anticipate differences between the two methods and procedures; thus, it could be essential to examine the aggregated time-series model and discuss the findings. The data are transformed from hourly into daily observations and an autoregressive quantile regression (Koenker and Xiao, 2006) including the same set of variables, as in models 1 and 2, is applied. The empirical results can be found in Tables C4, C5, C6 and C7 in Appendix C.

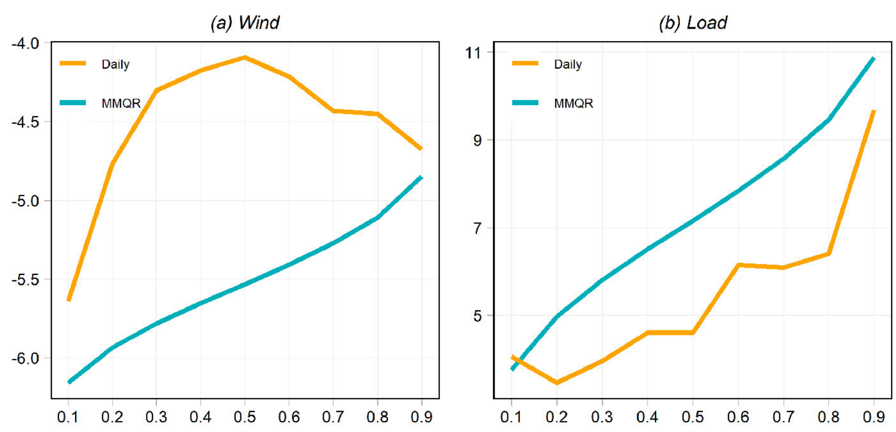

Figure 4. Baseline model 1 daily vs MMQR in DK1.

Fig. 5 illustrates the baseline Method of Moments Quantile Regression (MMQR) and daily estimates for wind, solar and load in Germany. While the MMQR wind and solar coefficients follow approximately the same pattern as the daily estimates, the hourly results reveal strongest impacts than the aggregated in all price quantiles. Only in the case of solar power and for high electricity price quantiles the daily estimate exceeds the MMQR. Additionally, load exhibits a more prominent impact in the hourly resolution compared to the daily. What is noteworthy, is that solar estimates seem to show the highest divergence which prompts us to suspect that the hourly-specific effect can be crucial in the case of RES production-specific characteristics and their influence in the market. Fig. 4 also shows the wind and load estimates in Denmark. We notice that the coefficients follow the same trend as in Germany, with the MMQR wind impacting stronger lower quantiles and daily wind influencing mostly low and upper price quantiles.

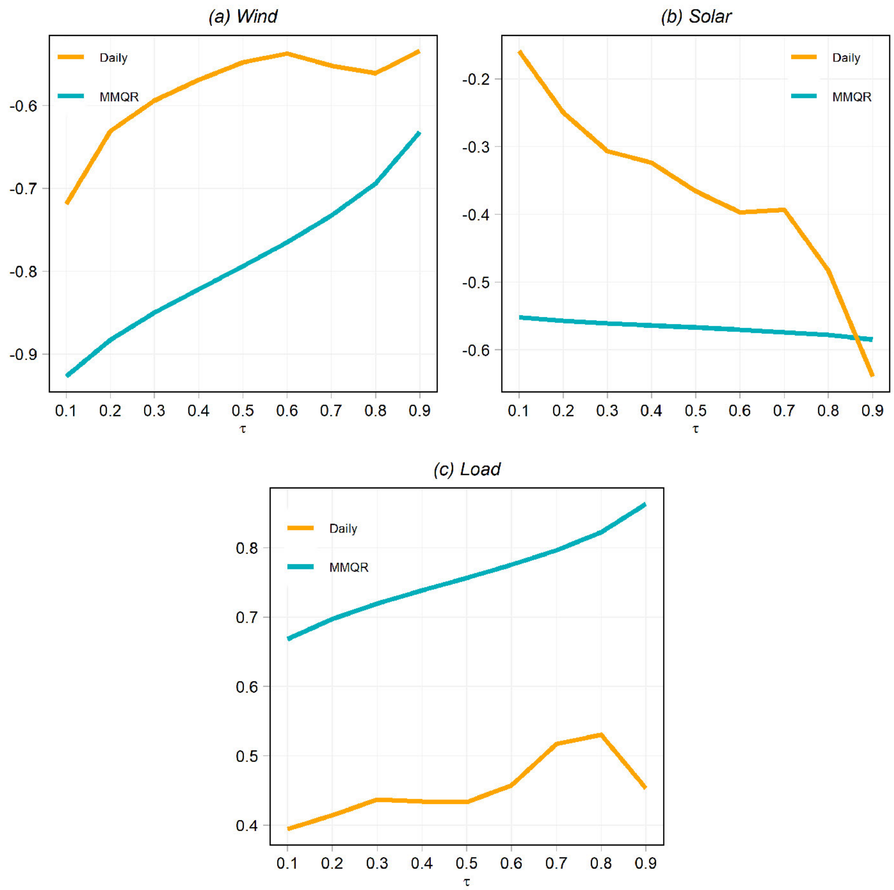

Figure 5. Baseline model 1 daily vs MMQR in DE.

Fig. 6 demonstrates the non-linear MMQR model and daily time series estimates in Germany. It can be observed that the daily and MMQR wind estimates for low and intermediate demand exhibit approximately the same pattern. As for high demand levels, the daily wind estimates are stronger for upper and lower price quantiles while the MMQR approach indicates that the wind impact is monotonically decreasing, having a higher impact on upper price quantiles. On the contrary, solar displays a highly diversified influence on electricity price quantiles. The daily coefficients show sharp fluctuations for all demand levels while the MMQR approach presents a smoother RES effect on the electricity price distribution. Especially for low demand, there is a striking contrast between the two results and their implications. In addition, the wind and solar MMQR coefficients show a higher negative impact than daily estimates for most demand levels and price quantiles. Finally, in the case of load, we notice great diversity between the hourly and daily estimates, with hourly-resolution results displaying much higher impacts than the daily aggregated.

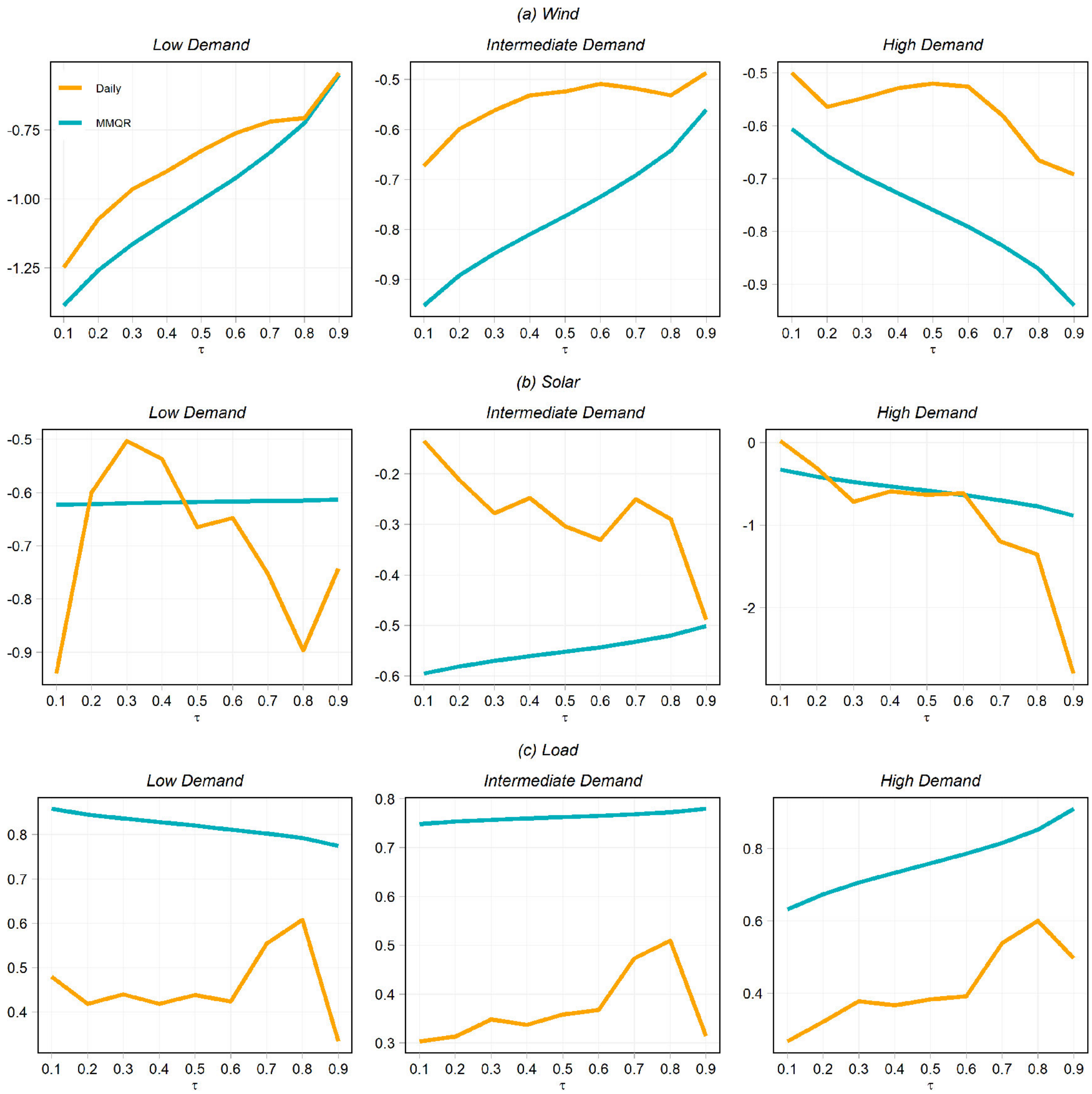

Figure 6. Model 2 - conditional on demand daily vs MMQR estimates in Germany.

When the non-linear case of the daily and MMQR results in Denmark (Fig. 7) is explored, it is observed that for low demand the two approaches outcomes follow a very similar pattern. For intermediate demand, the MMQR coefficient is increasing across quantiles while the daily result is strongest for low and upper quantiles. Furthermore, it is noted that in extreme positive price quantiles and for intermediate demand, the daily impact exceeds the MMQR. In the case of loads, the MMQR results show a smoother and stronger effect than the daily ones. Finally, both the daily wind and load results display again high fluctuations compared to the hourly estimates.

Individual hours and their specific characteristics can be highly significant in the case of renewable sources which depend on weather conditions and can display rapid and extreme variations. The analysis and comparison of aggregated time-series and hourly-panel results can verify, to some extent, this hypothesis. The diversity of the outcomes reveals that accounting for this hour-specific effect could be important for investigating the RES influence on electricity prices. Overall, the panel setting uncovers a higher distributional impact of renewable sources on electricity prices.

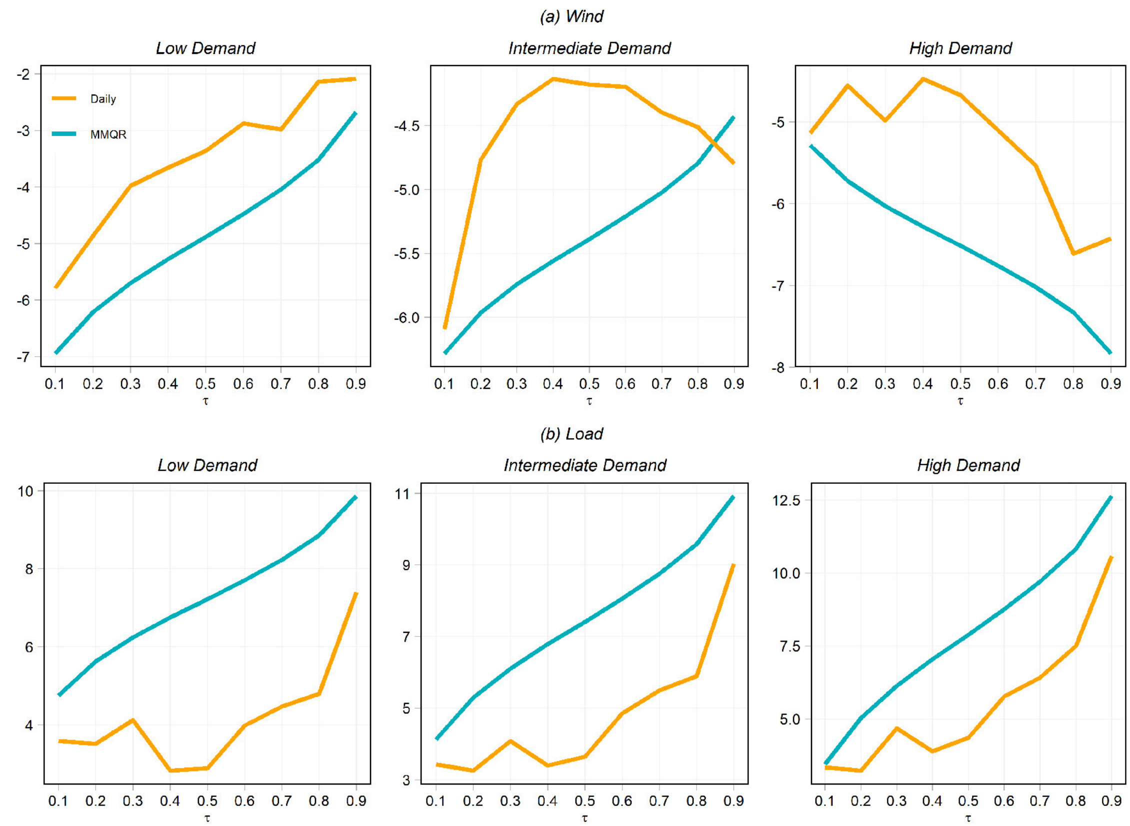

Figure 7. Model 2 - conditional on demand daily vs MMQR estimates in Denmark.

Since it is well-known that higher data resolution could provide more accurate estimates, we used the hourly data in a time-series setting, without aggregating them, and estimated the same models as in the aggregated case[5](see Appendix E). The hourly time-series results appear to be similar to the aggregated findings, but they suggest a smoother effect of RES across the price quantiles. Thus, using the hourly-data in a time-series setting would still yield underestimated RES impacts on the electricity price quantiles. This prompts us to believe that the difference between the aggregated and hourly results originates from the chosen methodology and the

[5]In the introduction and the methodological part, we argue that using the hourly data in a time-series setting could provide inaccurate estimates since the method does not account for the cross-sectional dimension between the variables. Thus, we are using the time-series to illustrate that our results do not originate from the higher data resolution but the inclusion of the hourly-specific effect.

inclusion of the hour-specific characteristics in the panel approach, and not from the higher data resolution. Hence, we believe that future research should account for the cross-sectional dimension in the data and use a panel approach to investigate the RES influence on electricity prices.

After analyzing the time-series (aggregated and hourly) results and the panel outcomes, we believe that our chosen method offers many benefits in comparison to time-series (aggregated or not). Firstly, using the hourly data resolution provides a higher informative setting, than time-series data, that results in improved efficiency of the econometric estimates. Renewable energy production can strongly diversify among hours, thus including this hourly variation offers valuable information in the analysis. Thus, through the panel approach we can identify and measure impacts that are not detectable in pure time-series data. Secondly, electricity price formation and risk vary highly during the day, for instance extremely low or high prices. Electricity is a unique commodity that needs to be produced and consumed simultaneously, and that does not have high storage capacity. Therefore, the field should be investigated through a dynamic approach that utilizes all the information that is disclosed in the data. The panel approach allows us to control for time invariant characteristics that exist between hour groups while time series focus only on the time dimension and do not recognize this cross-sectional dimension. The panel approach and its higher prediction accuracy can offer wider and more precise information about the dynamics in power markets. In this way, market participants such as producers, regulators, etc., can use this methodological tool to efficiently adjust to existing risks and recognize future profit opportunities.

7 Robustness analysis

The robustness of the RES effect on the distribution of electricity prices and their variability is corroborated by altering model 2. Since the results depend highly on the chosen demand thresholds, new chosen thresholds are applied to verify the estimates. The new demand thresholds are set at $\tau_L = 0.2$ and $\tau_L = 0.8$. The use of high-frequency hourly data, while providing richer information, can create many challenges, especially in the case of solar power. Hourly solar data are zero when there is no sunlight. Hence, we believe that lower demand thresholds can bias the solar estimates by including an inadequate number of observations. The robustness check results can be found in Appendix F.

In the renewable sources and electricity prices literature, another common way to verify the estimation results has been the addition of fuel prices (e.g., gas, coal) in regressions. Unfortunately, the gas (or coal) prices that we have access to are provided in daily resolutions and would need to be interpolated to be incorporated in this research. Furthermore, it has been shown that although fuel prices impact electricity prices, they do not affect the RES estimates on them (Gelabert et al., 2011; Cludius et al., 2014; Maciejowska, 2020: Sirin and Yilmaz, 2020).

The results reported in Appendix F confirm the RES impacts obtained in previous sections. There are slight quantitative differences in the solar coefficients and variability effects in Germany, but this is to be expected due to the sensitivity of solar on the number of observations as explained earlier. Nevertheless, the final interpretation of the results is not affected by these minor differences.

8 Conclusion

The increasing variable renewable energy has become an important factor in power markets that affects market fundamentals, such as electricity prices. In this paper, a panel quantile approach is applied to investigate the distributional impact of RES on electricity prices. The analysis focuses on both the effect on electricity price levels and price variability. We apply two models, including a non-linear case through the interaction between RES and electricity demand, which draws a more accurate picture of the electricity market. We explore three demand levels – low, intermediate, and high - chosen by the unconditional quantile distribution of loads.

Previous research has used electricity prices in daily resolution or investigated individual hours of the day. In our paper, we argue that group hours are heterogeneous (Huisman et al., 2007), and we should choose a methodology that can account for this heterogeneity. The main contribution of our research is the use of the hourly resolution electricity data in a panel approach, considering the cross-sectional dimension of the data. The panel approach, using hourly electricity prices and RES, can give more informative data and include the dynamic characteristics of power markets. Furthermore, it allows for the control of time invariant (group hour) characteristics that are embedded in the cross sectional dimension of electricity prices. Therefore, we believe that the panel setting provides better predictions which is of high value since electricity is considered as a unique commodity since supply and demand needs to be continuously balanced. Thus, through this novel methodological approach we attempt to provide important insights of the power market and improve the operations and decisions made by market participants. The additional information revealed by the panel approach, compared to traditional time-series, can support future investments in flexible system assets such as demand-response technologies, and ensure that long-term sustainability goals in the energy sector can be reached.

The results confirm the merit-order effect from wind and solar. The findings show similar patterns concerning wind power in both Denmark and Germany. Wind power shows to have a stronger impact on the lower tail of the price distribution, a result connected to market dynamics. In Germany, the renewable energy source type seems to be important for the electricity market structure. In contrast to wind, solar power impacts stronger upper electricity price quantiles. Thus, the strong interaction between renewable source types could yield important benefits to governments and organizations, if recognized and managed accordingly. Moreover, wind and solar appear to influence the electricity price median in a similar manner, limiting potential gains from the RES type interplay in the market.

In this paper, the relationship between RES and price variability is also examined. The results show that wind increases price variability in both countries. While this result is already established in Germany (Paraschiv et al., 2014; Rintamäki et al., 2017), it comes as a surprise in Denmark. Rintamäki et al. (2017) has shown that the flexible electricity system structure in Denmark curtails the variability impact of wind on electricity prices. Our results imply that the strong wind influence on the low tail of electricity prices, and higher wind capacity could increase uncertainty-in the form of price variability-, although Denmark has one of the most flexible systems in Europe. When we investigate the RES impact on price variability, acknowledging potential non-linearities, we notice that the results insinuate extra information on the explored relationships. Wind power appears to increase electricity price variability for lower and intermediate demand levels, while reduces variability for high demand levels. In Germany, wind and solar seem to impact variability in a similar pattern, with solar having a stronger influence than wind for high demand.

Finally, the difference between exploiting hourly data and aggregated daily data is explored. It is shown that the results are highly diversified in both countries, and between the different renewable source type. The aggregated data appear to underestimate the RES impact on the electricity price distribution with the difference being more prominent on solar power. This suggests that solar is more sensitive on data aggregation which could emerge from the solar-specific generation patterns – solar is only available during sunlight hours. The results illustrate that exploiting higher frequency electricity data, without aggregating them, could provide significantly different information in the market. In order to verify that the differences between the aggregated time-series and the hourly panel results are not driven by the higher frequency data resolution, we also use the hourly data in a time series setting and estimate the same models as in the aggregated-daily case. The results show that using hourly data in a time series manner would still yield underestimated RES effects on the electricity price distribution (as in the aggregated-daily case). Therefore, these findings prompt us to believe that the time-invariant (hourly-specific) effect plays an important role in the market and support our claims that it should be further considered in future electricity research.

The findings of this analysis are important for policy makers and practitioners since they illustrate the importance of renewable sources on the structure and operation of power markets. The results could be used by governments and organizations for different course of action. Understanding the fundamental variables that control electricity price fluctuations could help policy makers to strategically design energy plans that optimize variable renewable sources inclusion in electricity systems. For instance, regulators could consider the disproportionate impact of wind power on electricity prices and apply RES support schemes that could minimize these imbalances in the market. Another important aspect drawn by the results is the diverse impact of renewable source type (wind and solar) on electricity price levels and variability. This interaction is important to governments for regulating energy markets. They could allocate future RES infrastructure in strategic positions to improve electricity flow in the system or recognize the need to expand the electricity grid and establish stronger interconnections. Moreover, organizations could use the information on market uncertainty to discover future profit opportunities. In particular, real-option investors, such as power storage companies, could benefit from higher electricity price fluctuations. In such way, investments on flexible systems which are set to play a crucial role in market decarbonization and energy security in the following years, could be further employed.

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A Appendix

The electricity markets in Europe.

The EU electricity system includes three key markets– the day-ahead, intraday, and balancing market - depending on power exchange frequency. The day-ahead market (or spot market) clears supply and demand with a price for each of the 24 h of the following day. Thus, the buyers and sellers in the market, place their bids in an hourly resolution for the following day. These bids are aggregated, and the system price is determined by the intersection between demand and supply. The last required generation technology to meet demand determines the price through a marginal price setting procedure (Huisman et al., 2014). Electricity prices can be affected by generation capacity, transmission constraints and meteorological factors (Nord Pool S.A., 2021). The intraday and balancing markets, in which the participants trade closer to the physical delivery time, aim to correct forecast errors, and eventually secure a balance between electricity supply and demand. Day-ahead prices have been the main field of investigation regarding RES influence on electricity prices. The liberalization of electricity markets increased trade interest in day-ahead markets, and although complementary markets (e.g., intraday) emerged through the years, the role of day-ahead markets remained prominent until today.

B Appendix

Table B1. Diagnostic tests for Denmark and Germany.

Variable	*Denmark*			*Germany*			
	Price	Wind	Load	Price	Wind	Solar	Load
Cross-sectional dependence							
CD-Pesaran (2004)	604.041***	615.183***	668.386***	575.403 ***	672.018***	378.329***	685.906***
P-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Unit root							
Breitung and Das (2005)	-6.803***	-4.636***	-2.081***	-5.445 ***	-6.038***	-2.725***	-3.046***
P-value	<0.01	<0.01	=0.018	<0.01	<0.01	<0.01	<0.01
Breitung and Das with trend	5.886***	-8.015***	-1.481*	-5.125 ***	-8.958***	-2.369***	-3.802***
P-value	<0.01	<0.01	=0.0698	<0.01	<0.01	<0.01	<0.01

Notes: i) p-values close to zero indicate data are correlated across panel groups, ii) the unit root hypothesis is rejected when the p-value is lower than the chosen significance level.

C Appendix

Table C1. Model 1 estimates with standard errors.

Variables	Quantiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Denmark									
Wind	-6.159***	-5.935***	-5.782***	-5.653***	-5.534***	-5.409***	-5.273***	-5.110***	-4.848***
	(0.093)	(0.086)	(0.094)	(0.107)	(0.124)	(0.143)	(0.165)	(0.194)	(0.243)
Load	3.756***	4.971***	5.803***	6.506***	7.154***	7.833***	8.571***	9.458***	10.88***
	(0.289)	(0.232)	(0.225)	(0.238)	(0.265)	(0.308)	(0.365)	(0.431)	(0.552)
Observations	51,696	51,696	51,696	51,696	51,696	51,696	51,696	51,696	51,696
Germany									
Wind	-0.927***	-0.883***	-0.850***	-0.822 ***	-0.794***	-0.765***	-0.733***	-0.694 ***	-0.632***
	(0.023)	(0.021)	(0.02)	(0.019)	(0.019)	(0.019)	(0.021)	(0.022)	(0.025)
Solar	-0.552***	-0.557***	-0.561***	-0.564***	-0.567***	-0.570***	-0.574***	-0.578***	-0.585***
	(0.039)	(0.033)	(0.028)	(0.024)	(0.023)	(0.022)	(0.022)	(0.025)	(0.032)
Load	0.668***	0.697***	0.719***	0.738***	0.756***	0.775***	0.796***	0.822***	0.863***
	(0.029)	(0.027)	(0.025)	(0.024)	(0.023)	(0.023)	(0.024)	(0.025)	(0.029)
Observations	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors in parentheses are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table C2. Model 2 estimates with standard errors in Denmark.

τ	Wind			Load		
	$\beta_{1,L}^{W}$	$\beta_{2,M}^{W}$	$\beta_{3,H}^{W}$	$\beta_{1,L}^{L}$	$\beta_{2,M}^{L}$	$\beta_{3,H}^{L}$
0.1	-6.944***	-6.284***	-5.283***	4.748***	4.119***	3.445***
	(0.220)	(0.122)	(0.248)	(0.416)	(0.364)	(0.358)
0.2	-6.209***	-5.964***	-5.723***	5.630***	5.291***	5.029***
	(0.190)	(0.108)	(0.260)	(0.357)	(0.331)	(0.344)
0.3	-5.699***	-5.742***	-6.028***	6.241***	6.104***	6.127***
	(0.173)	(0.105)	(0.269)	(0.374)	(0.350)	(0.367)
0.4	-5.274***	-5.557***	-6.283***	6.752***	6.782***	7.043***
	(0.159)	(0.105)	(0.276)	(0.423)	(0.391)	(0.401)
0.5	-4.884***	-5.388***	-6.516***	7.220***	7.404***	7.883***
	(0.150)	(0.110)	(0.284)	(0.487)	(0.443)	(0.446)
0.6	-4.478***	-5.211***	-6.759***	7.708***	8.053***	8.759***
	(0.142)	(0.117)	(0.294)	(0.570)	(0.511)	(0.505)
0.7	-4.044***	-5.022***	-7.019***	8.228***	8.745***	9.694***
	(0.139)	(0.127)	(0.305)	(0.668)	(0.591)	(0.575)
0.8	-3.522***	-4.795***	-7.331***	8.854***	9.577***	10.82***
	(0.136)	(0.143)	(0.318)	(0.784)	(0.683)	(0.654)
0.9	-2.682***	-4.43***	-7.834***	9.862***	10.917***	12.63***
	(0.149)	(0.172)	(0.344)	(0.986)	(0.845)	(0.796)
Obs	51,696	51,696	51,696	51,696	51,696	51,696

Notes: (i) Standard errors in parentheses are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table C3. Model 2 estimates with standard errors in Germany.

τ	Wind			Solar			Load		
	$\beta^W_{1,L}$	$\beta^W_{2,M}$	$\beta^W_{3,H}$	$\beta^S_{1,L}$	$\beta^S_{2,M}$	$\beta^S_{3,H}$	$\beta^L_{1,L}$	$\beta^L_{2,M}$	$\beta^L_{3,H}$
0.1	-1.387***	-0.952***	-0.606***	-0.623***	-0.595***	-0.329***	0.858***	0.748***	0.632***
	(0.048)	(0.044)	(0.014)	(0.12)	(0.048)	(0.045)	(0.049)	(0.045)	(0.035)
0.2	-1.259***	-0.892***	-0.657***	-0.622***	-0.581***	-0.415***	0.845***	0.753***	0.674***
	(0.045)	(0.039)	(0.01)	(0.102)	(0.041)	(0.037)	(0.044)	(0.04)	(0.032)
0.3	-1.164***	-0.848***	-0.695***	-0.620***	-0.570***	-0.478***	0.836***	0.756***	0.706***
	(0.042)	(0.035)	(0.009)	(0.09)	(0.035)	(0.032)	(0.041)	(0.037)	(0.03)
0.4	-1.083***	-0.810***	-0.727***	-0.619***	-0.561***	-0.532***	0.828***	0.759***	0.733***
	(0.039)	(0.033)	(0.009)	(0.081)	(0.031)	(0.029)	(0.039)	(0.034)	(0.028)
0.5	-1.005***	-0.773***	-0.759***	-0.618***	-0.552***	-0.584***	0.820***	0.762***	0.759***
	(0.037)	(0.03)	(0.01)	(0.076)	(0.028)	(0.029)	(0.037)	(0.032)	(0.028)
0.6	-0.924***	-0.735***	-0.791***	-0.617***	-0.543***	-0.638***	0.811***	0.765***	0.786***
	(0.035)	(0.028)	(0.011)	(0.072)	(0.026)	(0.031)	(0.035)	(0.03)	(0.027)
0.7	-0.832***	-0.692***	-0.828***	-0.616***	-0.532***	-0.700***	0.802***	0.768***	0.816***
	(0.033)	(0.025)	(0.014)	(0.073)	(0.025)	(0.035)	(0.034)	(0.028)	(0.027)
0.8	-0.725***	-0.642***	-0.871***	-0.615***	-0.520***	-0.771***	0.792***	0.772***	0.852***
	(0.032)	(0.021)	(0.017)	(0.079)	(0.026)	(0.042)	(0.034)	(0.027)	(0.028)
0.9	-0.551***	-0.561***	-0.940***	-0.613***	-0.501***	-0.887***	0.774***	0.779***	0.910***
	(0.03)	(0.016)	(0.024)	(0.097)	(0.032)	(0.056)	(0.035)	(0.027)	(0.031)
Obs	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table C4. Daily estimates of the baseline model in Denmark.

Variables	Quantiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Wind	-5.641***	-4.770***	-4.302***	-4.177***	-4.092***	-4.215***	-4.433***	-4.452***	-4.676***
	(0.364)	(0.264)	(0.222)	(0.204)	(0.198)	(0.242)	(0.230)	(0.231)	(0.337)
Load	4.067***	3.465***	3.959***	4.603***	4.602***	6.153***	6.093***	6.404***	9.683***
	(1.092)	(0.790)	(0.856)	(0.776)	(0.797)	(0.699)	(0.731)	(0.959)	(1.423)
Constant	-1.607	-0.521	-0.750	-0.504	0.615	-1.183	1.083	2.722	-1.449
	(2.578)	(1.722)	(1.893)	(1.817)	(1.748)	(1.619)	(1.815)	(2.172)	(3.504)
Observations	2154	2154	2154	2154	2154	2154	2154	2154	2154

Notes: (i) Standard errors in parentheses are computed with the bootstrapped approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table C5. Daily estimates of the baseline model in Germany.

Variables	Quantiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Wind	-0.719***	-0.631***	-0.594***	-0.569***	-0.548***	-0.537***	-0.552***	-0.561***	-0.534***
	(0.037)	(0.029)	(0.024)	(0.025)	(0.023)	(0.023)	(0.028)	(0.039)	(0.062)
Solar	-0.159*	-0.250***	-0.307***	-0.324***	-0.366***	-0.397***	-0.393***	-0.483***	-0.639***
	(0.083)	(0.066)	(0.072)	(0.067)	(0.07)	(0.059)	(0.069)	(0.088)	(0.122)
Load	0.394***	0.414***	0.437***	0.434***	0.433***	0.457***	0.517***	0.530***	0.453***
	(0.078)	(0.063)	(0.056)	(0.058)	(0.056)	(0.052)	(0.058)	(0.075)	(0.115)
Constant	-8.965**	-8.994**	-9.351***	-7.807**	-6.119*	-5.883**	-7.059**	-4.321	4.807
	(4.259)	(3.605)	(3.318)	(3.266)	(3.183)	(2.879)	(3.294)	(4.267)	(6.981)
Observations	2149	2149	2149	2149	2149	2149	2149	2149	2149

Notes: (i) Standard errors in parentheses are computed with the bootstrapped approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table C6. Daily estimates of model 2 in Denmark.

τ	Wind			Load		
	$\beta^W_{1,L}$	$\beta^W_{2,M}$	$\beta^W_{3,H}$	$\beta^L_{1,L}$	$\beta^L_{2,M}$	$\beta^L_{3,H}$
0.1	-5.787***	-6.092***	-5.137***	3.588	3.427*	3.341**
	(0.927)	(0.412)	(0.634)	(2.361)	(1.836)	(1.697)
0.2	-4.862***	-4.767***	-4.555***	3.518**	3.247**	3.224***
	(0.778)	(0.280)	(0.487)	(1.616)	(1.355)	(1.207)
0.3	-3.979***	-4.331***	-4.984***	4.118***	4.079***	4.682***
	(0.377)	(0.269)	(0.509)	(1.263)	(1.094)	(1.026)
0.4	-3.659***	-4.135***	-4.474***	2.822***	3.398***	3.894***
	(0.476)	(0.260)	(0.503)	(1.426)	(1.305)	(1.175)
0.5	-3.366***	-4.181***	-4.673***	2.891*	3.643***	4.357***
	(0.573)	(0.226)	(0.473)	(1.481)	(1.332)	(1.230)
0.6	-2.877***	-4.197***	-5.105***	3.981***	4.847***	5.772***
	(0.546)	(0.264)	(0.415)	(1.467)	(1.294)	(1.120)
0.7	-2.986***	-4.398***	-5.533***	4.471***	5.488***	6.414***
	(0.696)	(0.238)	(0.523)	(1.288)	(1.131)	(1.012)
0.8	-2.143***	-4.513***	-6.610***	4.799***	5.892***	7.499***
	(0.744)	(0.241)	(0.654)	(1.589)	(1.313)	(1.221)
0.9	-2.092***	-4.798***	-6.427***	7.396***	9.026***	10.575***
	(0.593)	(0.345)	(0.728)	(2.115)	(1.805)	(1.679)
Obs	2154	2154	2154	2154	2154	2154

Notes: (i) Standard errors in parentheses are computed with the bootstrapped approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table C7. Daily estimates of model 2 in Germany.

τ	Wind			Solar			Load		
	$\beta^W_{1,L}$	$\beta^W_{2,M}$	$\beta^W_{3,H}$	$\beta^S_{1,L}$	$\beta^S_{2,M}$	$\beta^S_{3,H}$	$\beta^L_{1,L}$	$\beta^L_{2,M}$	$\beta^L_{3,H}$
0.1	-1.249***	-0.673***	-0.500***	-0.940***	-0.135	0.018	0.479***	0.303***	0.267***
	(0.123)	(0.039)	(0.07)	(0.333)	(0.104)	(0.443)	(0.11)	(0.089)	(0.09)
0.2	-1.074***	-0.599***	-0.564***	-0.600***	-0.212***	-0.312	0.418***	0.313***	0.321***
	(0.132)	(0.035)	(0.064)	(0.29)	(0.067)	(0.347)	(0.095)	(0.081)	(0.082)
0.3	-0.965***	-0.562***	-0.548***	-0.503***	-0.278***	-0.717*	0.439***	0.348***	0.378***
	(0.097)	(0.031)	(0.053)	(0.191)	(0.082)	(0.428)	(0.078)	(0.066)	(0.065)
0.4	-0.900***	-0.532***	-0.529***	-0.537***	-0.248***	-0.592	0.418***	0.337***	0.367***
	(0.086)	(0.029)	(0.051)	(0.153)	(0.071)	(0.364)	(0.08)	(0.067)	(0.063)
0.5	-0.826***	-0.524***	-0.520***	-0.665***	-0.304***	-0.633*	0.438***	0.358***	0.383***
	(0.086)	(0.027)	(0.046)	(0.163)	(0.075)	(0.359)	(0.082)	(0.068)	(0.066)
0.6	-0.762***	-0.509***	-0.526***	-0.648***	-0.331***	-0.614	0.423***	0.367***	0.392***
	(0.08)	(0.033)	(0.048)	(0.184)	(0.083)	(0.402)	(0.092)	(0.075)	(0.069)
0.7	-0.720***	-0.518***	-0.582***	-0.753***	-0.250***	-1.198**	0.554***	0.473***	0.539***
	(0.095)	(0.031)	(0.064)	(0.186)	(0.077)	(0.559)	(0.106)	(0.085)	(0.079)
0.8	-0.707***	-0.532***	-0.665***	-0.897***	-0.290***	-1.353**	0.608***	0.509***	0.600***
	(0.105)	(0.05)	(0.061)	(0.217)	(0.091)	(0.546)	(0.12)	(0.103)	(0.097)
0.9	-0.543***	-0.487***	-0.692***	-0.743**	-0.489***	-2.795***	0.333**	0.314**	0.497***
	(0.2)	(0.056)	(0.118)	(0.374)	(0.142)	(0.89)	(0.166)	(0.129)	(0.135)
Obs	2149	2149	2149	2149	2149	2149	2149	2149	2149

Notes: (i) Standard errors are computed with the bootstrapped approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

D Appendix

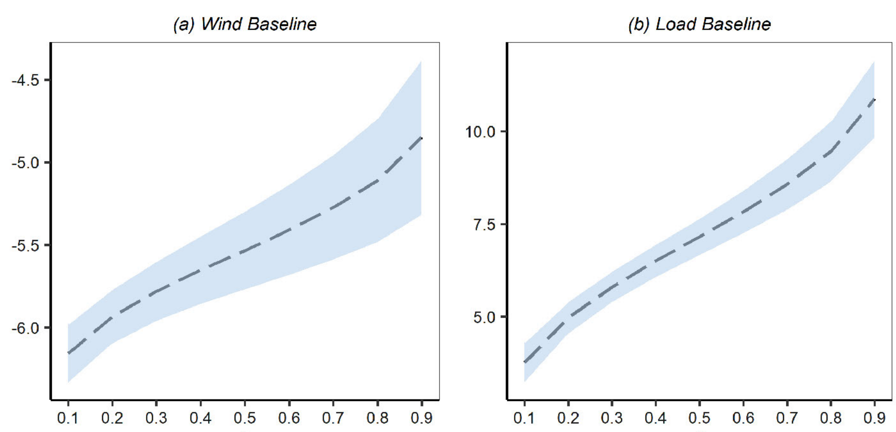

Figure D.1. Baseline model estimates in Denmark. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

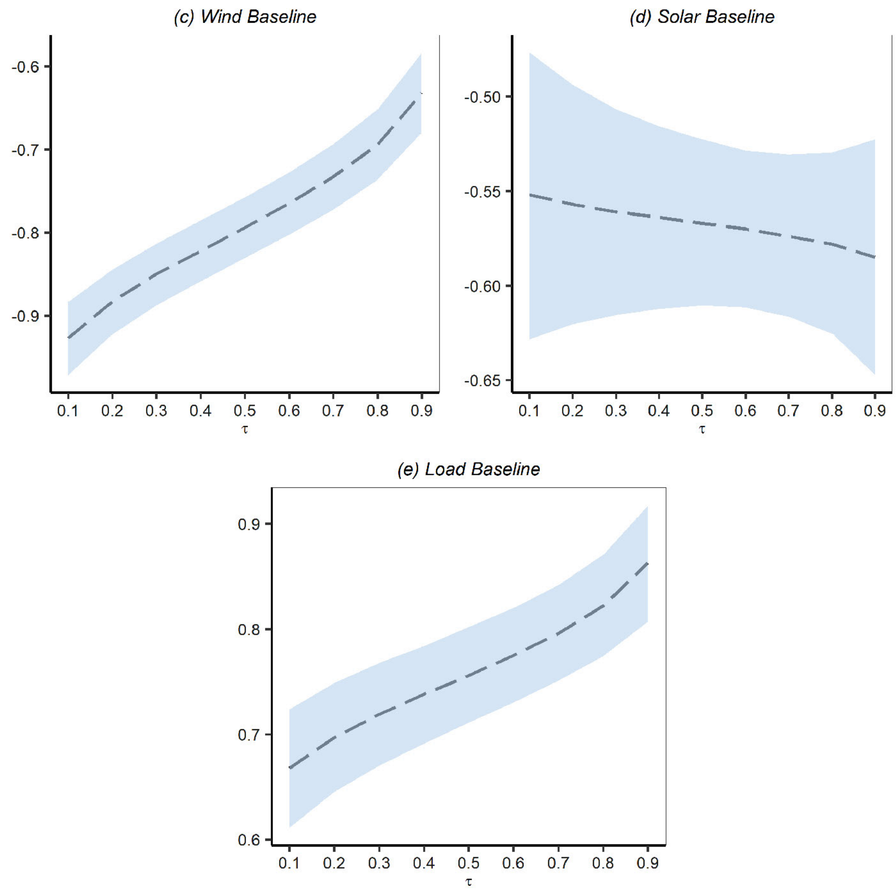

Figure D.2. Baseline model estimates in Germany. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

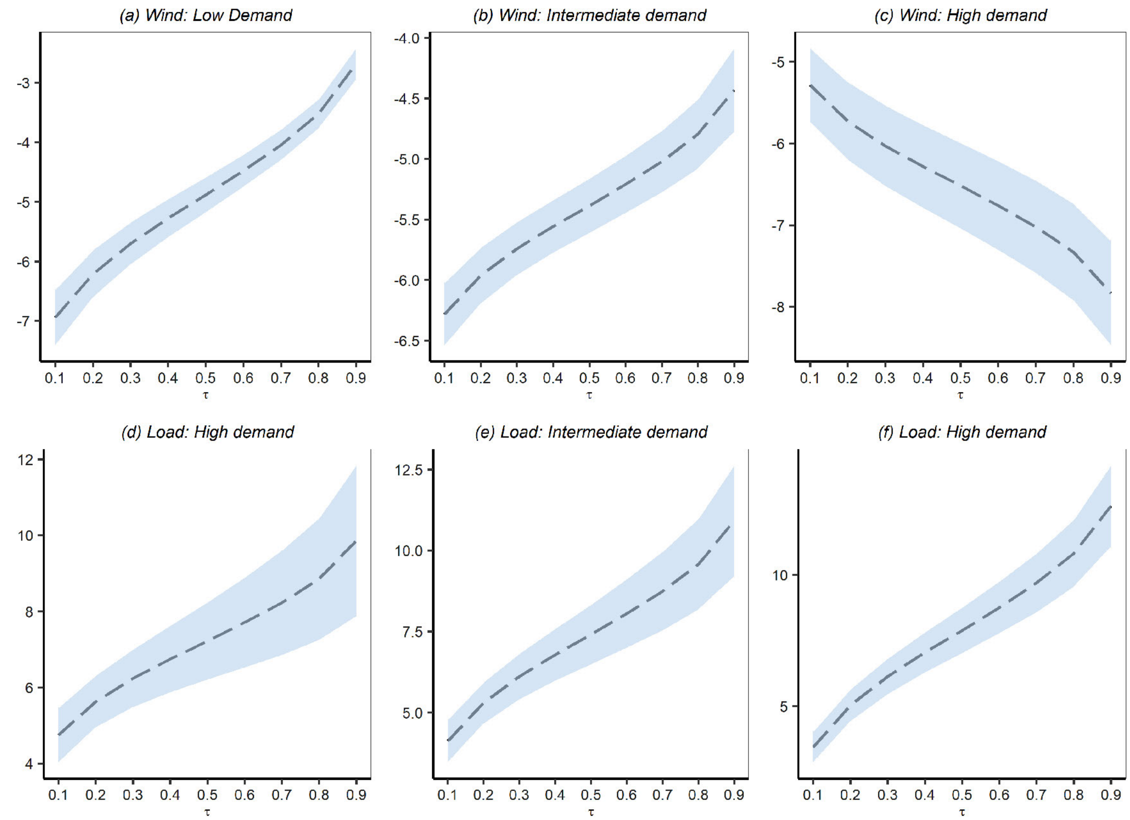

Figure D.3. Conditional on demand estimates-model 2 in Denmark. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

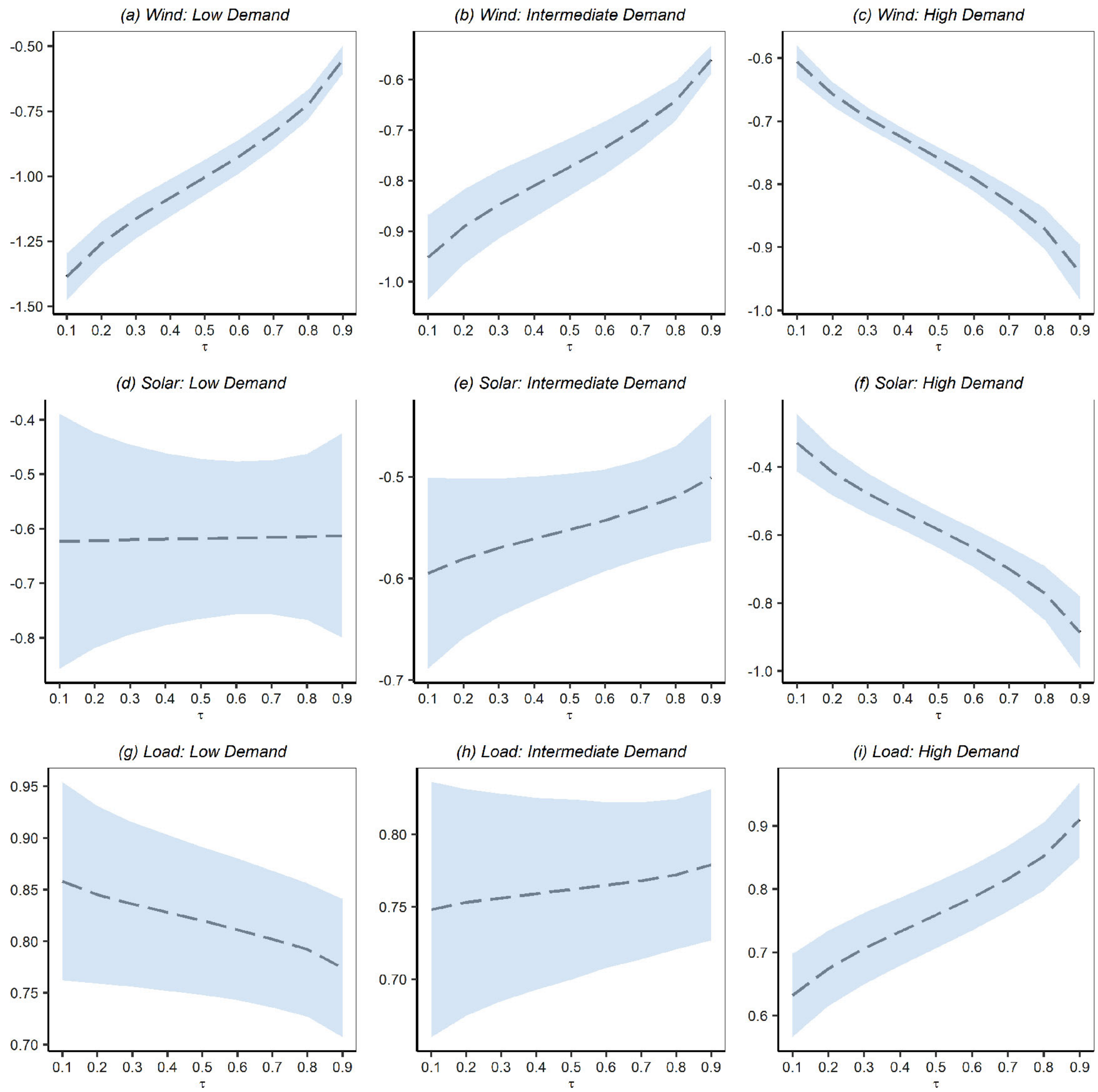

Figure D.4. Conditional on demand estimates-model 2 in Germany. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

E Appendix

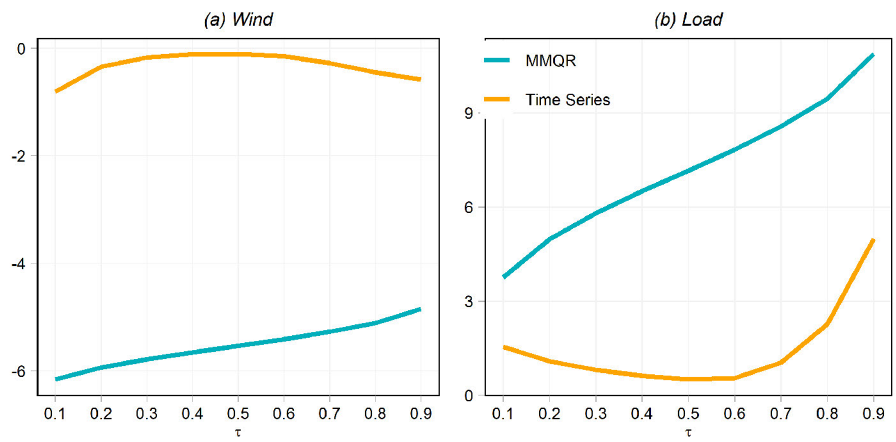

Figure E.1. Model 1 estimates in Denmark using the hourly data in a time-series setting. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

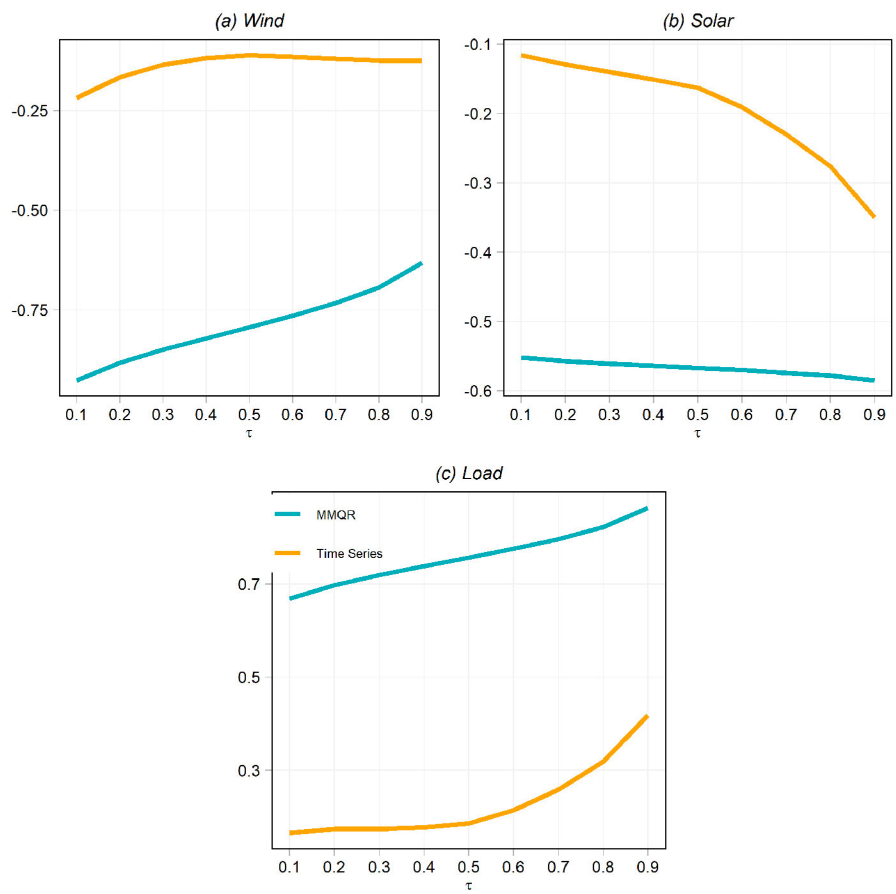

Figure E.2. Model 1 estimates in Germany using the hourly data in a time-series setting. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

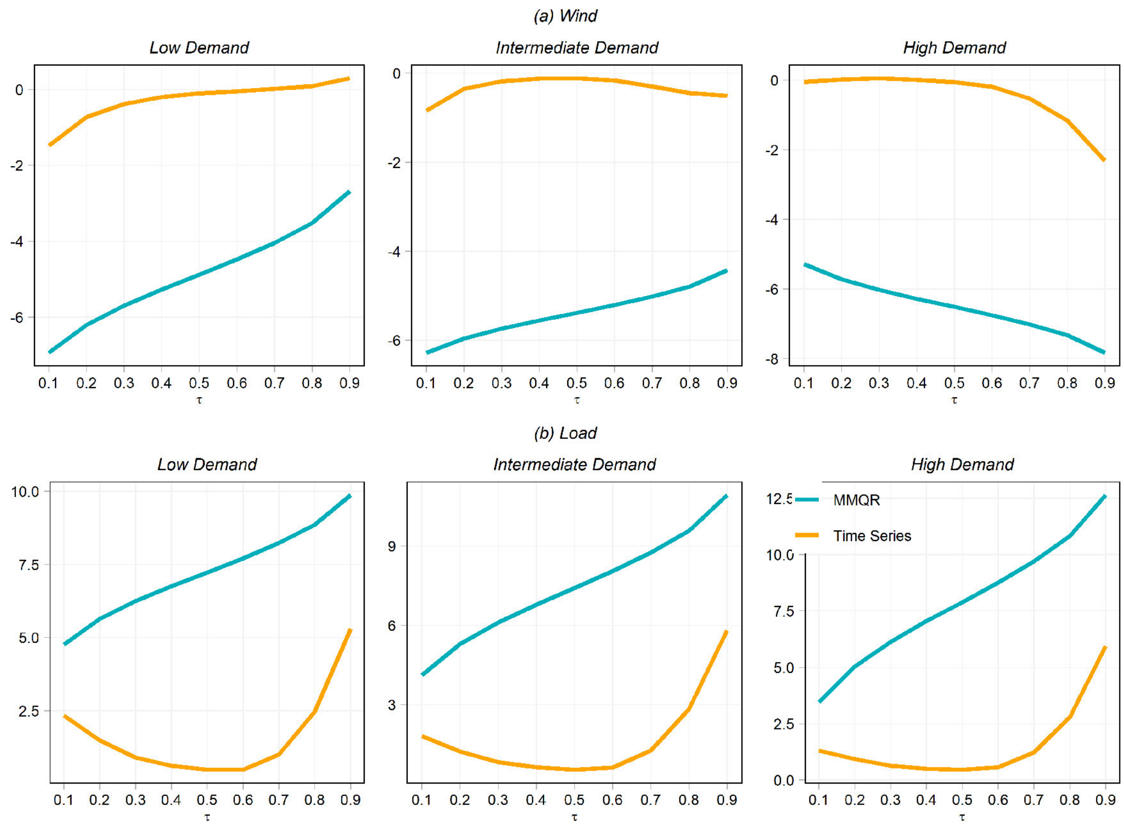

Figure E.3. Model 2 estimates in Denmark using the hourly data in a time-series setting. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

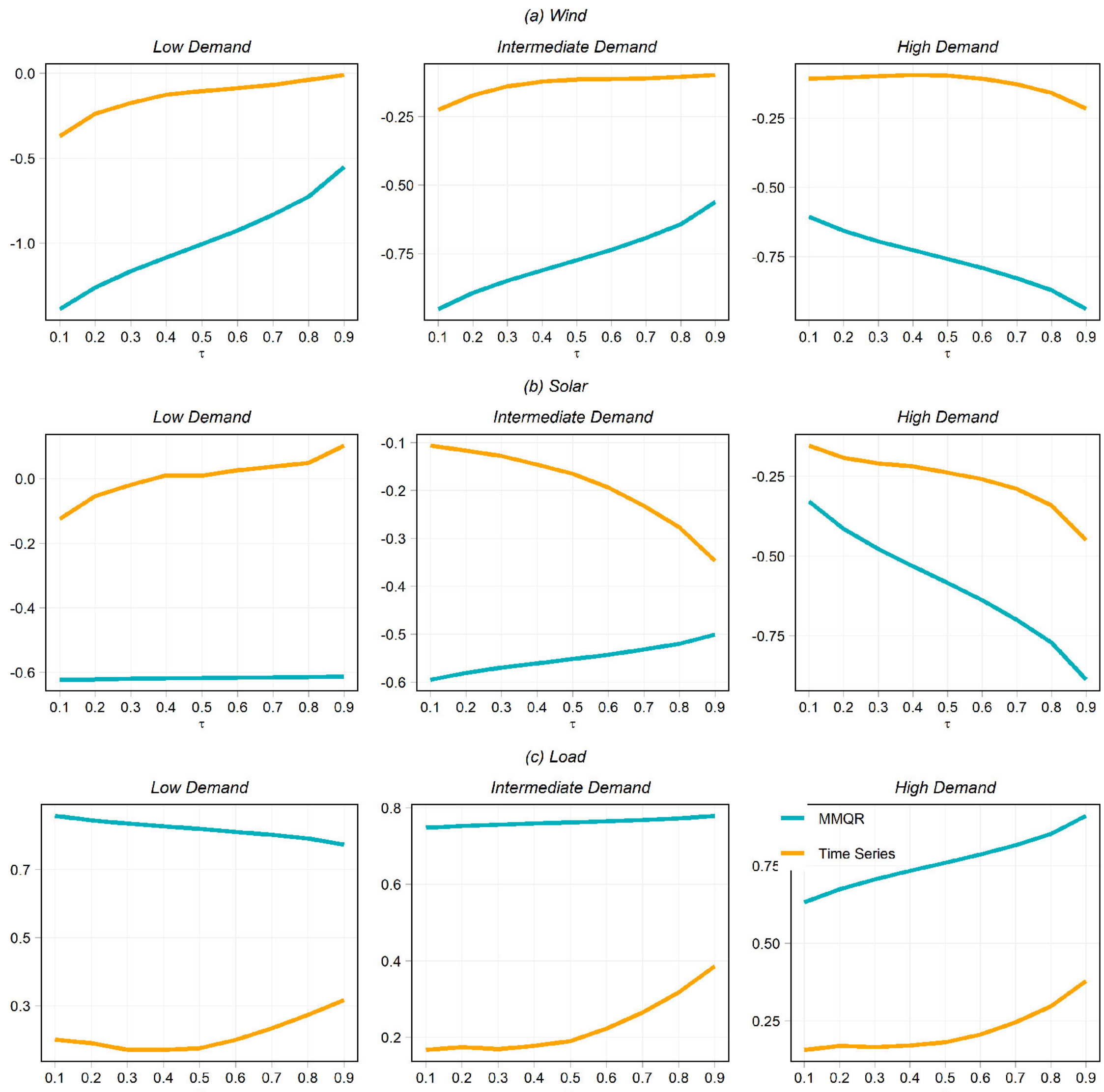

Figure E.4. Model 2 estimates in Germany using the hourly data in a time-series setting. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

F Appendix

Table F1. Model 2 estimates with different demand thresholds.

τ	Denmark						Germany								
	Wind			Load			Wind			Solar			Load		
	$\beta^W_{1,L}$	$\beta^W_{2,M}$	$\beta^W_{3,H}$	$\beta^L_{1,L}$	$\beta^L_{2,M}$	$\beta^L_{3,H}$	$\beta^W_{1,L}$	$\beta^W_{2,M}$	$\beta^W_{3,H}$	$\beta^S_{1,L}$	$\beta^S_{2,M}$	$\beta^S_{3,H}$	$\beta^L_{1,L}$	$\beta^L_{2,M}$	$\beta^L_{3,H}$
0.1	-7.014***	-6.350***	-5.184***	4.779***	4.169***	3.420***	-1.334***	-0.958***	-0.605***	-0.850***	-0.620***	-0.286***	0.869***	0.761***	0.639***
	(0.177)	(0.140)	(0.222)	(0.419)	(0.359)	(0.346)	(0.057)	(0.051)	(0.014)	(0.107)	(0.056)	(0.043)	(0.042)	(0.04)	(0.029)
0.2	-6.287***	-6.003***	-5.592***	5.612***	5.270***	4.948***	-1.214***	-0.895***	-0.650***	-0.789***	-0.601***	-0.366***	0.860***	0.768***	0.682***
	(0.157)	(0.120)	(0.232)	(0.380)	(0.336)	(0.340)	(0.051)	(0.044)	(0.011)	(0.083)	(0.047)	(0.035)	(0.039)	(0.037)	(0.028)
0.3	-5.781***	-5.762***	-5.875***	6.192***	6.035***	6.011***	-1.126***	-0.849***	-0.683***	-0.745***	-0.587***	-0.426***	0.854***	0.773***	0.713***
	(0.146)	(0.112)	(0.240)	(0.384)	(0.345)	(0.359)	(0.046)	(0.04)	(0.009)	(0.068)	(0.041)	(0.03)	(0.037)	(0.034)	(0.027)
0.4	-5.359***	-5.561***	-6.112***	6.675***	6.673***	6.897***	-1.051***	-0.809***	-0.711***	-0.707***	-0.576***	-0.476***	0.849***	0.777***	0.739***
	(0.136)	(0.109)	(0.247)	(0.408)	(0.369)	(0.386)	(0.042)	(0.037)	(0.009)	(0.057)	(0.036)	(0.026)	(0.036)	(0.033)	(0.027)
0.5	-4.968***	-5.375***	-6.331***	7.123***	7.264***	7.717***	-0.979***	-0.771***	-0.738***	-0.670***	-0.565***	-0.524***	0.844***	0.781***	0.765***
	(0.129)	(0.112)	(0.253)	(0.443)	(0.401)	(0.421)	(0.038)	(0.033)	(0.009)	(0.048)	(0.031)	(0.024)	(0.036)	(0.032)	(0.027)
0.6	-4.569***	-5.184***	-6.554***	7.580***	7.869***	8.557***	-0.904***	-0.732***	-0.766***	-0.632***	-0.553***	-0.574***	0.838***	0.786***	0.791***
	(0.124)	(0.119)	(0.261)	(0.491)	(0.444)	(0.466)	(0.035)	(0.03)	(0.009)	(0.044)	(0.028)	(0.024)	(0.035)	(0.031)	(0.027)
0.7	-4.133***	-4.977***	-6.798***	8.079***	8.527***	9.471***	-0.819***	-0.688***	-0.798***	-0.589***	-0.540***	-0.631***	0.832***	0.790***	0.821***
	(0.121)	(0.129)	(0.271)	(0.555)	(0.501)	(0.524)	(0.032)	(0.026)	(0.011)	(0.046)	(0.025)	(0.026)	(0.036)	(0.03)	(0.028)
0.8	-3.616***	-4.730***	-7.088***	8.672***	9.310***	10.558***	-0.719***	-0.636***	-0.835***	-0.538***	-0.525***	-0.698***	0.825***	0.796***	0.857***
	(0.119)	(0.146)	(0.283)	(0.634)	(0.569)	(0.591)	(0.029)	(0.022)	(0.013)	(0.056)	(0.024)	(0.031)	(0.037)	(0.031)	(0.03)
0.9	-2.783***	-4.334***	-7.554***	9.626***	10.569***	12.306***	-0.560***	-0.552***	-0.895***	-0.457***	-0.500***	-0.805***	0.814***	0.806***	0.913***
	(0.127)	(0.179)	(0.303)	(0.774)	(0.688)	(0.708)	(0.026)	(0.016)	(0.018)	(0.083)	(0.028)	(0.041)	(0.04)	(0.033)	(0.034)
Obs	51,696	51,696	51,696	51,696	51,696	51,696	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

The cannibalization effect of intermittent renewables: The case of wind and solar power in Germany

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Abstract

Over the past few decades, European states have applied various measures to expand the role of renewable energy in electricity generation. With the existing energy crisis, renewable energy sources are crucial to sustain a reliable energy system while reaching the EU sustainability goals. In this article, we explore the cannibalization and cross-cannibalization effect of renewable energy sources. The cannibalization (cross-cannibalization) effect describes how an increase in wind or solar power reduces its own (or each other's) unit revenues or market value in the electricity market. First, we construct two daily indices that present measures of the unit revenues and market value of wind and solar power. Subsequently, we employ a quantile regression model to analyze the cannibalization and cross-cannibalization effects at different levels of unit revenues and market values, while considering extreme market conditions. The results suggest that both wind and solar exhibit cannibalization and cross-cannibalization in certain parts of their distribution, predominantly in lower quantiles where the market values of wind and solar are low. We also find that cannibalization is more pronounced for higher levels of wind and solar penetration, and consumption. Additionally, we observe that solar power can raise the market value of wind in some cases, particularly for upper wind value quantiles, highlighting a complementary relationship between the two sources. To ensure the economic sustainability of renewable energy in electricity markets, governments should consider the cannibalization and cross-cannibalization impacts in policy-making regarding renewable energy. Market participants can also make better-informed investment plans and decisions by identifying cannibalization and assessing its impact on profitability and risk.

JEL Classification: C21, C22, C52, C58, Q21

Keywords: Variable renewable sources, Unit revenues, Value Factor, Quantile regression

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1 Introduction

Renewable Energy Sources (RES) are viewed as a sustainable alternative to conventional energy production technologies, and have been promoted by various institutions and governments that set specific climate ambitions (EU Renewable Energy Directives). In order to attract investors and expand renewable energy capacity, governments have offered support to renewable producers in various forms. Nowadays, many governments aspire to liberalize the European RES market and reduce the subsidies provided to renewable energy plants. This raises the question of the economic sustainability of these technologies without state intervention, and consequentially, the ability of such technologies to attract private investment.

Renewable energy is characterized by high sunk costs for infrastructure but almost zero marginal production costs. The levelized cost of energy (LCOE) has been declining[1]; nevertheless, the nature of RES and their low marginal costs can still result in risk regarding their short-term profitability. When a new low marginal cost technology producer enters the electricity market, the aggregate supply curve shifts to the right. The increase in aggregate supply will push the residual load curve to move to the left, reducing the electricity price (Fischer et al., 2006). The merit-order effect, as this phenomenon is called, has been empirically documented across both European markets, such as Germany (Tveten et al., 2013; Cludius et al., 2014) and Italy (Clò and D'Adamo, 2015), and non-European markets, such as the U.S. (Woo et al., 2016, for Texas; Prol et al., 2020, for California). This effect, based on the behavior of demand and supply, stems from the nature of RES production and distribution technologies. Additionally, the measures that are available to assess RES efficiency are neither consistent nor accurate. For instance, the levelized cost of energy, which has been used as an indicator of cost efficiency – and therefore a measure comparable to wholesale energy prices for investors - is not necessarily an apt metric as it completely excludes variability, especially for prices (Nissen and Harfst, 2019).

In this article, we estimate the absolute and relative cannibalization effect for wind and solar power in the German wholesale electricity market[2]. Essentially, the cannibalization effect occurs when the revenue and value of a specific renewable energy technology (in our case wind and solar) or other renewable energy technologies decline due to increased penetration of that renewable power technology. Cannibalization is then a parameter that, if present, can affect both the profitability and the risk for RES investors. Investigating the existence and structure of cannibalization is an essential task. It is important not only to examine the existence and

[1]Declining cost of energy for renewable energy means that the cost of electricity produced by renewable generators decrease throughout the lifetime of renewable energy plants.

[2]Absolute cannibalization represents the decline of unit revenues when renewable energy penetration increases while relative cannibalization represents the decline of value factors as penetration increases.

extent of cannibalization, but additionally link this effect to other market parameters that may influence its intensity. Given the environmental dangers of carbon intensive fuels, it is critical that alternative and sustainable sources of energy exist. If cannibalization leads to a decrease in investment in RES, or similar technologies, then we should account for that into state policies and budgets.

First, we construct two daily indices that serve as the unit revenue and value factor[3] of renewable energy sources. Then, we perform a quantile regression to investigate the entire distribution of our indices and explore if the cannibalization and cross-cannibalization [4] effect influence the economic sustainability of renewable energy under specific market conditions. The quantile approach allows us to link the share of renewable energy in the market with the shape of the unit revenue and value factor distribution. According to Davino et al. (2013), the quantile regression does not assume a distributional form of the error term, and allows the incorporation of non-linear relationships among variables in the model. Thus, we extend our model to include non-linearities with a specific emphasis on varying levels of renewable penetration and electricity consumption. Our objective is to investigate whether cannibalization and cross-cannibalization are linked with certain market conditions.

As climate change becomes an imminent challenge, governments and institutions attempt to use alternative, lower emission technologies. Renewable energy technologies present a viable alternative to traditional carbon-related energy production methods and are, thus, promoted as such by governments. In the case of Germany, subsidies to RES investors are introduced via a market incentives program. The success of the green transition is at least partially related to these benefits for RES investors. Thus, if the German government's plan to stop or reduce these subsidies were to be implemented, what would be the consequences? A reduction in state subsidies have been shown to have a negative effect on RES generation, at least in the short run (see Zhang et al., 2021, for the case of photovoltaic production in China). Hence, the "self-sustainability" of renewable energy technologies becomes a crucial consideration, as states seek their further expansion in electricity markets without governmental support, but also meet the goals of the Paris agreement.

Are RES technologies a viable investment without state subsidies? A similar question has been raised concerning district heating, that is also considered a viable way to reduce emissions. Liu et al. (2019) show that due to low marginal production costs and the link between pricing and these costs, district heating is not profitable for investors without state intervention. This

[3]The terms "value factor" and "market value" are being used interchangeably in this paper.

[4]The decline of the unit revenue or value factor of a renewable source due to the increase of the penetration of another renewable energy source in the market.

becomes clear when we investigate evidence about the impact the merit-order effect has on the marketability of alternative electricity sources in liberalized markets (Zipp, 2017).

This paper contributes to the literature in various aspects. Firstly, we use a quantile regression to explore different parts of the unit revenue and market value distributions. This method allows us to understand the cannibalization and cross-cannibalization effect in more detail. Previous studies have only focused on the average effect – the conditional mean of the distribution. Our approach allows us to investigate the intensity of the cannibalization effect on different parts of the distribution and evaluate if it could induce higher uncertainty in the German market. Secondly, we check for non-linearities by including different consumption and renewable energy penetration levels. Thus, we can evaluate the cannibalization impact across renewable penetration and demand ranges, information that could influence the viability of expanding wind and solar power in the German market. For instance, our research approach allows us to focus on the cannibalization effect on higher levels of RES penetration, shedding light on whether further expansion of wind and solar could jeopardize their economic sustainability.

2 The nature of RES and the German market

RES bare several characteristics that affect both their production and distribution. Renewable generation illustrates high variability between months, days and even hours, and their distribution can challenge the electricity grid creating, for instance, congestion. In addition, the geographical separation of Germany's electricity grid and the region-specific characteristics of renewable energy production within Germany are essential variables for this study.

Firstly, as we already mentioned above, renewable energy generators face low marginal costs, while the sunk and fixed costs are quite high (Heal, 2009). This translates in a large initial investment with declining prices for potential producers. Furthermore, a subsidy or another form of state support is unavoidable – at least during the plant establishment phase – as RES technologies have, for the time being, higher sunk costs and not fully internalised external costs, in comparison to conventional plants (Lehmann and Gawel, 2013). This probably explains the strategic choice of the German state to set in place Feed-in electricity tariffs (FiTs) that encourage the investment in RES by increasing the remuneration above the wholesale price. Additionally, electricity production by renewable sources is strongly connected to the natural resource that energy is drawn from (wind, sun, etc.), and the geographic characteristics that are necessary for the availability of the resource. For instance, it would be impossible to produce electricity by photovoltaic systems (PV) during the night hours or produce hydroelectric energy when hydropower dams are not possible to be established due to the topography of a region (for instance, Denmark)(Leijon et al., 2010; Zipp, 2017). On the other side of the spectrum, conventional plants, whose production is based mostly on fuels such as coal, oil or natural gas, face a completely different cost structure. Conventional technologies do not deal with the same high fixed and entry costs but face high and often - after a certain production level- increasing marginal costs. In addition, conventional plants do not encounter the same issues regarding time (day and period of the year seasonality) as their primary material is fuels whose availability is less time and location dependent. RES production is, thus, more variable and uncertain, as the type of technology often would not allow the supply to meet the demand at all hours and periods (Ambec and Crampes, 2012).

Germany is one of the largest RES markets in Europe and the authorities aim to increase the participation of RES in total electricity production significantly to meet the EU energy transition goals. Additionally, there is extensive literature about electricity prices, risk and RES regarding the German market (Kyritsis et al., 2017; Zipp, 2017, Tselika, 2022 to name a few). This vast pool of information facilitates comparisons and inference regarding the results of this paper. Moreover Germany, through its legislation allowed and promoted the renewable energy technologies to expand (German Renewable Energy Act). This regulatory framework is under constant revision in order to adapt to technological, economic and social changes. Some important variables considered are the stability of electricity prices on the consumer level and competition between RES producers which promotes innovation and cost efficiency (IEA, 2020). Given that the energy transition goal is set to 65% of electricity sources originating by renewable technologies by 2030, it is important to look at distinct characteristics of the German market and the risks that may deter potential renewable energy investors. The German energy action plan has been modified twice since its introduction to accommodate RES inclusion, reduce financial pressure to final consumers, promote competition, and eventually, improve cost efficiency in the market.

Renewable energy technologies can be characterized as profit-motivated, which means that their response depends on financial incentives (Steffen, 2020). Thus, renewable energy investors consider risk-return ratios to evaluate long-term investments. The merit-order effect discussed above is present in the German market with significant distributional effects and an important added risk due to price variability (Zipp, 2017; Tselika, 2022). Furthermore, the German market is organized in a bidding zone that operates under a common price but faces many grid disruptions. Given the issues occurring with transmission and the production specific mechanisms – solar energy being dominant in the south while wind power being stronger in the North (Paraschiv et al., 2014)- several issues with congestion arise (Trepper et al., 2015).

Germany is an example of a decentralized energy market, with strong investor incentives, due to political consensus regarding RES, that has served as a model for many markets that wish to transition to more environmentally sustainable energy sources (Hinrichs-Rahlwes, 2013).

In addition to the above, the standard LCOE that has been used by the German authorities in order to determine the level of the FiTs, does not account for risks that originate from price variability, cost of storage, transmission constraints and contractual limitations - maximum or minimum quantities in power purchase agreements (Bruck et al., 2018; Nissen and Harfst, 2019; Maciejowska, 2020). The above adds to the risk created by the cannibalization effect of both revenues and value in RES for existing and future investors. Lastly, the German authorities aim to limit the use of FiTs which have been criticized extensively as they are related to a rise in electricity prices for consumers (social effect) (Frondel et al., 2015). If cannibalization in RES revenue and market value is unavoidable under the current technological constraints, then unsubsidized renewable energy, which is proposed as a viable solution by the existing consensus (see Mahalingam et al., 2014) should be re-examined. Therefore, these characteristics lead us to explore the German market as an attractive case of possible cannibalization and cross-cannibalization, and significant policy implications for electricity producers and consumers.

3 Data and Descriptive Statistics

3.1 Variables

We use hourly data from the German wholesale electricity market for the period January 1, 2017 to July 31, 2021. Specifically, we use day-ahead electricity prices (€/MWh), forecasted wind and solar power (GWh), and net imports (MWh). All the data were obtained by the ENTSO Transparency Platform (`https://transparency.entsoe.eu/`).

We follow Jónsson et al. (2010), Kyritsis et al. (2017), Rintamäki et al. (2017) and Prol et al. (2020) and calculate the share of wind, solar and imports in the electricity market as the ratio of the sum of the hourly forecasted solar generation, wind generation and net imports (W, S, I) divided by the sum of the hourly forecasted consumption(d_h):

$$SH_t^{\{S,W,I\}} = \frac{\sum_{h=1}^{24} q_h^{\{S,W,I\}}}{\sum_{h=1}^{24} d_h} \tag{1}$$

We will use these variables in our models to investigate the effect of wind and solar energy on their own and each other's revenues and market values.

3.2 Unit Revenue and Value Factor

In this study, we will examine the cannibalization effect through the unit revenue and value factor for solar and wind power. This way we can investigate the extent of cannibalization per unit of production but also on an aggregate technology level, scaled by the daily average electricity price, which accounts for general market conditions. Two separate indices are constructed for each production technology as in Clò and D'Adamo (2015) and Prol et al. (2020). Unit revenues ($UR_t^{\{S,W\}}$) are defined as the solar or wind ($\{S,W\}$) production-weighted electricity prices, as shown in eq. 2. Thus, the unit revenue represents the average price attained by wind and solar over a 24-hour period.

$$UR_t^{\{S,W\}} = \frac{\sum_{h=1}^{24} p_h q_h^{\{S,W\}}}{\sum_{h=1}^{24} q_h^{\{S,W\}}} \tag{2}$$

where $UR_t^{\{S,W\}}$is the daily unit revenues for wind (W) or solar (S) in €/MWh; p_h is the hourly day-ahead electricity price in €/MWh, and $q_h^{S,W}$ is the hourly forecasted generation of wind or solar in GWh.

Then, we calculate the Value Factor index (in %, see eq. 3.) by dividing the daily unit revenues by the average daily price ($\overline{p_t}$). This index represents the market value of wind and solar and captures the effect of the market by comparing the price achieved by renewable producers relative to the average price across all producers. Additionally, it bares the advantage of being a net ratio, which means that it is independent of the unit of measurement for revenue.

$$VF_t^{\{S,W\}} = \frac{UR_t^{\{S,W\}}}{\overline{p_t}} = \frac{\sum_{h=1}^{24} p_h q_h^{\{S,W\}} / \sum_{h=1}^{24} q_h^{\{S,W\}}}{\sum_{h=1}^{24} p_h / 24} \tag{3}$$

3.3 Trends

Before moving into the description of the indices described above, it is important to examine the evolution of renewable energy supply which depends heavily on physical restrictions. We will also explore the electricity prices development, delving into the electricity market and its unique characteristics. Figure 1 describes, for each month and year, the hourly average generation (for each 24-hour segment), in Germany for both wind and solar. Linked to hours of sunlight, solar generation is concentrated around noon hours, and is stronger between March and September. Wind has a more consistent generation over the 24 hours of a day, while over the seasons wind is stronger in winter. Wind generation is relatively stable, with the exception of February 2020, when higher wind levels were observed. It is important to note that in addition to the unique features of renewable energy sources that impact the market value of wind and solar, the structure of the German market can also have an impact on the economic sustainability of renewable energy. Germany has a distinct distribution of renewable energy production, with the northern region being recognized for its substantial wind power generation, and the southern region known for its significant solar power generation (Paraschiv et al., 2014). Therefore, we expect the electricity generation process that is strongly dependent on geographical attributes, transmission constraints and scarce energy storage possibilities to impact the economic development of renewable energy.

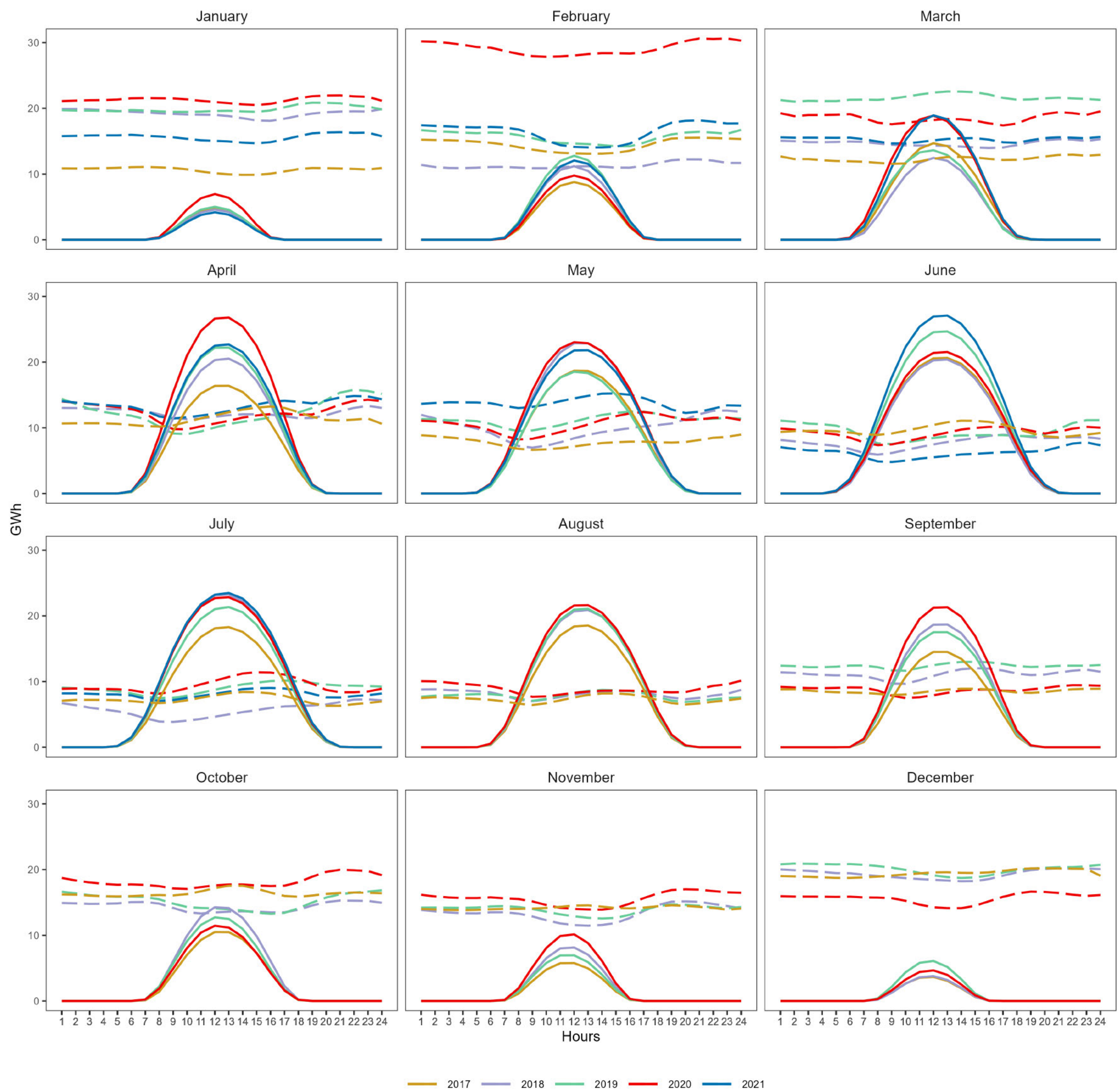

Figure 1. Per hour per month renewable generation.

Apart from the generation part of RES, electricity prices are another component that influence revenues for market participants. Since RES is a considerable portion of electricity generation in Germany (more that 40% in 2021), where conventional generation also plays a significant role, we expect prices to reflect this interdependence. Figure 2 displays the hourly average electricity prices per month. Hourly average prices mirror the demand, as during the day and productive hours electricity prices are higher on average. While the overall shape of the price curves remains consistent from year to year, the actual price levels do fluctuate. The curves are indicative of what the literature predicts in terms of shape. It is important to highlight that the intensity of the intraday variability of electricity prices follows a seasonal pattern. Figure 2 illustrates this pattern, showing that from March to September, we observe higher price peaks and greater intraday variability. In contrast, the curves appear smoother during the other months.

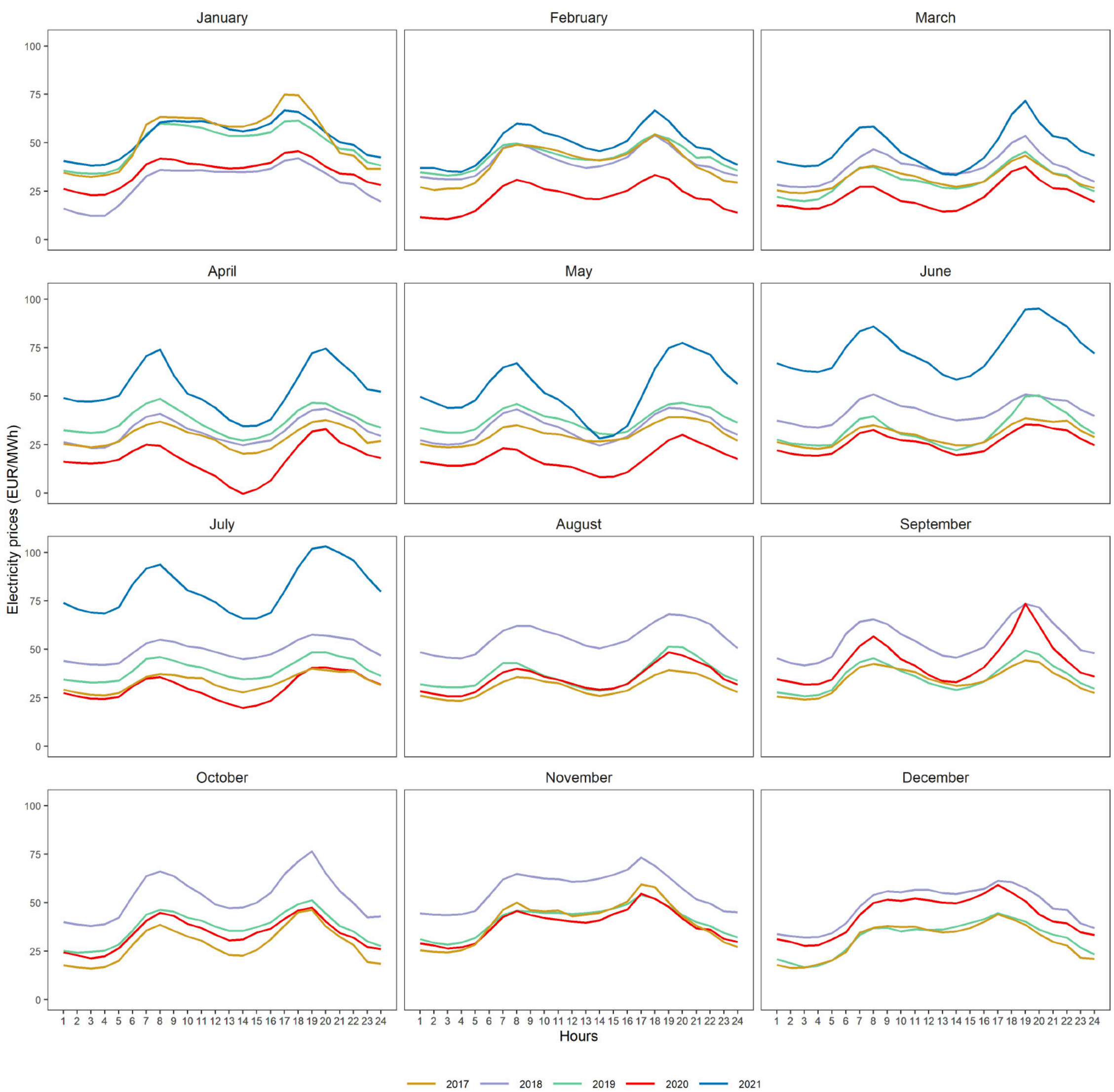

Figure 2. Per hour per month electricity prices.

After examining the generation and prices, we now explore the indices that can capture the cannibalization effect, the unit revenue and value factor indices. Figure 3 depicts the distributions of wind and solar unit revenues and value factors. The figure reveals that both unit revenues and value factors are characterized by extreme observations, reflecting a higher number of outliers (the distributions are leptokurtic). Therefore, the revenue generating process leads to exceptionally low and high observations, which can be attributed to periods of low renewable energy supply or high prices. Additionally, an asymmetric concentration on the left tail of the distribution suggests disproportionally negative extreme observations compared to positive. The type of technology and the structural features of the supply-demand price determination are related to the distribution of unit revenues. Similarly, the value factor distribution shows higher levels of leptokurtosis and extreme outliers. It is noteworthy that while wind and solar power have similar expected unit revenues, their respective market values exhibit noticeable differences in the scale.

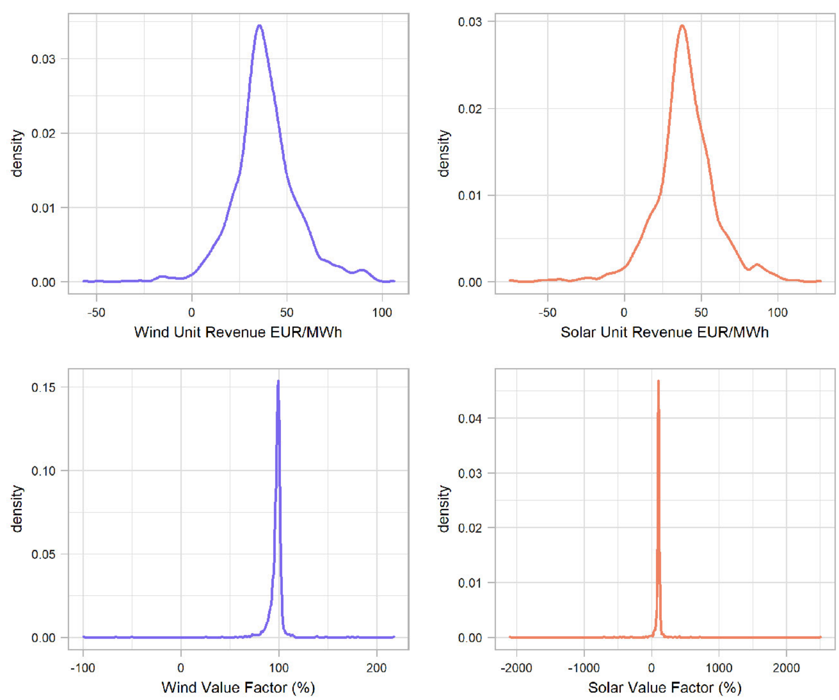

Figure 3. The distribution of unit revenues and value factor for wind and solar.

Focusing on the unit revenues, as displayed in Figure 4, we can notice that the revenues increase from 2018 to 2019 but then decline until the middle of 2020. Afterwards, they have been following a steady positive pattern until mid-2021 possibly due to higher electricity demand after the pandemic. When we examine the value factors, wind power shows a more stable value while solar power exhibits a seasonal pattern with extreme low values, especially, from the middle of 2019. Exploring the summary statistics of our indices (see Appendix A), we observe that the unit revenues decrease for both renewable sources until 2021 and then start to increase. Moreover, the solar value factor is 104.2% and 100.7% for 2017 and 2018, respectively. That means that during these years solar earned 4.2% and 0.7% more than the average unit of traded electricity in the market. After 2019, the solar value factor was below 100%. In contrast, wind's value factor remained below 100% for the entire investigated period ranging from 96.6% to 97.4%.

It is important to underline in this section our interest in the differences between wind and solar. A good example concerning the market value, is the stable trend of the wind value factor which can lead to wind earning prices lower than the average daily price (see fig. 4, panel B). For instance, wind power producers may opt to sell their electricity even during periods of low prices because their production is reliant on wind, a natural source. Upon examining the value factor for solar, it becomes apparent that it often earns prices above the daily average, potentially because of better coincidence with demand. We also observe that wind and solar show different seasonal patterns with wind producing at higher levels during winter and solar generation peaking in the summer. Additionally, we notice that as solar production increases at noon, electricity prices drop, while the hours that solar is scarce, prices spike. Overall, the descriptive analysis implies that as renewable penetration increases over the years, the value factor of renewable sources may decrease.

Before proceeding with the empirical analysis, we tested the data for the presence of a unit root by performing the Dickey-Fuller (ADF) and Phillips-Perron (PP) test (see Appendix B). The number of lags were chosen by the AIC and Schwarz's BIC information criteria. In both cases, we manage to reject the null hypothesis of a unit root for all the variables in our model.

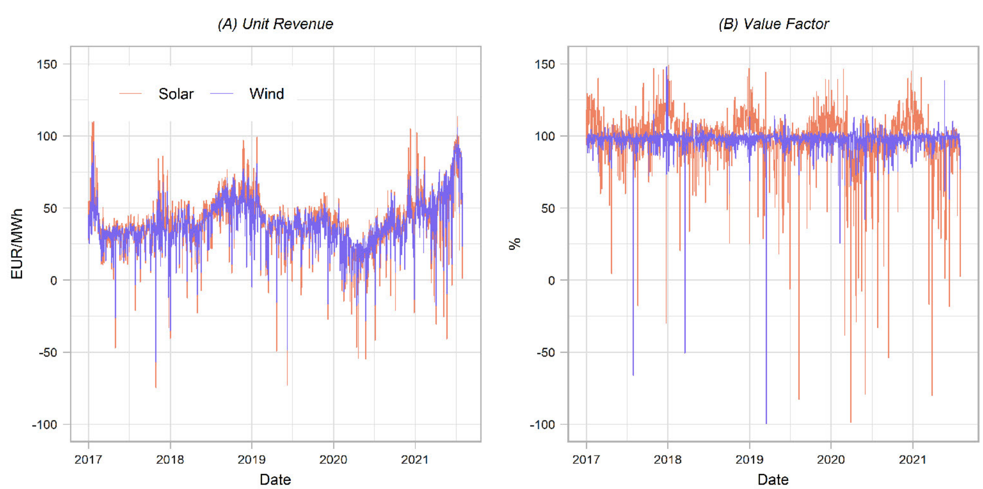

Figure 4. Daily wind and solar unit revenues and value factors.

4 Quantile regression model

Our methodology consists of two parts that attempt to examine the cannibalization effect from two different perspectives. First, we formulate a linear quantile regression model that links the

τ quantile of wind and solar unit revenues and market values with their respective production in the electricity market. This model allows us to assess whether there is cannibalization and cross-cannibalization of renewable energy in the market and to make arguments about the future economic self-sustainability of wind and solar. In the second step, we focus on only the value factors and apply three non-linear quantile regression models that account for different levels of electricity consumption, as well as wind and solar penetration. We employ quantile regressions to capture the distributional effects on the wind and solar unit revenues and value factors. This approach enables us to investigate the effects of cannibalization and cross-cannibalization while considering the extreme ends of the unit revenue and value factor distributions.

4.1 The Baseline Model

At first, we investigate how different variables impact the revenue generated by solar or wind energy. The baseline model explores the existence of absolute and relative cannibalization between the two examined renewable technologies. We apply four linear quantile regressions (Koenker and Bassett Jr, 1978) to link the $\tau = 0.1, ..., 0.9$ quantile of the unit revenues and value factors with a vector of independent variables. These independent variables comprise the wind share (Sh_t^W) and solar share (Sh_t^S), which were define in the previous section, along with the forecasted electricity consumption (L_t). Additionally, we incorporate, as Prol et al. (2020), the net imports share (Sh_t^I) which is defined as the difference between day-ahead imports and exports between Germany and France. The latter serves as the principal interconnector between Germany and another European country. We also include weekend, monthly and yearly effects (C_t) to control for trends and seasonality. The model specification takes the following form:

$$Q(\tau)_t^{S,W} = \alpha_{0,\tau} + \beta_\tau^W Sh_t^W + \beta_\tau^S Sh_t^S + \beta_\tau^L L_t + \beta_\tau^I Sh_t^I + \gamma_\tau' C_t \tag{4}$$

This model allows us to link the quantile τ of the unit revenue or market values of solar/wind, $Q(\tau)_t^{S,W}$, with the chosen independent variables. In this paper, we perform two different applications of this model. Firstly, we examine the unit revenue as the dependent variable. Secondly, we apply the same regression for the value factor of each technology. In this way, we can investigate both the absolute and relative cannibalization in the electricity market. By employing a quantile approach, we measure the effects of renewable sources not only on the average cannibalization, but also across the quantiles of the unit revenues and value factors.

4.2 Non-Linear Model

Electricity consumption and the market penetration of wind and solar are crucial factors that can impact the revenue and value of renewable energy sources, and ultimately determine the economic sustainability of these technologies. Hence, we expand the linear baseline model to account for these potential non-linear effects. To accommodate various consumption levels and solar/wind penetration levels, we construct three different models. To simplify matters, we will present a general model and elucidate the selected variables for all three models.

We consider three levels of consumption and solar/wind penetration levels (low, intermediate, and high) which are represented by the following indicator variables, $Z_{1,t} = 1_{V_t \leq V(\tau_L)}$, $Z_{2,t} = 1_{V(\tau_L)<V_t<V(\tau_H)}$, $Z_{3,t} = 1_{V_t \geq V(\tau_H)}$. The indicator variables are derived by the unconditional quantile of each of the consumption, solar or wind share distribution. The thresholds are initially set to $\tau = 0.2$ and $\tau = 0.8$, but we use different thresholds for the robustness checks to validate our results (see Tables C3, C4, C5 in Appendix C). These thresholds were chosen to ensure a sufficient number of observations for the estimation, but also allow us to investigate extreme cases of renewable penetration and demand levels. Therefore, $Z_{1,t} = 1$ implies that the consumption (or solar or wind, depending on the model) is below its 0.2 quantile while $Z_{3,t} = 1$ refers to its 0.8 quantile. These indicator variables interact with the independent variables in our models developing a measure of the non-linear effects between electricity market determinants.

The following quantile regression is used to investigate the relationship between wind and solar generation and their value factors.

$$Q(\tau)_t^{S,W} = \alpha_{0,\tau} + \sum_{j=1}^{3} \beta_{j,\tau}^{W} Sh_{j,t}^{W} + \sum_{j=1}^{3} \beta_{j,\tau}^{S} Sh_{j,t}^{S} + \sum_{j=1}^{3} \beta_{j,\tau}^{L} L_{j,t} + \sum_{j=1}^{3} \beta_{j,\tau}^{I} Sh_{j,t}^{I} + \gamma_\tau' C_t \tag{5}$$

where $Sh_{j,t}^{W} = Z_{j,t} Sh_t^{W}$, $Sh_{j,t}^{S} = Z_{j,t} Sh_t^{S}$, $L_{j,t} = Z_{j,t} L_t$ and $Sh_{j,t}^{I} = Z_{j,t} Sh_t^{I}$.

We computed the standard errors by using the bootstrap method to treat possible serial correlation in our series (Angrist and Pischke, 2009). We also tested the equality of the estimates for different quantiles which can be found in Appendix F, tables F1, F2, and F3. The results indicate varying slopes among the quantile estimates, especially at the extremes of the wind and solar value distribution, which aligns with our chosen methodology.

I have conducted equality tests among the quantile estimates, and the results indicate varying slopes, particularly at the extremes of the wind and solar value distribution. These findings align with our chosen methodology.

The non-linear models, can provide rich information on the market structure, as well as the future economic sustainability which is crucial to fully decarbonizing electricity markets. Specifically, we are able to focus on cannibalization for higher levels of RES penetration and assess if further expansion of renewables in the market could affect their development in the power system. Additionally, the results can serve as a reference for economies that attempt to transition to RES technologies and the institutional measures they may consider, as they also focus on lower RES penetration cases. It is equally important to consider that cannibalization could be disproportionate at different consumption levels (Maciejowska, 2020; Prol et al., 2020; Tselika, 2022). The findings could potentially serve as a motivation for policies that attempt to lower electricity demand, as RES economic sustainability may relate to these levels. Therefore, it becomes imperative to consider the non-linear aspect in our model.

After the estimation, we applied some diagnostic tests to verify that our results are robust. Specifically, we plotted the autocorellation function (ACF) of the error terms for most quantiles and we noticed that the residuals stay within the accepted confidence intervals, with very few exceptions in the baseline model. Nevertheless, we estimated alternative models with different specifications regarding the control variables, and concluded that the estimated variables of wind and solar are robust. The results are available in Appendix D.

5 Empirical results

5.1 Baseline Model

5.1.1 Unit Revenues (Absolute Cannibalization)

Figure 5 presents the unit revenue results for solar and wind. Focusing on the solar unit revenues, the negative and significant coefficients for the solar power across all solar unit revenue (UR) quantiles indicate that an increase in solar within the generation mix leads to a decrease in the unit revenues earned by solar producers. The effect becomes more prominent in the lower and upper quantiles of the unit revenue distribution.

The findings are in line with previous research on the merit-order effect and how lower market prices result in reduced revenues for producers. The upfront costs for solar energy producers are high while the marginal production costs are almost zero. Thus, an increase in solar generation can induce a price drop in the market that leads to reduced solar unit revenues. Additionally, solar URs are reduced by an increase in wind share, but the estimated effect is less profound, yet significant. This effect is known as the cross-cannibalization effect.

The results indicate that higher RES share, in general, leads to decreased unit revenues for solar producers. This effect is observed across the entire unit revenue distribution but is stronger in lower and upper quantiles. Therefore, the cannibalization and cross-cannibalization is more pronounced in very low or high solar revenues. There is a high chance that solar producers facing the possibility of lower revenues in electricity markets have less motives to enter the market, thinking purely about revenues.

Regarding the other variables in the model (see the results in Appendix C, Table C1), the net imports share is negatively related to solar unit revenues with the effect being stronger around the centre of the distribution. Our results align with the findings of Prol et al. (2020), who also concluded that the share of net imports has a negative impact on solar unit revenues. In contrast, solar unit revenue is positively linked, as expected, to electricity consumption. Consumption may be seen as an indicator of electricity demand. The merit-order literature (Cludius et al., 2014; Prol et al., 2020) indicates that demand raises electricity prices, which is directly reflected on the technology's unit revenues in our results. The positive effect is stronger in the extreme quantiles of the UR distribution, especially for lower solar unit revenues.

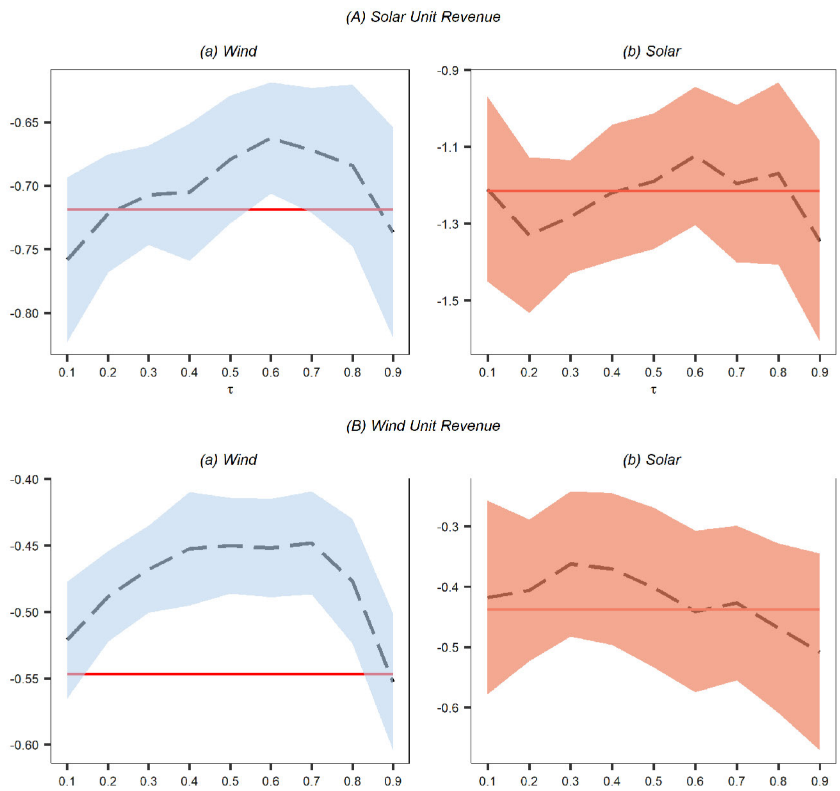

Figure 5. The baseline results for wind and solar unit revenues across different quantiles τ=0.1,...0,9 with 95% confidence intervals. Notes: (i) Panel A demonstrates the effect of (a)wind and (b)solar on the Solar Unit Revenue while panel B shows the effect of (a)wind and (b)solar on Wind Unit Revenue, (ii) The red line represents the OLS estimate, (iii) All the results are significant at 1% level

Shifting the attention to wind unit revenues, the results follow a similar pattern as for the solar UR, but the effects are weaker and seem more stable across the UR distribution, especially in the case of wind share. These results further support the cannibalization and cross-cannibalization of renewable producers' revenues in the German market. Although the coefficients are lower than the solar UR model, they are statistically significant, sealing the qualitative relation of revenue with all the explanatory variables.

5.1.2 Value Factors (Relative Cannibalization)

Figure 6 presents the results regarding the effect of wind and solar on their own and each other's value factors – the relative cannibalization. The results confirm the cannibalization and cross-cannibalization effect, but suggest that these effects appear under specific market conditions.

Specifically, for the solar value factor, we observe that relative cannibalization occurs across the entire distribution spectrum. The strongest negative effect appears in the lower solar market value quantiles. On the other hand, the effect of wind power on the solar value factor yields mixed results. An increase in wind share decreases the solar VF when the market value is low, but increases the solar VF when the market value is high. This can be related to the electricity market structure. In Germany, solar energy production is concentrated in the southern region, whereas wind energy production is primarily in the northern region. Meanwhile, the demand for electricity is mostly centered around the south. Additionally, electricity transmission between the two regions can be challenging due to congested transmission lines. Therefore, when the value of solar is high, an increase of wind in the market does not impact the solar value as it is scaled for the average daily price, which can be mainly set by higher cost technologies such as gas plants. Furthermore, in the descriptive analysis part, we noticed that wind power and prices exhibit a similar pattern of variability, unlike solar energy. This suggests that the impact of value cannibalization, which encompasses the effect of pricing, could be less pronounced for wind power. This could be attributed to the fact that wind generation peaks during the winter season when electricity demand is also at its highest. The relationship between consumption and value seems inconclusive while there are indications of consumption positively relating to the solar value in lower quantiles.

When analyzing the wind value factor, we discover mixed results. Although an increase in wind power reduces the market value of wind, this effect is observed only in cases of low wind value factors. On the other hand, for higher wind values, there seems to be a positive effect between the wind share and the value of wind. Wind is a technology that can generate power round the clock, unlike solar power that cannot produce energy at night. Consequently, wind production can be greater during peak hours/days when the electricity demand is high, which can increase its market value. In situations where solar production is scarce, such as during the evening hours when solar generation decreases but the electricity demand is high, causing electricity prices to spike, the value of wind may increase (see fig. 1 and fig. 2). The positive effect of wind on its own value in upper quantiles is not as statistically strong, as the negative effect in the lower quantiles.

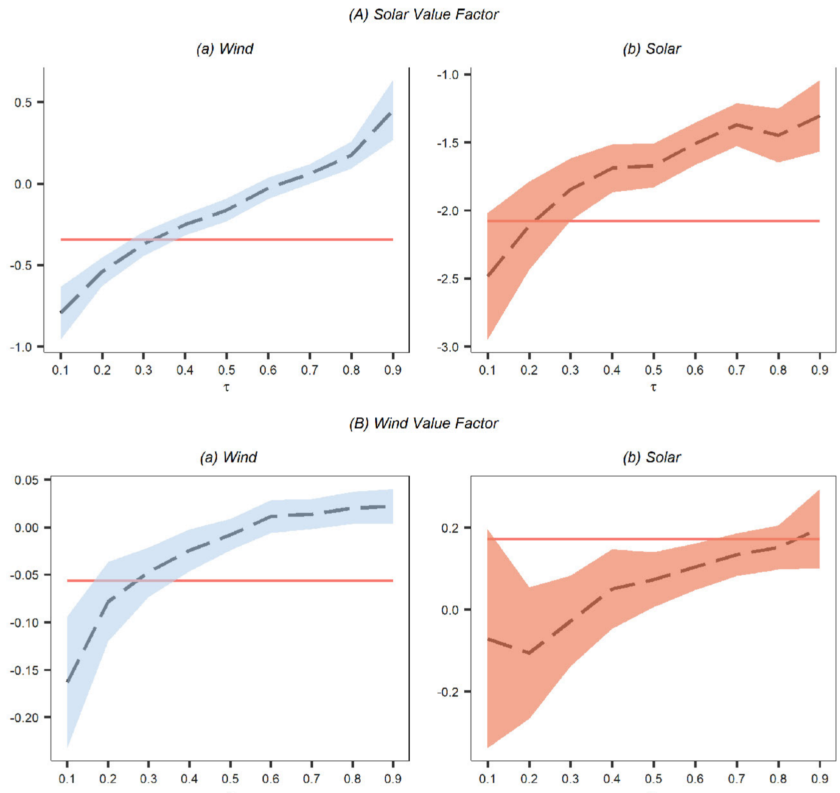

Figure 6. The baseline results for the wind and solar value factor across different quantiles τ=0.1,...0,9 with 95% confidence intervals.Notes: (i) Panel A demonstrates the effect of (a)wind and (b)solar on the Solar Value Factor while panel B shows the effect of (a)wind and (b)solar on Wind Value Factor, (ii) The red line represents the OLS estimate, (iii) The estimates for the Solar Value Factor are significant at 1% level for all quantiles and variables. For Wind Value Factor, the significance of estimates vary, with the results being significant mainly for lower and higher quantiles.

Solar share is negatively associated with the wind VF for low value quantiles, but the only statistically significant results are found in intermediate-upper value quantiles (τ =0.5 to 0.9), where solar increases the wind value in the market. This could be a result of the varying production restrictions faced by these two technologies due to their distinct nature. Additionally, intraday price structure (Tselika, 2022) may have an impact on the findings since the value factor relies on the average aggregated electricity price, that stems from hourly electricity prices.

If we additionally compare the quantile regression results with that of an OLS regression (the red line in Figure 6), we can observe that by accounting for the distributional effects, we are able to identify the quantiles of the value factors - the lower ones - where the cannibalization is more profound.

Regarding the control variables, both the estimates for consumption and net imports share are, overall, not significant in both models. There are some exceptions in the extremes of the value factor quantiles.

The results indicate that relative cannibalization for both technologies and cross-cannibalization for solar power are prevalent in the lower quantiles of the value factor distribution. This implies that transitioning to decarbonized markets and achieving the EU sustainability goals may prove more challenging, given the potential impact of the cannibalization and cross-cannibalization in electricity markets.

5.2 Non-linear Model

In this section, we will present the results of the second model described in eq. 5. This model allows us to link the value factor quantiles with extreme versus moderate levels of renewable penetration and consumption. Consumption serves as an identifier of the demand, and the structure of our model allows for a more accurate estimation of the complex relationships between our variables.

5.2.1 Solar penetration levels

Table 1 displays the results concerning the solar and wind value factor for different solar penetration levels. Overall, we observe that different quantiles, both for wind and solar value factors, are affected differently by the level of solar penetration. Furthermore, the results highlight a greater sensitivity of solar value to the relative parameters in the models.

Focusing on the solar value factor, we notice that in the lower quantiles of the value factor, and across all three solar penetration levels, an increase in wind and solar power will result in a decrease in the solar market value. This effect is stronger when solar penetration is either low or high in the market. Therefore, in the non-linear scenario, there is evidence of both cannibalization and cross-cannibalization in the market. Additionally, the most significant and profound negative impact on the solar value factor is found when solar penetration is low. This finding could be related to the fact that solar energy is generated only during daylight hours, while electricity demand follows a daily circular pattern. Our findings also reveal that wind power is negatively linked to the solar value factor, but only up to a certain value level, implying that cross-cannibalization tends to diminish for high value levels. For intermediate solar penetration levels, both solar and wind power share a negative relation with solar value.

This effect is stronger for solar, and only present for wind in the lower value quantiles. In summary, the cannibalization and cross-cannibalization effect is apparent for the solar market values in all penetration levels, but it diminishes in intensity as the value rises.

Table 1. The estimates of parameters β_j^W and β_j^S for three solar penetration levels.

τ	Wind			Solar		
	β_1^W	β_2^W	β_3^W	β_1^S	β_2^S	β_3^S
Wind VF						
0.1	-0.059	-0.175***	-0.474***	1.97	-0.143	0.086
0.2	-0.008	-0.089***	-0.275***	1.083	-0.141	0.328*
0.3	-0.014	-0.052***	-0.254***	0.439	-0.062	0.377**
0.4	0.008	-0.022*	-0.132**	0.009	-0.03	0.419***
0.5	0.032**	-0.013	-0.098***	0.136	0.003	0.430***
0.6	0.031***	-0.002	-0.085***	-0.173	0.011	0.542***
0.7	0.026**	0.011	-0.043	-0.064	0.023	0.603***
0.8	0.01	0.011	0.014	-0.114	0.029	0.635***
0.9	0.01	0.007	0.098	-0.004	0.038	0.752***
Solar VF						
0.1	-0.225***	-0.796***	-2.061***	-6.246***	-2.222***	-3.431***
0.2	-0.172**	-0.56***	-1.678***	-6.186***	-1.949***	-2.519***
0.3	-0.056	-0.408***	-1.362***	-5.749***	-1.82***	-2.351***
0.4	0.059	-0.305***	-0.99***	-4.785***	-1.736***	-2.261***
0.5	0.085*	-0.209***	-0.601***	-3.671***	-1.739***	-2.105***
0.6	0.146***	-0.134***	-0.495***	-2.539**	-1.69***	-1.888***
0.7	0.218***	-0.035	-0.312**	-3.269**	-1.648***	-1.695***
0.8	0.361***	0.114**	-0.066	-3.504*	-1.629***	-1.464***
0.9	0.613***	0.342***	0.736	-1.883	-1.702***	-1.242***

Notes: (i) *, ** and ***, respectively denote rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels, (ii) The coefficient β_1^W (β_1^S) represents the impact of wind (solar) at low levels of solar penetration, while β_3^W (β_3^S) refers to the effect of wind (solar) at high levels of solar penetration.

For the wind value factor, the results are less conclusive. For moderate and high levels of solar penetration, wind value cannibalization exists, in the lower and central quantiles of the wind value factor. Particularly, at high levels of solar penetration, the cannibalization effect on the value of wind is the most pronounced. However, significant cross-cannibalization is not observed. On the contrary, higher solar penetration is related to an increase in the value of wind which could be due to the fact that solar generation is higher during the day when demand and prices are higher. Ultimately, solar penetration has a less intense and less conclusive effect on the wind value factor compared to the solar value factor.

5.2.2 Wind penetration levels

Table 2 depicts the results of eq. 5 across different wind penetration levels. Considering the solar value factor, we observe that at low and intermediate wind penetration, solar value relates negatively to both wind and solar generation. Interestingly, our model shows that the strongest estimates for solar power are at high wind penetration levels. Therefore,, at high wind power penetration, solar power cannibalizes substantially its market value, particularly in the lower value quantiles. However, an interesting observation is that wind power has a positive impact on the value factor of solar, bot only in the upper quantiles of the solar value factor. This result may relate to the fact that wind power can be generated during periods of high electricity prices (see figure 1 and 2).

Regarding the wind value factor, we notice that the extent of cannibalization is relatively small and lacks statistical significance. It is only at high levels of wind penetration that solar power appears to have a significant negative effect on the value factor of wind, and it is limited to the low value quantiles. Hence, our results suggest that cross-cannibalization also occurs in this case, affecting the lower end of the value distribution. On the other hand, when wind penetration is intermediate or low, an increase in solar power results in an increase in the value of wind. Focusing on the wind cannibalization aspect, it becomes evident that wind energy experiences a decline in its market value only in low value quantiles and when there is intermediate or high wind penetration. Consequently, cannibalization is implied in cases of low wind value and intermediate to high wind penetration. This finding could potentially have implications for markets with relatively low share of renewable energy and requiring additional investments. On the contrary, in the case of low wind penetration, wind share exhibits a positive relationship with its value.

In general, the results illustrate lower sensitivity, and thus, risk when the wind value is high. Therefore, at all levels of renewable penetration, investors face a consistently higher market risk for lower renewable energy values.

Table 2. The estimates of parameters β_j^W and β_j^S for three wind penetration levels.

τ	Wind			Solar		
	β_1^W	β_2^W	β_3^W	β_1^S	β_2^S	β_3^S
Wind VF						
0.1	0.215	-0.19***	-0.236	0.068	-0.09	-1.109***
0.2	0.05	-0.08***	-0.152*	0.088	-0.137*	-1.068***
0.3	0.169	-0.069***	-0.115**	0.159**	0.014	-0.456**
0.4	0.185**	-0.048**	-0.042	0.202***	0.049	-0.339***
0.5	0.156	-0.043***	0.017	0.171***	0.062*	-0.284***
0.6	0.162*	-0.022	0.026	0.178***	0.056*	-0.214**
0.7	0.219***	-0.003	0.035	0.225***	0.097***	-0.067
0.8	0.237**	-0.003	0.049**	0.246***	0.115***	0.084
0.9	0.196	-0.013	0.098	0.312***	0.187***	0.484
Solar VF						
0.1	-0.151	-0.59***	-0.896	-1.682***	-2.437***	-12.041**
0.2	-0.11	-0.455***	-0.383	-1.566***	-2.071***	-8.008***
0.3	-0.366**	-0.359***	-0.213	-1.512***	-1.867***	-6.127***
0.4	-0.273**	-0.328***	0.233	-1.534***	-1.766***	-5.947***
0.5	-0.294**	-0.256***	0.368*	-1.525***	-1.716***	-5.285***
0.6	-0.259*	-0.202***	0.71***	-1.37***	-1.526***	-5.007***
0.7	-0.111	-0.096**	1.016***	-1.282***	-1.359***	-4.126***
0.8	-0.1	-0.04	1.65***	-1.259***	-1.4***	-2.871*
0.9	-0.154	0.046	2.895***	-1.163***	-1.252***	0.316

Notes: (i) *, ** and ***, respectively denote rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels, (ii) The coefficient β_1^W (β_1^S) represents the impact of wind (solar) at low levels of wind penetration, while β_3^W (β_3^S) refers to the effect of wind (solar) at high levels of wind penetration.

5.2.3 Consumption levels

The results for the solar and wind value factors at different consumption levels are displayed in table 3. Similarly to the previous sections, the solar value demonstrates higher sensitivity compared to wind, yielding results with greater magnitudes. At high consumption, both wind and solar power reduce the solar value for lower value quantiles. This result signifies a greater risk and sensitivity of solar value to high consumption when the solar value factor is low. For low consumption levels, both wind and solar exhibit a negative relationship with the solar value factor across its distribution, with the impact being more prominent, particularly for lower quantiles. Additionally, wind energy is negatively linked to the solar value for intermediate consumption levels in lower quantiles, but the relationship is reversed for higher quantiles of solar value. The cannibalization effect on solar is more profound for high consumption levels since solar power is predominantly available during periods of high demand.

Regarding the wind value factor, we observe that cannibalization is more intense for lower wind value quantiles, which is in line with our findings in the baseline model. The results suggest that wind is more robust and less risky in higher quantiles of wind value. Finally, significant cross-cannibalization is identified only for high consumption levels and upper quantiles of wind value.

Table 3. The estimates of parameters β_j^W and β_j^S for three consumption levels.

τ	Wind			Solar		
	β_1^W	β_2^W	β_3^W	β_1^S	β_2^S	β_3^S
Wind VF						
0.1	-0.616***	-0.167***	0.057	-0.26	-0.006	-0.613
0.2	-0.418***	-0.059***	0.043*	-0.132	-0.089	-0.012
0.3	-0.336***	-0.047***	0.029	-0.038	-0.036	-0.066
0.4	-0.258***	-0.032**	0.035**	0.019	0.001	-0.083
0.5	-0.131**	-0.014	0.033***	0.093	0.015	-0.124
0.6	-0.056	-0.003	0.032**	0.23***	0.067**	-0.081
0.7	-0.004	0.005	0.024*	0.317***	0.088***	-0.071
0.8	0.059	0.01	-0.002	0.365***	0.065**	-0.192***
0.9	0.159	0.003	0.002	0.474***	0.067***	-0.208***
Solar VF						
0.1	-2.498***	-0.698***	-0.383***	-3.64***	-2.127***	-3.52***
0.2	-1.514***	-0.421***	-0.212***	-2.92***	-1.732***	-3.305***
0.3	-1.187***	-0.305***	-0.156***	-2.747***	-1.618***	-2.864***
0.4	-0.819***	-0.227***	-0.11**	-2.463***	-1.578***	-2.472***
0.5	-0.4**	-0.118**	-0.048	-1.979***	-1.445***	-2.15***
0.6	-0.144	-0.04	-0.008	-1.834***	-1.371***	-2.075***
0.7	0.175	0.048	0.025	-1.506***	-1.316***	-2.088***
0.8	0.574***	0.162***	0.081	-1.381***	-1.337***	-2.068***
0.9	1.201***	0.457***	0.223**	-0.854*	-1.294***	-2.312***

Notes: (i) *, ** and ***, respectively denote rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels, (ii) The coefficient β_1^W (β_1^S) represents the impact of wind (solar) at low levels of consumption, while β_3^W (β_3^S) refers to the effect of wind (solar) at high levels of consumption.

5.3 Robustness analysis

We verify our results in two different ways: first, we modify the choice of independent variables in our baseline model, and second, we alter the renewable penetration and demand thresholds (τ_L, τ_H) in the non-linear model. Prol et al. (2020) have shown that gas prices may effect wind and solar unit revenues and market value in the Californian market. Therefore, we include gas prices (Dutch TTF gas prices from Bloomberg) in our baseline model (eq. 4) to investigate if our estimates change.The results are presented in Appendix C (see Table C2). Consequently, eq. 4 becomes:

$$Q(\tau)_t^{S,W} = \alpha_{0,\tau} + \beta_\tau^W Sh_t^W + \beta_\tau^S Sh_t^S + \beta_\tau^L L_t + \beta_\tau^I I_t + \beta_\tau^G G_t + \gamma_\tau' C_t \tag{6}$$

On the other hand, the non-linear model results are dependent on the chosen renewable penetration and demand thresholds. Thus, we select new thresholds ($\tau_L = 0.25$, $\tau_H = 0.75$) to examine the robustness of model 5. The results are presented in Tables C3, C4, C5 in Appendix C.

The robustness analysis confirms the findings obtained by the original models. Although there are some minor quantitative differences with the original estimates, the overall interpretation of the results is not altered.

6 Conclusion

Over the past decade, there has been a consistent increase in the supply of renewable energy, both at the EU and global level, driven by the goal of meeting CO2 emission reduction targets. Previous research (Clò and D'Adamo, 2015; Prol et al., 2020) has shown that increasing renewable energy could result in reduced unit revenues and, ultimately, market value for renewable energy producers. This phenomenon is called cannibalization. In addition, it has been demonstrated that different renewable energy sources, such as solar and wind, may also reduce each other's unit revenues and market value, referred to as cross-cannibalization. As an increasing number of nations advocate for renewable energy to compete without any government support, a decrease in the value of renewable energy, combined with the phasing out of support policies, could jeopardize its competitiveness and hinder its expansion.

In this paper, a quantile regression is applied to explore the effects of wind and solar generation on their own and each other's unit revenues and market value. Firstly, we construct two daily indices that represent the renewable unit revenues and market value. Specifically, we calculate the solar and wind unit revenue as their respective generation-weighted electricity prices, and their value factors as the unit revenues divided by the market average wholesale electricity price. We then use a quantile regression to investigate the relationship between renewable energy generation and the unit revenue and value factor indices. The quantile approach allows us to take the cannibalization and cross-cannibalization research a step further by considering the entire distribution of wind and solar unit revenue and value factor. Earlier research has focused on average (central) effects, disregarding extreme market conditions in their analysis. By exploring the entire distribution of unit revenue and market value, we can obtain a better understanding of the cannibalization effect and how it can be efficiently handled by market participants.

The results confirm the existence of both cannibalization and cross-cannibalization in the German electricity market. The observed effects are not uniform across the distributions of wind and solar unit revenues and value factors. The strongest cannibalization and cross-cannibalization effects are identified in the lower quantiles of both wind and solar power. The low part of the wind and solar value factor distribution indicates that the unit revenues are lower compared to average power prices in the market. When the value factor is low and renewable generation increases, the market value of renewables can be further reduced, resulting in lower profit margins for producers. Additionally, cannibalization at these low-value levels can create greater market uncertainty particularly[5]. Our findings indicate that solar power is more susceptible to cannibalization and cross-cannibalization, as our estimates for these effects are of greater magnitude than for wind.

Finally, we have assessed the effects of cannibalization and cross-cannibalization under different levels of wind and solar penetration, and electricity consumption. The results suggest that cannibalization and cross-cannibalization are greater when there is high penetration of wind and solar power, and also for high electricity consumption. We observe that solar power is more prone to and experiences stronger cannibalization compared to wind power. In contrast, wind power seems to be more resilient and less risky, particularly for higher value factors where significant cannibalization is absent. For instance, in circumstances such as high solar penetration and wind value, solar power can actually raise the market value of wind. Our non-linear results suggest that solar power can be more sensitive to variations in renewable energy and consumption levels, and can exhibit more pronounced cannibalization.

The findings of our paper have significant implications for policymakers and industry professionals. Our results highlight how the unique characteristics of renewable energy sources can lead to cannibalization of their own unit revenues and market value in electricity markets, which can potentially compromise their long-term economic viability. They also raise questions regarding about the feasibility of reducing renewable energy subsidies in the face of high renewable penetration, as suggested in existing literature (Newbery, 2012; Mahalingam et al., 2014; Grubb and Newbery, 2018; Boute, 2020). These findings underline the challenges faced by various countries as they transition to cleaner energy sources.

[5] Given the already low value of renewable energy, any increase in wind or solar power could further decrease their value. As a result, profit margins may become uncertain, which could ultimately impact future investments.

The results can be useful to different market stakeholders such as governments, organizations and investors for future strategic decisions. First, governments could utilize the information on the extent of cannibalization and cross-cannibalization in order to make informed decisions regarding support schemes. Our analysis shows that cannibalization is present in lower wind and solar unit revenues and market value quantiles, which could compromise the competitiveness of renewable sources. This result, in combination with high risks due to extreme energy prices, interest rates fluctuations, and changes in government support schemes (such as the phase out of feed-in tariffs in Germany), could discourage renewable energy producers from investing in renewable infrastructure. Thus, it is imperative that regulators consider cannibalization when formulating policies for renewables which are vital to achieving a net zero society by 2060. Second, the information on cannibalization can aid current renewable energy producers and potential investors in identifying profitable strategies. Third, our non-linear findings, which show that greater cannibalization occurs at high levels of renewable energy penetration and consumption, highlight the need for diversity and flexibility, in terms of infrastructure, grid modernization, and integration. Lastly, the varying cannibalization and cross-cannibalization effects between wind and solar energy, and the greater sensitivity of solar, can assist governments in determining an optimal electricity generation mix by taking into account the complementary nature of the two sources.

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A Appendix

Table A1. Descriptive Statistics.

		2017				2018				2019				2020			
Variable	Unit	Mean	SD	Kurtosis	Skew	Mean	SD	Kurtosis	Skew	Mean	SD	Kurtosis	Skew	Mean	SD	Kurtosis	Skew
Wind UR	€/MWh	33.1	13.957	7.82	-0.502	43.3	14.342	2.46	-0.845	36.7	11.945	9.32	-1.623	29.5	13.668	1.6	-0.547
Solar UR	€/MWh	35.7	18.794	7.51	0.053	45.5	16.917	2.57	-0.74	38	15.569	10.88	-1.777	29.9	18.981	3.53	-0.74
Wind VF	%	97.1	11.936	122.29	-4.123	97.4	10.307	126.44	-6.728	97	11.459	234.3	-13.932	96.6	8.997	26.29	-1.184
Solar VF	%	104.2	49.444	98.41	2.808	100.7	49.946	183.12	-10.872	94.1	118.017	322.81	-17.524	96.9	148.372	188.31	10.883
Wind share	%	20.9	14.538	0.39	0.954	21.7	14.363	0.65	1.047	25.6	16.069	0.43	1.014	27.1	17.476	-0.19	0.762
Solar share	%	7.6	5.227	-1.03	0.341	8.7	5.728	-1.18	0.196	9	6.092	-0.96	0.361	10.1	6.83	-1.25	0.276
Net Imports share	%	-2.79	2.67	0.01	-0.45	-1.88	3.10	0.22	-0.44	-0.5	4.14	-0.62	-0.33	-0.46	3.29	-0.51	0.13
Load	GWh	55.73	6.05	-0.58	-0.41	56.48	5.99	-0.63	-0.4	54.66	5.80	-0.67	-0.33	54.09	6.20	-0.65	-0.32

B Appendix

Table B1. Unit Root Tests.

	Wind UR	Solar UR	Wind VF	Solar VF	Wind %	Solar %	Net Imports %	Consumption
ADF (levels)	-14.784***	-17.125***	-28.19***	-28.719***	-18.493***	-8.416***	-6.356***	-24.53***
ADF (trend)	-15.17***	-17.242***	-28.183***	-16.285***	-18.614***	-8.571***	-6.564***	-24.808***
ADF (diff)	-40.519***	-41.576***	-48.878***	-50.294***	-38.681***	-38.399***	-25.13 ***	-43.002***
PP(levels)	-15.915***	-20.674***	-40.166***	-40.543***	-18.89***	-7.869***	-16.167***	-20.661***
PP(trend)	-16.343***	-20.789***	-40.154***	-40.586***	-18.978***	-8.085***	-16.756***	-20.807***
PP(diff)	-59.291***	-69.796***	-129.05***	-129.542***	-56.179***	-59.28***	-67.44***	-48.344***

*Notes:(i)ADF indicates augmented Dickey-Fuller; PP indicates Phillips-Perron, (ii) *, ** and *** respectively denote rejection of null hypothesis of a unit root at significance level 10%, 5% and 1%.*

C Appendix

Table C1. The estimates of all parameters for the baseline model.

τ	β_τ^W	β_τ^S	β_τ^I	β_τ^L	τ	β_τ^W	β_τ^S	β_τ^I	β_τ^L
Wind UR					*Wind VF*				
0.1	-0.521***	-0.418***	-0.445***	0.707***	0.1	-0.163***	-0.071	-0.003	0.437***
0.2	-0.488***	-0.406***	-0.415***	0.628***	0.2	-0.078***	-0.105	-0.055	0.264**
0.3	-0.468***	-0.362***	-0.435***	0.584***	0.3	-0.047***	-0.028	-0.023	0.175**
0.4	-0.452***	-0.371***	-0.433***	0.478***	0.4	-0.024**	0.05	0.006	0.062
0.5	-0.449***	-0.401***	-0.474***	0.382***	0.5	-0.008	0.073**	0.011	0.019
0.6	-0.452***	-0.441***	-0.501***	0.391***	0.6	0.011	0.104***	0.045	-0.011
0.7	-0.448***	-0.427***	-0.459***	0.384***	0.7	0.014*	0.134***	0.068**	-0.077*
0.8	-0.477***	-0.469***	-0.439***	0.315***	0.8	0.02***	0.152***	0.087***	-0.066
0.9	-0.553***	-0.508***	-0.609***	0.368***	0.9	0.022**	0.198***	0.106**	-0.152
Solar UR					*Solar VF*				
0.1	-0.692***	-1.076***	-0.299**	0.931***	0.1	-0.795***	-2.483***	0.333	0.687***
0.2	-0.657***	-1.163***	-0.462***	0.795***	0.2	-0.539***	-2.112***	0.137	0.287
0.3	-0.63***	-1.085***	-0.517***	0.582***	0.3	-0.371***	-1.847***	-0.024	0.099
0.4	-0.601***	-1.012***	-0.574***	0.67***	0.4	-0.253***	-1.691***	0.017	-0.03
0.5	-0.59***	-0.992***	-0.535***	0.553***	0.5	-0.162***	-1.669***	0.01	-0.158
0.6	-0.569***	-0.938***	-0.522***	0.551***	0.6	-0.028	-1.509***	0.042	-0.258
0.7	-0.573***	-0.95***	-0.534***	0.579***	0.7	0.059*	-1.37***	0.091	-0.395*
0.8	-0.613***	-1.069***	-0.407***	0.469***	0.8	0.175***	-1.449***	0.012	-0.905***
0.9	-0.656***	-1.135***	-0.408***	0.55***	0.9	0.451***	-1.304***	0.208	-0.929*

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

Table C2. The estimates of parameters β_τ^W and β_τ^S for the baseline model including gas prices.

τ	β_τ^W	β_τ^S	τ	β_τ^W	β_τ^S
Wind UR			*Wind VF*		
0.1	-0.549***	-0.44***	0.1	-0.171***	-0.031
0.2	-0.535***	-0.416***	0.2	-0.079***	-0.099
0.3	-0.513***	-0.402***	0.3	-0.049***	-0.021
0.4	-0.499***	-0.379***	0.4	-0.025**	0.048
0.5	-0.496***	-0.389***	0.5	-0.007	0.074**
0.6	-0.486***	-0.378***	0.6	0.011	0.106***
0.7	-0.496***	-0.389***	0.7	0.014*	0.135***
0.8	-0.493***	-0.328***	0.8	0.021**	0.15***
0.9	-0.507***	-0.298***	0.9	0.022**	0.195***
Solar UR			*Solar VF*		
0.1	-0.737***	-1.229***	0.1	-0.791***	-2.489***
0.2	-0.673***	-1.128***	0.2	-0.539***	-2.104***
0.3	-0.655***	-1.122***	0.3	-0.372***	-1.838***
0.4	-0.635***	-1.119***	0.4	-0.248***	-1.706***
0.5	-0.605***	-1.072***	0.5	-0.153***	-1.655***
0.6	-0.589***	-1.051***	0.6	-0.027	-1.495***
0.7	-0.598***	-1.022***	0.7	0.058*	-1.388***
0.8	-0.609***	-1.032***	0.8	0.179***	-1.366***
0.9	-0.615***	-1.038***	0.9	0.466***	-1.277***

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

Table C3. The estimates of parameters β_j^W and β_j^S for three solar penetration levels with different thresholds ($\tau_L = 0.25$ and $\tau_H = 0.75$).

τ	Wind			Solar		
	β_1^W	β_2^W	β_3^W	β_1^S	β_2^S	β_3^S
Wind VF						
0.1	-0.022	-0.191***	-0.464***	0.417	-0.145	0.085
0.2	0.022	-0.107***	-0.265***	1.285*	-0.193	0.3*
0.3	0.017	-0.068***	-0.15**	0.757	-0.049	0.305**
0.4	0.0316**	-0.034**	-0.133***	0.576	-0.024	0.351***
0.5	0.041***	-0.024**	-0.099***	0.356	-0.025	0.386***
0.6	0.035***	-0.007	-0.078***	0.097	0.012	0.462***
0.7	0.029***	-0.002	-0.045	-0.022	0.013	0.508***
0.8	0.014	0.009	0.002	-0.021	0.039	0.553***
0.9	0.007	0.011	0.061	0.098	0.053	0.705***
Solar VF						
0.1	-0.208***	-0.853***	-1.802***	-4.846***	-2.13***	-3.349***
0.2	-0.103*	-0.611***	-1.484***	-4.689***	-2.027***	-2.654***
0.3	-0.021	-0.455***	-1.296***	-4.685***	-1.859***	-2.169***
0.4	0.067	-0.353***	-0.871***	-4.797***	-1.789***	-2.215***
0.5	0.113**	-0.259***	-0.549***	-4.133***	-1.737***	-2.021***
0.6	0.163***	-0.16***	-0.473***	-3.551***	-1.7***	-1.763***
0.7	0.255***	-0.054	-0.334***	-3.848***	-1.621***	-1.548***
0.8	0.432***	0.062	-0.156	-3.603***	-1.636***	-1.462***
0.9	0.687***	0.236**	0.219	-5.877**	-1.674***	-1.137***

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

Table C4. The estimates of parameters β_j^W and β_j^S for three wind penetration levels with different thresholds ($\tau_L = 0.25$ and $\tau_H = 0.75$).

τ	Wind			Solar		
	β_1^W	β_2^W	β_3^W	β_1^S	β_2^S	β_3^S
Wind VF						
0.1	0.077	-0.215***	-0.247*	0.012	-0.164	-1.178***
0.2	0.061	-0.139***	-0.145*	0.059	-0.068	-0.791***
0.3	0.107	-0.093***	-0.103**	0.158**	0.05	-0.4**
0.4	0.111	-0.068**	-0.046	0.182***	0.088*	-0.319***
0.5	0.053	-0.058***	0.007	0.152***	0.065**	-0.306***
0.6	0.084	-0.045**	0.018	0.142***	0.069**	-0.243***
0.7	0.061	-0.026	0.018	0.159***	0.101***	-0.105
0.8	0.046	-0.029	0.034**	0.198***	0.129***	0.069
0.9	0.032	-0.027	0.087*	0.27***	0.187***	0.368
Solar VF						
0.1	-0.422***	-0.564***	-0.624	-1.789***	-2.413***	-12.087**
0.2	-0.257	-0.422***	-0.435*	-1.626***	-2.071***	-6.29***
0.3	-0.237	-0.351***	-0.221	-1.571***	-1.891***	-5.724***
0.4	-0.23*	-0.29***	0.152	-1.546***	-1.751***	-5.233***
0.5	-0.311***	-0.273***	0.31**	-1.509***	-1.708***	-4.806***
0.6	-0.25**	-0.203***	0.474**	-1.418***	-1.593***	-3.919***
0.7	-0.162	-0.096**	0.909***	-1.307***	-1.372***	-3.259***
0.8	-0.083	-0.036	1.491***	-1.17***	-1.343***	-2.331***
0.9	0.002	0.088	2.443***	-1.199***	-1.232***	-0.427

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

Table C5. The estimates of parameters β_j^W and β_j^S for three demand levels with different thresholds ($\tau_L = 0.25$ and $\tau_H = 0.75$).

τ	Wind			Solar		
	β_1^W	β_2^W	β_3^W	β_1^S	β_2^S	β_3^S
Wind VF						
0.1	-0.554***	-0.124***	0.005	-0.187	-0.163	-0.051
0.2	-0.359***	-0.05***	0.032	-0.039	-0.16**	0.056
0.3	-0.264***	-0.049***	0.023	0.028	-0.059	0.053
0.4	-0.149***	-0.034**	0.029**	0.077	-0.001	0.038
0.5	-0.102***	-0.016	0.033***	0.113	0.016	-0.001
0.6	-0.039	-0.004	0.033***	0.23***	0.043	0.047
0.7	0.009	-0.002	0.026**	0.309***	0.073***	0.035
0.8	0.027	0.002	0.0145	0.315***	0.026	0.027
0.9	0.06	0.007	0.006	0.475***	0.031	0.055
Solar VF						
0.1	-2.218***	-0.686***	-0.404***	-3.07***	-1.891***	-3.36***
0.2	-1.339***	-0.428***	-0.209***	-2.931***	-1.667***	-2.77***
0.3	-0.918***	-0.308***	-0.175***	-2.714***	-1.542***	-2.365***
0.4	-0.598***	-0.246***	-0.081*	-2.29***	-1.514***	-2.231***
0.5	-0.27**	-0.166***	-0.034	-1.941***	-1.393***	-2.148***
0.6	-0.045	-0.062	0.02	-1.698***	-1.282***	-2.149***
0.7	0.208	-0.002	0.067*	-1.519***	-1.255***	-2.152***
0.8	0.666***	0.116**	0.12**	-1.385***	-1.238***	-2.334***
0.9	1.213***	0.299**	0.238***	-0.935***	-1.213***	-2.322***

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

D Appendix

Table D1. The estimates of parameters β_τ^W and β_τ^S for the baseline model including different control variables.

τ	β_τ^W	β_τ^S	τ	β_τ^W	β_τ^S
Wind UR			*Wind VF*		
0.1	-0.509***	-0.278***	0.1	-0.169***	0.101
0.2	-0.461***	-0.256***	0.2	-0.073***	0.059
0.3	-0.455***	-0.346***	0.3	-0.036***	0.044
0.4	-0.447***	-0.385***	0.4	-0.021*	0.057*
0.5	-0.434***	-0.386***	0.5	-0.009	0.054**
0.6	-0.435***	-0.435***	0.6	0.009	0.05**
0.7	-0.446***	-0.399***	0.7	0.01*	0.047**
0.8	-0.485***	-0.473***	0.8	0.017*	0.052**
0.9	-0.546***	-0.585***	0.9	0.024**	0.059**
Solar UR			*Solar VF*		
0.1	-0.669***	-0.905***	0.1	-0.812***	-1.901***
0.2	-0.631***	-0.861***	0.2	-0.509***	-1.925***
0.3	-0.596***	-0.864***	0.3	-0.384***	-1.698***
0.4	-0.577***	-0.87***	0.4	-0.262***	-1.569***
0.5	-0.556***	-0.894***	0.5	-0.133***	-1.489***
0.6	-0.562***	-0.939***	0.6	-0.051	-1.437***
0.7	-0.561***	-0.964***	0.7	0.062	-1.292***
0.8	-0.611***	-1.113***	0.8	0.157***	-1.306***
0.9	-0.689***	-1.326***	0.9	0.531***	-1.261***

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

E Appendix

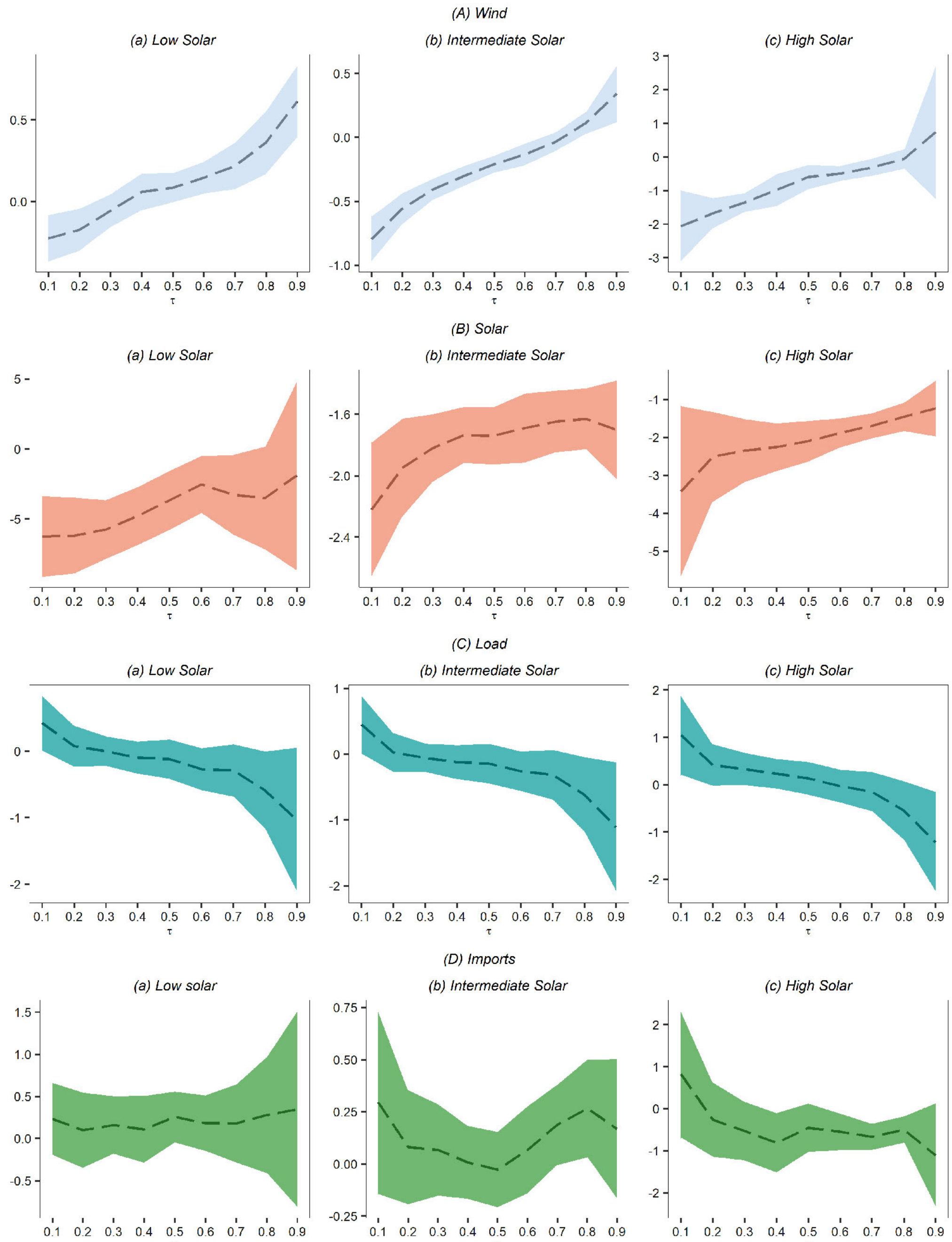

Figure E.1. The non-linear results for the **solar value factor** across different quantiles τ=0.1,...0,9 and three solar penetration levels with 95% confidence intervals. Notes: (i) The results with significance are presented in Table 1, (ii) Panel A represents the effect of wind on the VFS (cross-cannibalization) while Panel B shows the effect of solar on the VFS (cannibalization).

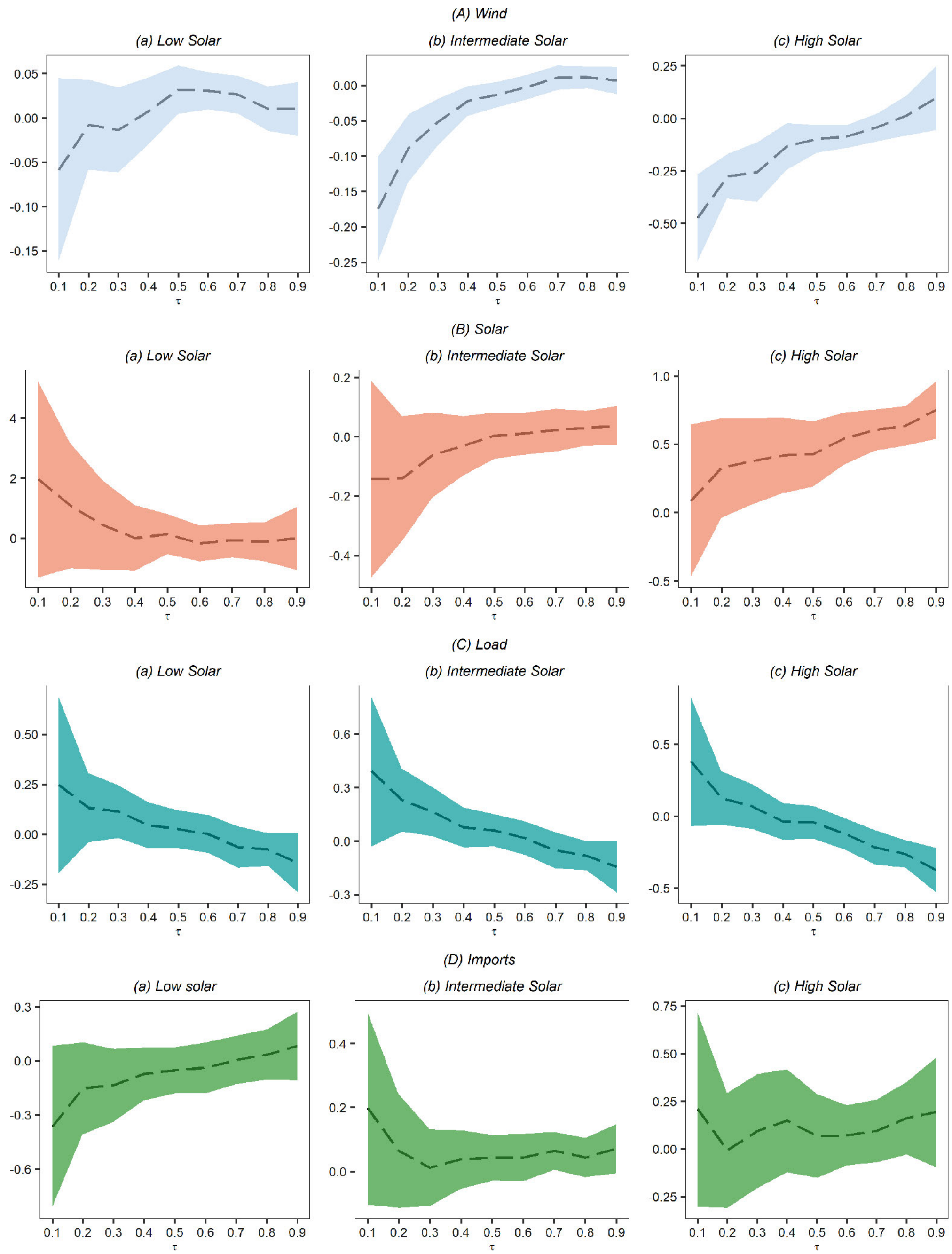

Figure E.2. The non-linear results for the **wind value factor** across different quantiles τ=0.1,...0,9 and three solar penetration levels with 95% confidence intervals. Notes: (i) The results with significance are presented in Table 1, (ii) Panel A represents the effect of wind on the VFW (cannibalization) while Panel B shows the effect of solar on the VFW (cross-cannibalization).

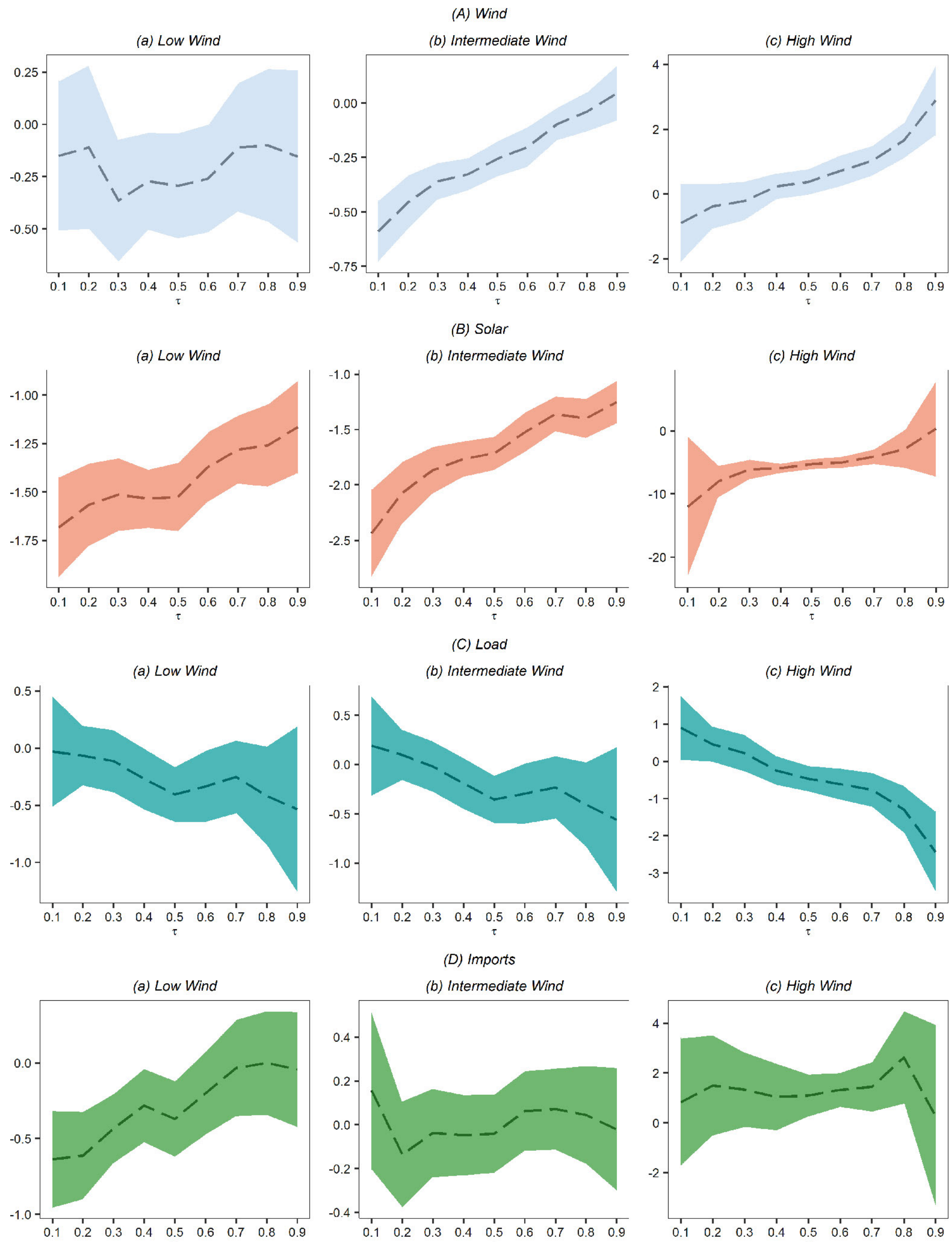

Figure E.3. The non-linear results for the **solar value factor** across different quantiles τ=0.1,...0,9 and three wind penetration levels with 95% confidence intervals. Notes: (i) The results with significance are presented in Table 2, (ii) Panel A represents the effect of wind on the VFS (cross-cannibalization) while Panel B shows the effect of solar on the VFS (cannibalization).

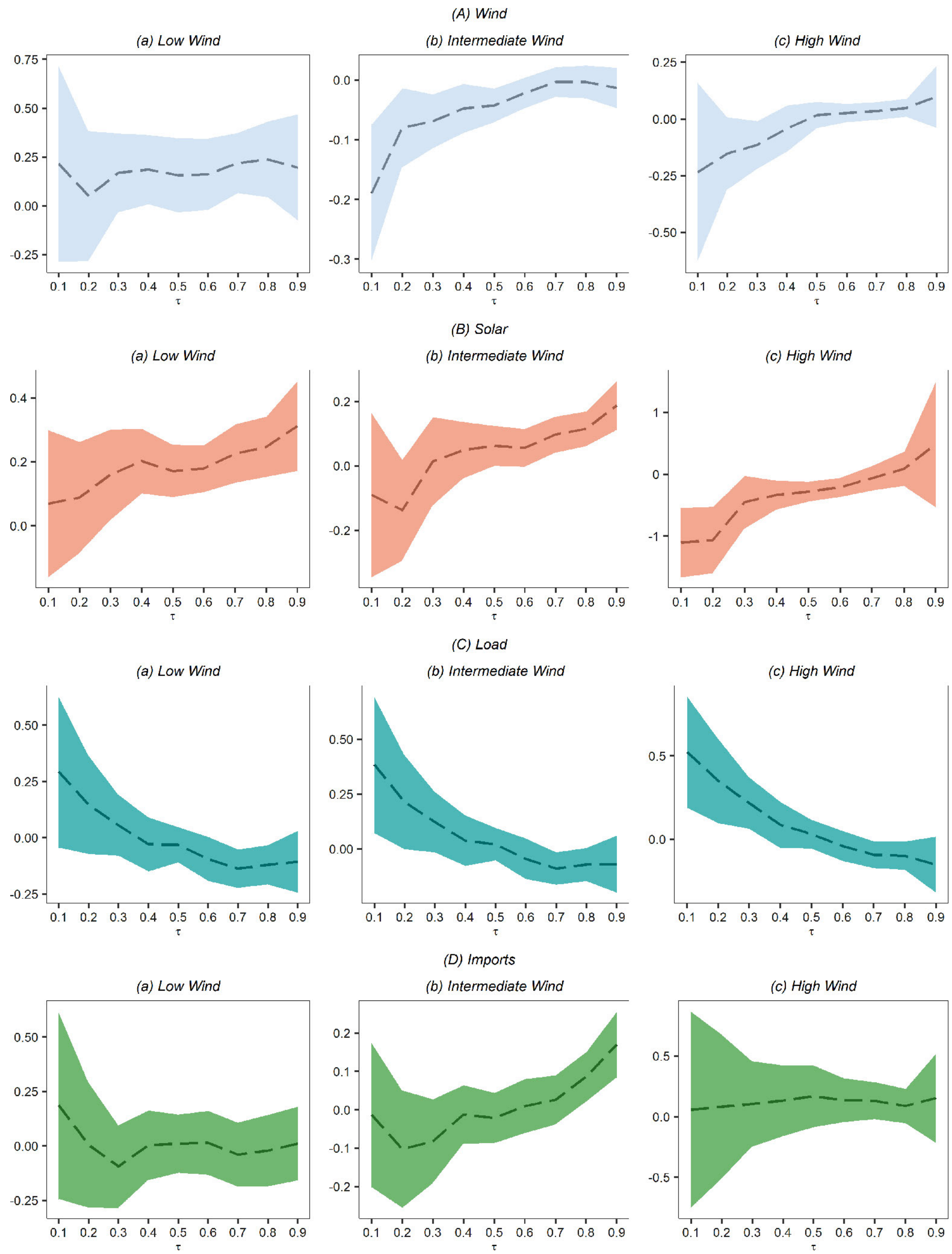

Figure E.4. The non-linear results for the **wind value factor** across different quantiles τ=0.1,...0,9 and three wind penetration levels with 95% confidence intervals. Notes: (i) The results with significance are presented in Table 2, (ii) Panel A represents the effect of wind on the VFW (cannibalization) while Panel B shows the effect of solar on the VFW (cross-cannibalization).

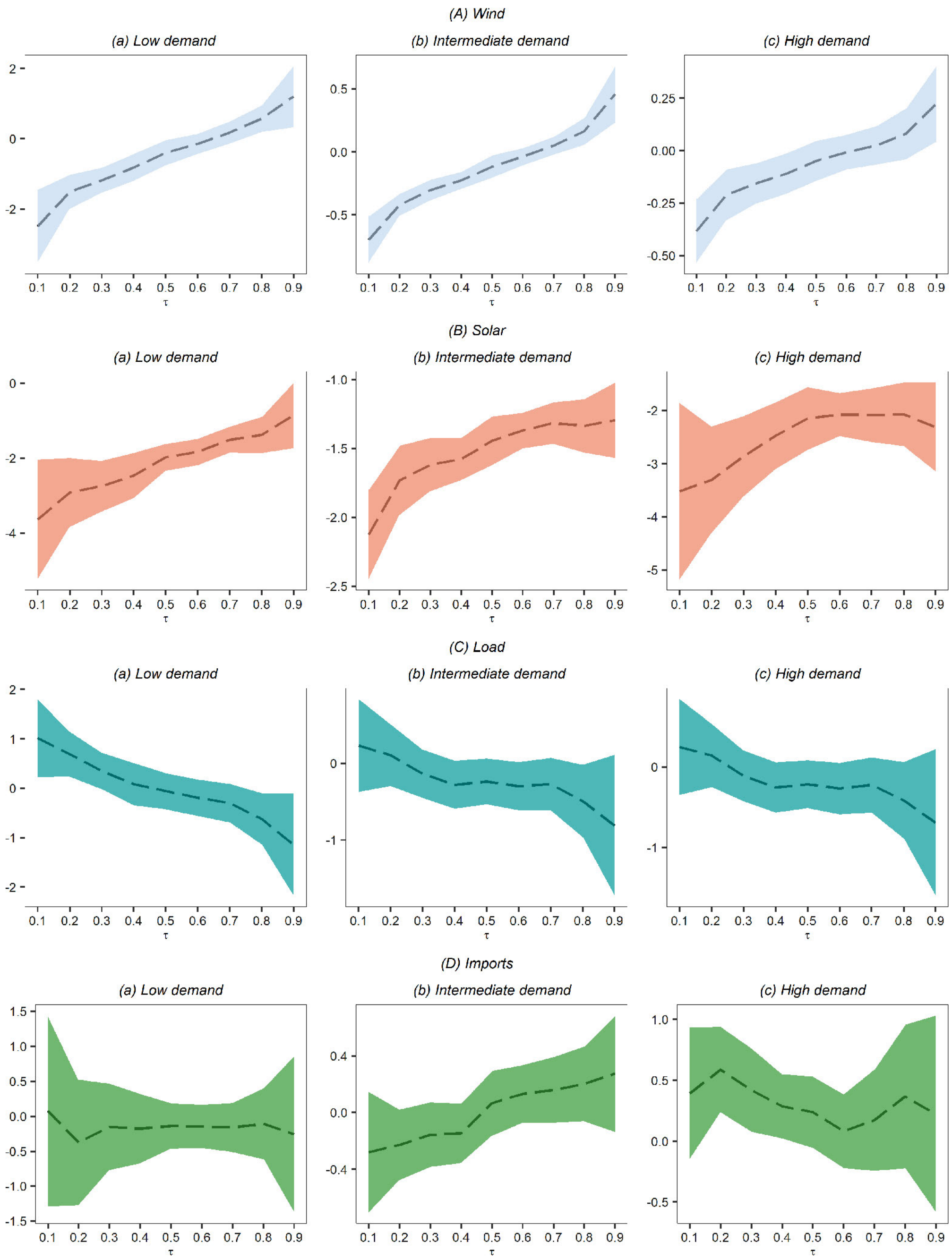

Figure E.5. The non-linear results for the **solar value factor** across different quantiles τ=0.1,...0,9 and three consumption levels with 95% confidence intervals. Notes: (i) The results with significance are presented in Table 3, (ii) Panel A represents the effect of wind on the VFS (cross-cannibalization) while Panel B shows the effect of solar on the VFS (cannibalization).

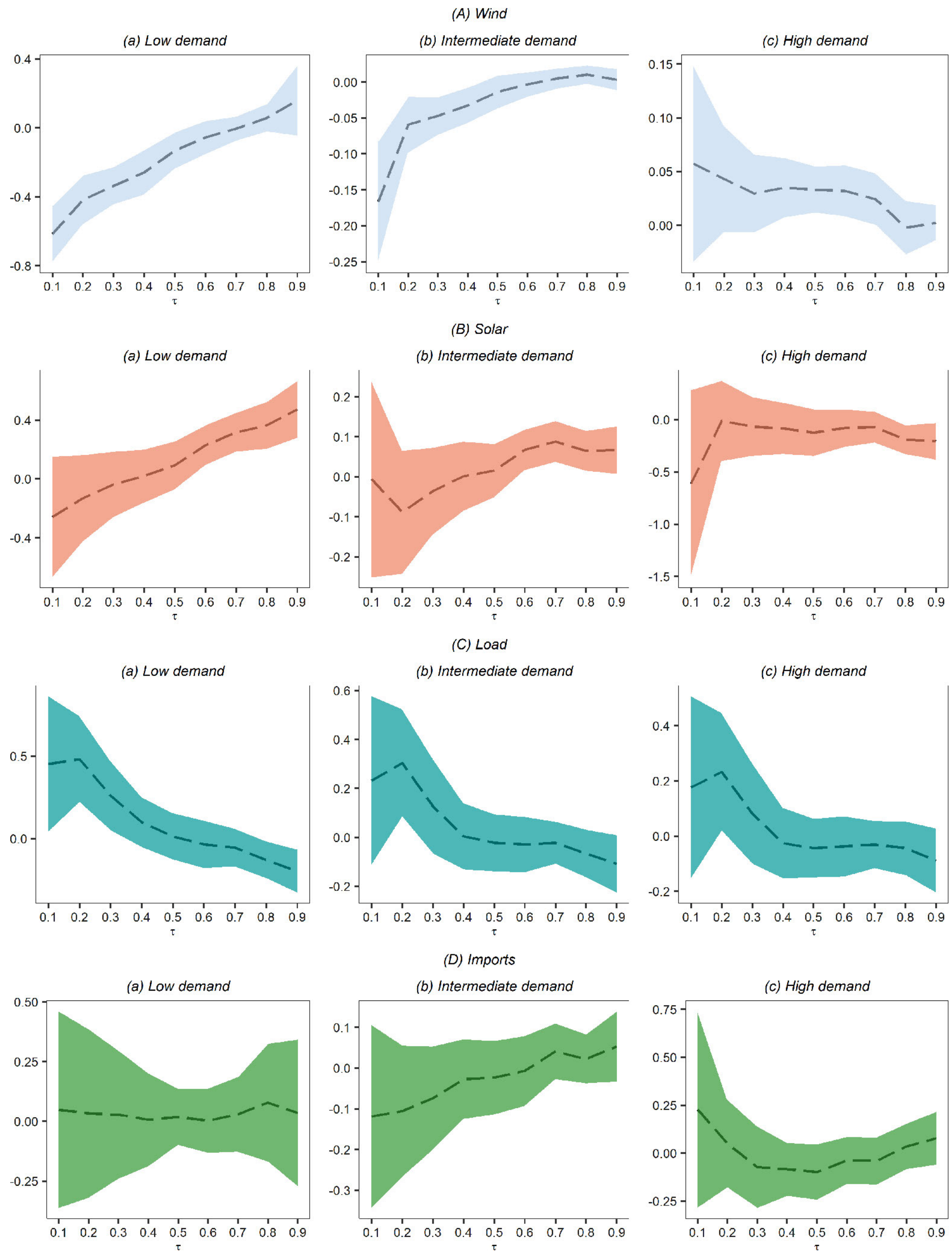

Figure E.6. The non-linear results for the **wind value factor** across different quantiles τ=0.1,...0,9 and three consumption levels with 95% confidence intervals. Notes: (i) The results with significance are presented in Table 3, (ii) Panel A represents the effect of wind on the VFW (cannibalization) while Panel B shows the effect of solar on the VFW (cross-cannibalization).

F Appendix

Table F1. Quantile slope equality test results for the solar penetration model (Table 1).

Quantiles	Wind			Solar		
	β_1^W	β_2^W	β_3^W	β_1^S	β_2^S	β_3^S
Wind VF						
0.1=0.9	1.74	14.47***	28.59***	1.53	1.23	6.61**
0.2=0.8	0.45	13.01***	20.71***	1.31	2.88*	3.12*
0.1=0.5	3.57*	13.77***	13.99***	1.48	0.91	1.71
0.5=0.9	1.02	2.79*	9.25***	0.08	0.37	5.45***
Solar VF						
0.1=0.9	25.38***	74.33***	5.51**	1.43	3.46*	5.00**
0.2=0.8	22.99***	134.72***	51.84***	1.35	3.01*	2.82*
0.1=0.5	16.95***	52.56***	4.83**	2.53	4.35**	2.18
0.5=0.9	12.71***	29.01***	2.15	0.27	0.07	2.98*

*Note: *, ** and ***, indicate significance at 1%, 5% and 10% level.*

Table F2. Quantile slope equality test results for the wind penetration model (Table 2).

Quantiles	Wind			Solar		
	β_1^W	β_2^W	β_3^W	β_1^S	β_2^S	β_3^S
Wind VF						
0.1=0.9	0.01	10.68***	2.96*	3.12*	4.55**	11.12***
0.2=0.8	1.07	4.36**	4.47**	3.32*	9.71***	12.94***
0.1=0.5	0.05	8.35***	2.17	0.75	1.76	7.99***
0.5=0.9	0.06	2.73*	1.26	3.36*	7.62***	4.12**
Solar VF						
0.1=0.9	0.01	46.21***	25.46**	10.85***	32.30***	2.72*
0.2=0.8	0.01	27.47***	21.54***	5.07**	16.79***	9.67***
0.1=0.5	0.64	22.88***	4.90**	1.51	16.39***	1.07
0.5=0.9	0.44	17.46***	20.16***	9.27***	17.16***	2.17

*Note: *, ** and ***, indicate significance at 1%, 5% and 10% level.*

Table F3. Quantile slope equality test results for the consumption penetration model (Table 3).

Quantiles	Wind			Solar		
	β_1^W	β_2^W	β_3^W	β_1^S	β_2^S	β_3^S
Wind VF						
0.1=0.9	55.65^{***}	17.66^{***}	1.50	11.44^{***}	0.31	0.88
0.2=0.8	44.44^{***}	17.57^{***}	4.38^{**}	12.79^{***}	3.90^{**}	0.79
0.1=0.5	42.32^{***}	13.85^{***}	0.29	3.58^{*}	0.03	1.53
0.5=0.9	11.32^{***}	2.31	6.00^{**}	11.14^{***}	2.10	0.47
Solar VF						
0.1=0.9	23.63^{***}	57.92^{***}	32.56^{***}	10.98^{***}	16.03^{***}	2.03
0.2=0.8	45.01^{***}	81.82^{***}	22.60^{***}	8.49^{***}	7.38^{***}	7.05^{***}
0.1=0.5	15.94^{***}	37.73^{***}	20.45^{***}	5.38^{**}	14.11^{***}	3.70^{*}
0.5=0.9	13.13^{***}	29.11^{***}	10.07^{***}	6.64^{**}	1.15	0.13

Note: *, ** and ***, indicate significance at 1%, 5% and 10% level.

Connectedness between green bonds, clean energy markets and carbon quota prices: Time and frequency dynamics

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Abstract

In this paper, we investigate the time and frequency dynamics of connectedness among green assets such as green bonds, clean energy markets, and carbon prices. Using daily price data, we explore return spillovers across these green financial markets by applying the novel framework on time and frequency dynamics proposed by Baruník and Krehlík (2018). This allows us to identify the direction of spillovers among our variables, and decompose the connectedness to differentiate between short-term and long-term return spillovers. Our results indicate that green bonds and carbon prices act as net receivers of shocks, but mainly in the short-term. We also observe a low level of connectedness among our clean energy markets across both low and high frequency bands, even during times of economic or political crisis. Additionally, there are periods in which connectedness between the clean energy assets is driven by the long-term. In periods of economic and political stability, carbon prices may also provide an interesting diversifying tool for short-term investors. Our results should be of interest for investors and portfolio managers who focus on green financial markets, by strengthening the notion that green financial markets can offer diversification opportunities, for both short-term and long-term investors. This paper is the first to use this framework to investigate systematic risks within green financial markets.

JEL Classification: Q40, G11, C52

Keywords: Green finance, Green Bonds, Energy Markets, Connectedness, Time-Frequency space, Systemic Risk, Portfolio Management

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1 Introduction

A key ingredient for a successful green transition is financial markets providing efficient and climate aligned capital. By facilitating the flow of capital towards climate aligned projects, the financial markets can aid in mitigating climate risk as we transition to a sustainable economy (Giglio et al., 2021). Over the years, regulators have put forth policies to facilitate this transition and discourage capital flowing towards carbon intensive investments, with the EU ETS carbon quota trading system being one of the most well-known policy instruments. However, policy regulation is not sufficient on its own. The world is depending both on public and private finance to achieve a green transition. According to Reuters, an estimated $5 trillion annually is needed until 2030 to finance a green and just transition (Thomson Reuters, 2021). A recent report from Averchenkova et al. (2020) indicates that climate finance is on an upward trajectory, albeit not as rapidly as necessary to facilitate a just transition. Therefore, giving priority to investments that are in line with climate objectives is essential.

Green bonds (GB) are fixed-income securities that are specifically designed to support environmentally friendly projects. Their main feature is their commitment to utilize the raised funds solely for financing or refinancing climate aligned projects, assets or business activities (ICMA, 2016). The first public issuance came in 2007, followed by the first corporate green bond in 2013 (Flammer, 2021). The green bond market is estimated to have grown by 49% in the five-year period prior to 2021 (WEF, 2021). Green bonds have proven especially popular as a financing tool used by banks and asset managers for clean energy and infrastructure investments (Odier, 2017). However, there are still significant gaps between the emissions of organizations' portfolios and the net-zero commitments they have declared (Bellesi and Miller, 2022). Amidst the current climate and energy crisis, it is imperative to direct capital towards projects like large scale energy and infrastructure projects that typically depend on long-term financial support (Wang and Zhi, 2016). These types of investments are also typically debt financed, meaning green bonds have the potential to play an important role in financing clean energy projects and infrastructure. This is prompting the need for thorough research in relation to the transition towards environmentally sustainable finance, and particularly green bonds (Pham and Huynh, 2020; Tang and Zhang, 2020).

Green financial assets have gained considerable popularity as sustainable investment choices. In our research, we focus on investigating three main green asset categories - green bonds (GB), clean energy stocks, and carbon prices. These assets are chosen for their relevance to environmental issues, interconnectedness, and potential financial significance. To begin with, these assets offer a clear environmental focus. Green bonds are designed to finance environmentally friendly projects, while clean energy stocks represent organizations actively engaged in producing and promoting clean energy solutions. On the other hand, carbon prices reflect the financial implications of carbon emissions and ways to mitigate them. Moreover, these assets are influenced by similar environmental factors. For instance, carbon prices, representing the cost of emitting greenhouse gases, could influence the attractiveness of green bonds and clean energy stocks. Conversely, governmental policies and the demand for renewable energy can affect both clean energy stocks and green bonds. Finally, the increasing interest of investors in aligning their portfolios with environmentally sustainable initiatives have spiked lately. Therefore, exploring these three green asset categories can provide valuable insights for investors seeking to incorporate green assets into their portfolios.

To investigate the dynamic interdependence among GB, clean energy markets and carbon quota prices, we use a novel framework by Baruník and Krehlík (2018) (BK18). This methodology is an extension of the Diebold and Yilmaz (2012) (DY12) approach and allows us to analyze the connectedness[1] among green financial assets in both the time and frequency domain. While the DY12 method analyzes the connectedness in the time domain among financial assets, the BK18 model allows us to explore the return spillovers and their direction in the time and frequency space simultaneously. Thus, with the BK18 framework we can decompose the total connectedness found by the DY12 method into various frequencies, such as high and low frequency bands[2], and determine which frequency contributes the most to the connectedness within our green financial system. Therefore, we can provide an analysis of total and directional return spillovers within our green financial market to estimate net transmitters and receivers of return spillovers among our variables[3]. Hence, by incorporating the frequency dimension we are able to estimate how return spillovers transmit among all the variables of our system for both short-term and long-term oriented financial actors.

The main reason for considering the possibility that connectedness between GB, carbon prices and clean energy markets may differ across frequencies stems from the range of economic agents involved in these markets. Market participants may operate with different time horizons due to different objectives, beliefs, risk tolerance or even access to market information (Ferrer et al., 2018). For instance, investors with short-term horizons such as hedge funds are interested

[1]The measure of system connectedness provides useful information on how much of future uncertainty of variable i is due to shocks in variables k (Diebold and Yilmaz, 2009; Diebold and Yilmaz, 2012; Baruník and Krehlík, 2018).

[2]The high frequency band corresponds to the short-term while the low frequency band corresponds to the long-term horizon.

[3]It is important to note that this paper does not aim to infer causality between the variables under examination but rather focuses on exploring the connectedness or the relationships among them.

in short-term performance and responses while long-term investors such as pension funds are mainly concerned with long-term performance, and their responses are primarily manifested in the long-run.

Consequently, we believe that incorporating the frequency domain in the dynamics of a green financial system could assist green investors - with different preferences and goals - identify investment opportunities in both the short and long-term. The BK18 method, which considers the frequency domain, is preferred in this regard. By analyzing the interactions between GB, carbon prices, and clean energy stocks over different time horizons, the BK18 method offers a deeper understanding of how the relationships between these assets may vary over time. In this way, the BK18 method could enable the identification of strategies to finance environmentally friendly projects and create economic opportunities in sectors that promote the reduction of environmental damage. This knowledge is crucial for fostering green investment practices and driving positive change towards a sustainable future.

Overall, increasing climate-aligned capital through GB, clean energy stocks, and carbon prices has the potential to drive positive change and promote sustainability in both the short and long-term. By using the BK18 method, investors can make informed decisions about incorporating green assets into their portfolios, aligning their investments with environmentally sustainable initiatives, and contributing to a more sustainable and environmentally conscious financial market.

The increasing interest in green bonds is being observed in both financial markets and academia due to their potential to finance green projects and address climate change. A substantial portion of the literature has focused on investigating what is the fundamental purpose of green bonds, their related cost of capital and the effect of certification schemes for green bonds. Significant efforts have been made to examine the existence of a premium for green bonds paid by investors, often referred to as a "greenium" (Baker et al., 2018; Hachenberg and Schiereck, 2018;Bachelet et al., 2019; Zerbib, 2019; Fatica et al., 2021; MacAskill et al., 2021; Caramichael and Rapp, 2022). As there is yet to be a consensus about the greenium (Hyun et al., 2021), issuers are focusing on transparency, often through labeling of green bonds. According to Kapraun et al. (2021) the credibility of a green label is especially important for corporate issuers. If a premium were to emerge, it is most likely in a situation where the green bond is certified by a third party (Kapraun et al., 2021). One such certifier is CICERO providing their Shades of Green assessment (CICERO, 2021) of green bonds in order to enhance transparency and credibility in the green bond market. There have also been several discussions and research efforts on the risk of using green bonds for greenwashing purposes. Flammer (2021) finds evidence that using green bonds for greenwashing purposes is too costly for firms, indicating a low risk of greenwashing being related to green bond issuance.

The BK18 framework has been widely used in exploring the connectedness among various financial assets. Ferrer et al. (2018) are among the first to exploit the BK18 framework to analyze connectedness between renewable energy stocks and oil in the time and frequency domain. In their paper, they demonstrate the recent decoupling of the alternative energy industry from the traditional energy market across frequency bands. Tiwari et al. (2018) study the volatility connectedness among stocks, sovereign bonds, CDS, and currencies. Their findings indicate that there is generally low connectedness among these assets, and that the level of connectedness varies across frequencies. Similarly, Lovcha and Perez-Laborda (2020) investigate the connectedness between the oil and gas markets, and find that the level of connectedness between these markets also varies across frequencies. Moreover, they demonstrated that the connectedness between the oil and gas markets typically occur at low frequencies, and transmitted shocks between these markets have long-lasting effects. This finding contrasts with several other studies (Ferrer et al., 2018; Jiang and Chen, 2022; Le et al., 2021) that have found that connectedness tends to occur at the high frequency band. However, Zhang and Hamori (2021) provide a more nuanced perspective, suggesting that return spillovers exhibit high frequency connectedness , whereas volatility spillovers exhibit low-frequency connectedness as showed by Lovcha and Perez-Laborda (2020). Jiang and Chen (2022) and Kang et al. (2019) both exploit the BK18 framework to analyze connectedness between oil and various assets linked to the green transition. Lastly, Kang et al. (2019) explore agricultural commodities and Jiang and Chen (2022) concentrate on new energy markets, material markets and carbon markets.

An important strand of related literature is focused on understanding and estimating the connectedness between green assets (Liu et al., 2021) and various other variables, such as different assets (Ferrer et al., 2018; Park et al., 2020; Reboredo, 2018; Reboredo et al., 2020; Alkathery and Chaudhuri, 2021; Asl et al., 2021; Le et al., 2021; Tan et al., 2021; Jiang and Chen, 2022; Tiwari et al., 2022), macroeconomic events (Naeem et al., 2020), or uncertainty measures (Pham, 2016; Haq et al., 2021; Leitao et al., 2021; Pham and Nguyen, 2022). Understanding and estimating such connectedness can help investors and portfolio managers in various areas of finance, including business cycle analysis, portfolio allocation and risk management (Baruník and Krehlík, 2018). Reboredo (2018) investigates co-movement and spillover effects between green bonds and assets such as the corporate and treasury bond market, stocks, and energy commodity markets. They find that connectedness is mainly generated in the short-term, and that green bonds display strong connectedness with corporate and treasury bonds, while the connectedness between green bonds and energy commodities is fairly weak. In 2020, Reboredo et al. (2020) corroborate these results by using the Vector Autoregression (VAR) and wavelet-based methods. However, they find that green bonds can offer important diversification benefits for energy and stock market investors, as well as low-carbon market investors due to low connectedness (Reboredo, 2018; Reboredo et al., 2020; Reboredo et al., 2022). Liu et al. (2021) focus on the interaction among green financial assets, and exploit a CoVar model to explore the dependence and risk spillovers between green bonds and clean energy markets. Their results indicate that there is significant asymmetric connectedness and risk spillovers between GB and clean energy markets, particularly in the short-term. Tiwari et al. (2022) also investigate dynamic spillover effects between green bonds and renewable energy stocks as well as carbon markets using a TVP-VAR approach. They emphasize the practical significance of connectedness estimates by demonstrating that a portfolio that minimizes connectedness reaches a higher Sharp ratio than a portfolio that minimizes correlation or variance.

Our research may have important implications for investors and governments. First, we use a novel methodology to examine the connectedness among green assets, while considering both time and frequency dynamics. In financial markets, there are diverse economic agents that may have different preferences, goals, information or risk tolerance. These agents generally operate within heterogeneous time horizons. For instance, we would expect day traders and arbitrageurs to be concerned about short-term connectedness in a financial system. Therefore, our research incorporates the time horizon through the frequency domain, and can provide further insights on diversification opportunities for green investors. Second, we put emphasis on a green financial market and the potential diversification opportunities within this kind of market, recognizing the crucial role that green finance will play in achieving a low-carbon future. Our results can provide support for investing in environmentally-friendly initiatives which can benefit not only the planet, but also create new opportunities for economic growth and development. Hence, we believe that exploring the potential diversification opportunities within green financial markets is essential for achieving a more sustainable economy.

To the best of our knowledge, this is the first study to investigate return connectedness across GB, clean energy stocks and carbon prices at both the time and frequency domain. Tiwari et al. (2022) is the most closely related study to our research, and although they include similar indices, involving carbon markets, GB and clean energy markets, our research differs in two main aspects. Firstly, we extend the data time frame used by including the post-COVID period, and secondly, we investigate connectedness, as recommended by Liu et al. (2021), by considering not only time dynamics, but also frequency dynamics.

2 Methodology

We use two different methods to investigate both time and frequency spillovers among Green Bonds, CO2 prices and clean energy markets. First, we employ the Diebold and Yilmaz (2012) methodology to explore the time dynamic connectedness between these green financial markets. Subsequently, we apply the connectedness measure introduced by Baruník and Krehlík (2018) which extends the DY12 method to the frequency domain.

Generally, financial markets can experience turbulence due to macroeconomic events that can result in financial assets illustrating high volatility, which can spillover between different markets. Diebold and Yilmaz (2012) argued that financial models which include a single-fixed parameter model could ignore significant time-dependent movements in spillovers between financial markets. Therefore, they developed a model that can examine connectedness among markets including time dynamics. Their method measures spillovers based on the generalized vector autoregressive (VAR) framework by computing its forecast error variance decomposition (FEVD), and can examine connectedness among individual or multiple financial assets such as bonds, stocks, etc. through time. More specifically, they consider a covariance stationary N-variable VAR model of order p:

$$x_t = \phi(L)x_t + \varepsilon \tag{1}$$

where x_t denotes a $n \times 1$ vector of endogenous variables, $\phi(L) = [I_N - \phi_1 L - ... - \phi_P L]$ is the N x N matrix lag-polynomial and ε_t represents a white noise with covariance matrix Σ.

The moving average representation is:

$$x_t = \Psi(L)\varepsilon_t = \sum_{i=1}^{\infty} \Psi_i \varepsilon_{t-i} + \varepsilon_t \tag{2}$$

where $\Psi(L)$ is a matrix of infinite lag polynomials that can be calculated recursively.

According to the generalized identification of Pesaran and Shin (1998) which produces variance decompositions invariant to ordering, we can calculate the generalized FEVD. The variance decompositions allow us to assess the contribution of variables into components attributable to shocks to different variables in our green finance system for a forecast horizon H. Specifically, we have:

$$\theta_{ik}(H) = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} ((\Psi_h \Sigma)_{ik})^2}{\sum_{h=0}^{H} (\Psi_h \Sigma \Psi_h')_{ii}} \tag{3}$$

where Ψ_h is a $N \times N$ matrix of moving average coefficients at lag h, σ_{kk} is the k^{th} diagonal element of the Σ matrix and H is the forecast horizon. The $\theta_{jk}(H)$ denotes the contribution of the kth variable to the variance of forecast error of the variable ith, at horizon H.

In the generalized VAR framework, the row sum of the variance decomposition matrix is not necessarily equal to one. Therefore, each entry can be normalized by the row sum as:

$$\tilde{\theta}_{ik}(H) = \frac{\theta_{ik}(H)}{\sum_{k=1}^{n} \theta_{ik}(H)} \tag{4}$$

$\tilde{\theta}_{ik}(H)$ provides a measure of pairwise connectedness from k to i at horizon H. Using the variance contributions, the DY12 method allows us to compute various measures which reveal the level of connectedness among the variables in the financial system. Hence, we are able to obtain the overall connectedness of the system, the net directional spillovers of each market as well as the net pairwise spillovers among the markets.

Baruník and Krehlík (2018) argued that shocks in the financial sector can affect variables at different frequencies and magnitudes. Therefore, they extended the DY12 measure to include time and frequency dynamics simultaneously. This method allows us to measure connectedness among financial markets at different frequency bands such as the short-term, medium-term and long-term. The frequency dynamics can be important for financial investors that operate in different time horizons, but also regulators that want to apply policies that can impact either individual or multiple financial markets in the short-term or long-term.

In order to incorporate the frequency aspect, Baruník and Krehlík (2018) consider the spectral representation of variance decompositions based on frequency responses instead of impulse response to shocks. Thus, they recognize a frequency response function which can be obtained as a Fourier transformation of the coefficients Ψ_h, with $i = \sqrt{(-1)}$, which can be described as:

$$\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h \tag{5}$$

where ω denotes the frequency.

Subsequently, they define the power spectrum $S_x(\omega)$ which describes how the variance of the x_t is distributed over the frequency components ω. The power spectrum is given by:

$$S_x(\omega) = \sum_{h=0}^{\infty} E(x_t x_{t-h}) e^{-i\omega h} = \Psi(e^{-i\omega h}) \Sigma \Psi(e^{i\omega h}) \tag{6}$$

Using the spectral representation, Baruník and Krehlík (2018) extract the frequency domain fractions of variance decomposition. The generalized forecast error variance decomposition at a frequency ω is:

$$\theta_{ik}(\omega) = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{\infty} (\Psi(e^{-i\omega h})\Sigma)_{ik}^2}{\sum_{h=0}^{\infty} (\Psi(e^{-i\omega h})\Sigma(\Psi(e^{i\omega h}))_{ii}} \tag{7}$$

The $\theta_{ik}(\omega)$ represents the fraction of the spectrum of the ith variable at a specific frequency ω due to shocks in the kth variable. As with the DY12 method, the generalized forecast error variance decomposition can be normalized as follows:

$$\tilde{\theta}_{ik}(\omega) = \frac{\theta_{ik}(\omega)}{\sum_{h=1}^{n} \theta_{ik}(\omega)} \tag{8}$$

The $\tilde{\theta}_{ik}(\omega)$ measures pairwise connectedness from k to i at a given frequency ω. Thus, $\tilde{\theta}_{ik}(\omega)$ represents a within-frequency connectedness indicator while the DY12 measure, $\tilde{\theta}_{ik}(H)$, demonstrates pairwise connectedness at horizon H and reflects connectedness exclusively in the time domain. Consequently, the Diebold and Yilmaz (2012) method focuses on aggregate connectedness among frequencies and overlooks heterogeneous frequency responses to shocks.

In economic applications, market participants are usually concerned with short-medium-long-term connectedness rather than aggregate connectedness at a single frequency. Thus, it is important to follow the economic aspect and work with frequency bands. The incremental connectedness at a frequency band $d = (a, b)$: $a, b \in (-\pi, \pi), a < b$ is defined as:

$$\tilde{\theta}_{ik}(d) = \int_a^b \tilde{\theta}_{ik}(\omega)\, d\omega \tag{9}$$

Using the above generalized variance decomposition on frequency band d we can define various connectedness measures on the frequency domain. The overall connectedness within the frequency band d can be obtained as follows:

$$C^d = \frac{\sum_{i=1, i\neq k}^{n} \tilde{\theta}_{ik}(d)}{\sum_{ik} \tilde{\theta}_{ik}(d)} = 1 - \frac{\sum_{i=1}^{n} \tilde{\theta}_{ik}(d)}{\sum_{ik} \tilde{\theta}_{ik}(d)} \tag{10}$$

Furthermore, the BK18 method allows us to identify the direction of spillovers. For instance, the within *from* connectedness, which is the part of variance of i derived from all the other variables $i \neq k$ at the frequency band d, is given by:

$$C^d_{i\leftarrow \cdot} = \sum_{k=1, i\neq k}^{n} \tilde{\theta}_{ik}(d) \tag{11}$$

On the other hand, the within *to* connectedness, which is the contribution of i to all the other variables k ($i \neq k$) at the frequency band d is:

$$C^d_{i\rightarrow \cdot} = \sum_{k=1, i\neq k}^{n} \tilde{\theta}_{ki}(d) \tag{12}$$

By calculating the *from* and *to* connectedness we can then define the within *net* connectedness which is given by:

$$C^d_{i,net} = C^d_{i\rightarrow \cdot} - C^d_{i\leftarrow \cdot} \tag{13}$$

As shown by the equation the within net connectedness evaluates the difference between the variance transmitted and received by a variable. If net connectedness for a variable (for instance, i) is positive, the variable is called a net transmitter of information to the other variables in the system. On the contrary, if net connectedness is negative, the variable is called a net receiver of shocks from the rest of the variables in the system.

Except the system based connectedness measures, the BK18 method allows us to disaggregate connectedness even further and quantify pairwise relationships in our financial system. Hence, the net *pairwise* connectedness between two variables i and k can be obtained as:

$$C_{ik}^{d} = \tilde{\theta}_{ki}(d) - \tilde{\theta}_{ik}(d) \tag{14}$$

The pairwise measure enable us to recognize if a variable is a net receiver or transmitter of shocks from/to another variable in the system while considering different frequencies. In this way, we can conclude which variables are driving the spillovers in the short/long-term in our green financial system. As Tiwari et al. (2022) highlighted, it is important to investigate and understand the pairwise connectedness among green financial assets when constructing optimal portfolios. In their paper, they showed how a minimum connectedness portfolio yields a better Sharp ratio than the more typical minimum variance or minimum correlation portfolios using similar data for a green financial market. However, Tiwari et al. (2022) do not provide connectedness measures across frequencies. Thus, our chosen method extend their connectedness measures to provide insights for both long-term oriented and short-term oriented investors.

The dynamic connectedness measures have been estimated using a rolling window of 200 days and a forecast horizon (H) of 100 days. We have estimated our model with different rolling windows to confirm the robustness of our results. These robustness checks can be found in appendix B. For each rolling window we have chosen the optimal lag length of our eight variable VAR system according to the Schwarz information criterion (SIC).

In our research, we utilize two frequencies, a low and high frequency which is a common approach found in existing literature. Nevertheless, we have expanded our analysis to include a medium frequency range of 6-20 days. The results of this extended analysis can be found in Appendix B. Upon examining the findings, we observe that the medium frequency does not provide any additional information, nor does it significantly impact the main results concerning the patterns of the low and high frequencies. Hence, we can conclude that employing two frequencies in our analysis yields robust and valid results.

3 Data

3.1 Variables

Our dataset is constructed by calculated daily returns[4] for green bonds and clean energy stocks, as well as daily returns for carbon prices[5]. The dataset spans eight years, from July 30th, 2014,

[4]Following Liu et al., 2021, we calculate GB yields and Clean Energy stocks returns as follows: $[\ln(p_{it}) - \ln(p_{i,t-1})] \times 100$.

[5]As measured by the daily returns data for EU ETS quota prices.

until July 27th, 2022 and all data is based on indices, where the indices for green bonds and clean energy markets are sourced from Bloomberg while carbon quota prices are obtained from Refinitiv. To get a thorough coverage of the renewable energy sector, we include three general indices for renewable energy and two industry specific indices for wind and solar energy. In order to consider technological developments in the green transition, we include an index tracing the clean technology market. The wind and solar indices are used specifically since they represent the two renewable energy markets that attract the largest share of renewable energy investments on a global scale.

We use the S&P Green Bond index (GB) to represent the global green bond market (Reboredo, 2018; Liu et al., 2021). Bonds included in this index must be certified as "green" by The Climate Bonds Initiative (CIB, 2022). Consequently, all bonds in this index are directed at green and climate-aligned projects and investments. Further we use the S&P Global Clean Energy Index (SP_CLEAN), the Wilder Hill Clean Energy Index (ECO), and Renewable Energy Industrial Index (RENIXX) as proxies for the overall global clean energy market [6]. The S&P Clean Energy Index includes 100 companies from both developed and developing markets whose business related to clean energy. Wilder Hill Clean Energy Index is known to be the first index to track the development of the US renewable energy sector. The Renewable Energy Industrial Index reflects the 30 firms with the largest market capitalization related to the renewable energy industry, and it is the first index tracking the renewable energy sector in a global perspective. In addition our three sectoral indices are; ISE Global Wind Energy Index (ISE_WIND), MAC Global Solar Energy Stock Index (MAC_SOLAR), and finally S&P Renewable Energy and Clean Technology Index (TSX), which is similar to Liu et al. (2021). The global wind index includes active companies providing both products and services tied to the wind energy industry, while our global solar index includes companies whose core business is related to solar energy technologies and their entire value chain (raw materials and manufacturing, installation and operation, as well as financing). Our final index on renewable and clean technology tracks the performance of companies whose core business is anchored in green technologies and sustainable infrastructure projects. This range of indices has been selected to represent the clean energy, carbon, and green bond markets. Although prior studies, including those conducted by Liu et al. (2021) and Tiwari et al. (2022), have used similar data, we expand upon their research by taking into account frequency dynamics.

One potential data limitation in our study is the overlap of companies among certain indices. For example, a company operating in renewable energy infrastructure might be included in two

[6] S&P Clean Energy Index is used by Liu et al., 2021 and Tiwari et al., 2022, and Wilder Hill Clean Energy Index is also used by Liu et al. (2021) .

indices. However, it is worth noting that similar indices have been used in previous published research as demonstrated by Liu et al. (2021) and Tiwari et al. (2022). Furthermore, our chosen methodology, the BK18, can partially account for these kind of artificial spillovers by incorporating the optimal lag order into our models. This approach considers time-varying effects and can capture evolving interdependencies among those variables. Upon closer examination of the overlap between our indices and their constituents, we identified the highest overlap between RENIXX-SP_CLEAN (11.54%) and MAC_SOLAR-SP_CLEAN (14.58%). However, the remaining indices exhibit less than 10% overlap, and each index has unique weightings for the included companies and sectors. To further assess the robustness of our results, we conducted additional analyses, first excluding RENIXX, and then also excluding MAC_SOLAR. The results, available in Appendix D, confirm that even after excluding these indices, our findings and interpretations remain consistent. It is important to note that while we argue that this should not be a significant issue, we conducted these robustness analyses to further strengthen the validity of our findings.

3.2 Descriptive statistics

As a preliminary analysis, we investigate all our index return data, using GB as the main comparative return index. Each graph is scaled to show GB in relation to the other indices. Figure 1 shows all the plots with GB measured on the left-hand y-axis and the other indices measured on the right-hand axis. The graphs indicate that the clean renewable market has seen a rapid and steep increase since 2020 after the initial shock of the COVID-19 pandemic. In addition, all the market indices exhibit similar patterns with increased variability after reaching a peak in around 2021. One slight outlier is the carbon prices, which demonstrate a delayed peak and shows signs of lower variability than the rest of the renewable and clean market indices. Focusing on GB, we can observe that GB display a differing pattern compared to the other indices. Around 2016, GB experienced a peak with subsequent minor variability, followed by a substation increase from 2018 and a stabilization at a higher level. An interesting find is that even though GB were slightly affected during the early days of the pandemic, the return levels remained at a high level from mid-2020 until recently. We also notice that GB display a substantial drop since the end of 2021. This drop is likely in conjunction with rising interest rates from central banks, especially in the US and European Economic Area (EEA), after a long period with unprecedented low interest rates.

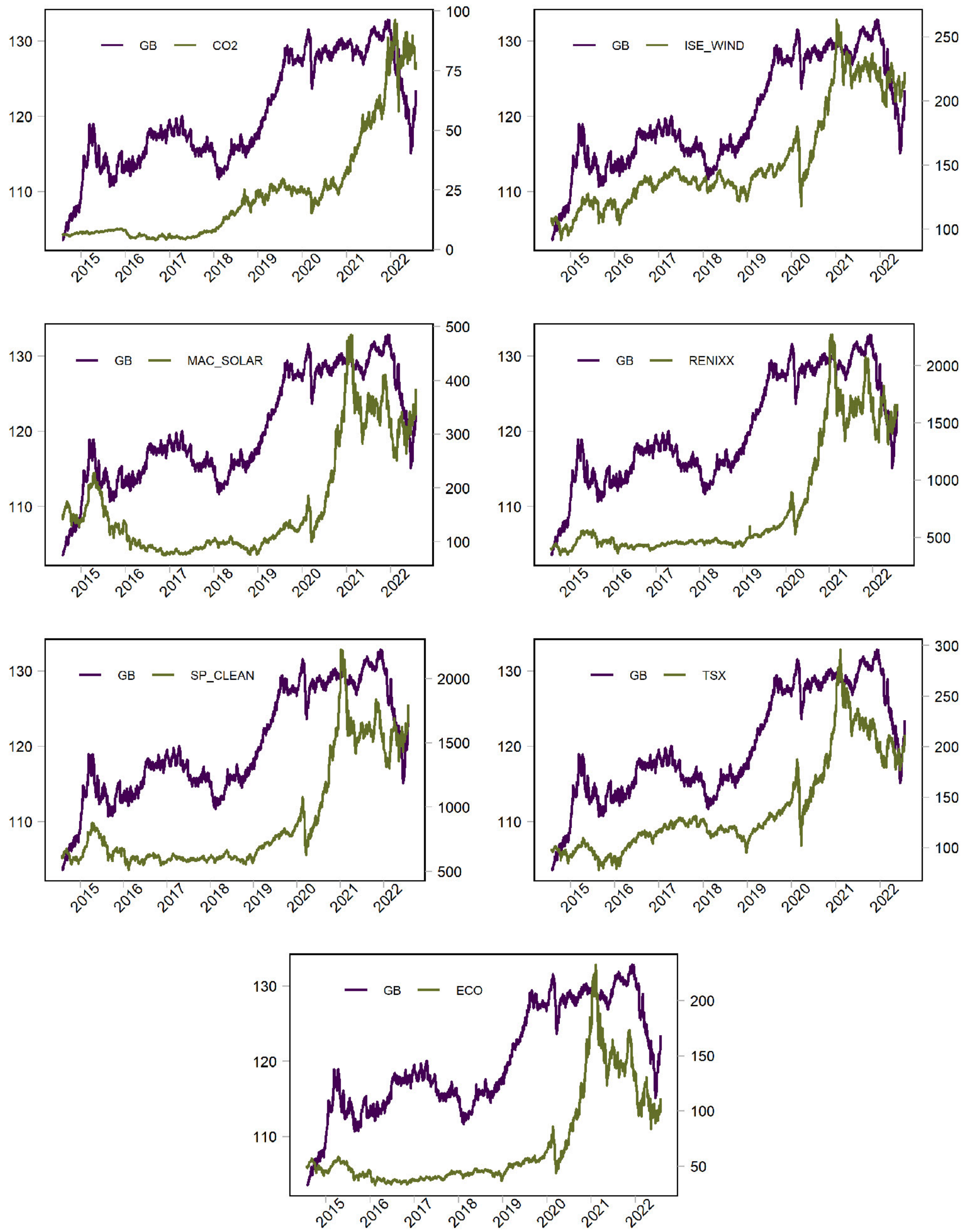

Figure 1. Scaled returns of all data series in relation to green bonds.

Further analysis of the descriptive statistics of our variables (see Appendix A) show that all the series are significantly left skewed and the kurtosis is above 3, suggesting a leptokurtic distribution. We also use the Jarque-Bera test as well as the ADF and KPSS tests to check the normality and stationarity of our data, respectively. The results indicate non-normality and stationarity for all indices. The results are available in Table A1 in Appendix A. Additionally, GB is shown to have the lowest mean and standard deviation compared to the other indices. This verifies the smoother trend we found for GB in figure 1. It also indicates that GB display lower volatility than carbon prices and CE stocks. By contrast, carbon prices are shown to have the highest mean and standard deviation from all the other indices. Investigating the correlation between all variables, we find that the lowest correlation is found between GB, CO2 and Clean Energy stocks. This finding motivates further detailed investigation of the relationship among green bonds, carbon prices and clean energy stocks.

In conclusion, the finding that GB exhibits a distinct pattern when compared to our other indices prompts additional investigation into the relationships and connectedness within our green financial system.

4 Empirical results

The main objective of this paper is to analyze the time and frequency dynamics of connectedness among green bonds, six clean energy markets and the EU carbon market. Thus, we put emphasis on the dynamic version of the connectedness method by Barunik and Krehlik (2018). After testing several frequency bands, we have found it most useful to discuss the connectedness measures for two frequency bands. We employ the high frequency (short-term) band for movements up to five days (one working week), while the low frequency (long-term) band comprises movements from 6 to 200 days. Hence, the first frequency band represents short-term connectedness, while the second frequency band represents long-term connectedness. As a robustness check, we also estimate the connectedness, including a medium frequency. The detailed results can be found in Appendix B. For the purpose of comparison, we have included a static estimation of net pairwise directional returns for both the DY12 and BK18 methods[7]. Additionally, we have incorporated some findings from the Diebold and Yilmaz (2012) pure time-domain framework.

4.1 Total return connectedness

Figure 2 shows the overall system connectedness measured by the DY12 and BK18 methods. The DY12 results show that overall connectedness varies between approximately 40% and 80% during the investigated period. Furthermore, we notice that the two largest connectedness peaks are found around 2015-2016 and 2020. We attribute the 2020 peak to the COVID-19 outbreak, which created unprecedented challenges for society and caused significant turbulence in financial markets. During 2015-2016 both Europe and the US experienced several events leading to higher uncertainty, which is also emphasized in the Economic Policy Uncertainty index by Baker et al.

[7]This is to clearly illustrate the direction and magnitude of directional connectedness among our green assets, and can be seen in figure 5.

(2016). A major event that took place in 2015 was the Greek referendum rejecting bailout terms set forth by the EU to aid the Greek debt-crisis. In addition, towards the end of 2015 leaders from around the world gathered for the COP 21 in Paris, where tough negotiations lead to the signing of the now world-famous Paris Agreement on climate change. Subsequently, several firms and organizations have used the Paris Agreement to align their climate change mitigation and adaptation efforts. Following this event, there was the ramp up of the Brexit referendum that culminated in the UK voting to leave the EU in June 2016. Additionally, the US was experiencing a highly polarized presidential race, which resulted in the election of Donald Trump as president. Other studies have similarly observed higher connectedness between financial markets during periods of economic and political turbulence (Tiwari et al., 2018; Naeem et al., 2020; Zhang and Hamori, 2021). This indicates that financial markets experienced a peak in connectedness during the financial crisis, as uncertainty transmission was high. Additionally, it is important to point out that our green financial market is significantly exposed to US and European markets, as well as the Chinese market, due to the geographical composition in our indices.

We proceed with the decomposed total connectedness by the BK18 framework which enables us to explore the short-term and long-term connectedness in our system. Our results displayed in figure 2 suggest that periods of high connectedness are mostly driven by the high frequency band (short-term). This finding is in line with previous literature investigating different systems (Diebold and Yilmaz, 2012; Ferrer et al., 2018; Tiwari et al., 2022; Kang et al., 2019; Le et al., 2021; Zhang and Hamori, 2021; Jiang and Chen, 2022). Thus, return spillovers among the GB, CO2 and clean energy markets occur mainly in the short-term, specifically within a week. As a result, during such periods, investors in green markets may encounter difficulties in diversifying their portfolios. Albulescu et al. (2019) have shown that identifying good diversification opportunities can be challenging for investors during periods of high connectedness.

In contrast, the low frequency band (long-term) connectedness in the system only varies between 10% and 20% (see figure 2). For long-term investors interested in green finance these results indicate interesting diversification opportunities in this green financial system. The relatively low connectedness at the low frequency band (long-term) indicates that return spillovers are not substantially transmitted among the variables in the long-term, thus it will be easier for long-term investors to construct green portfolios with minimum connectedness among the assets. On the other hand, it can be difficult for short-term investors such as day traders and hedge funds to find solid diversification opportunities, as there are higher return spillovers among the variables in the short-term (high frequency band). However, it also shows that most return spillovers within the green financial system is processed quite quickly. Thus, if short-term investors have solid liquidity and strong market knowledge, there could be some diversification opportunities during less volatile periods as connectedness seems to be lower in these periods. These insights can also be useful for policy makers focusing on designing optimal and efficient climate policies for both adaptation and mitigation efforts. Policy makers, just like investors, can make decisions on different frequency bands. Climate policy makers would likely focus on adaptation policies to deal with short-term challenges but emphasize more mitigation policies to find long-term solutions to the climate crisis. Thus, understanding market spillovers at both the high frequency (short-term) and low frequency (long-term) band could be valuable for policy makers.

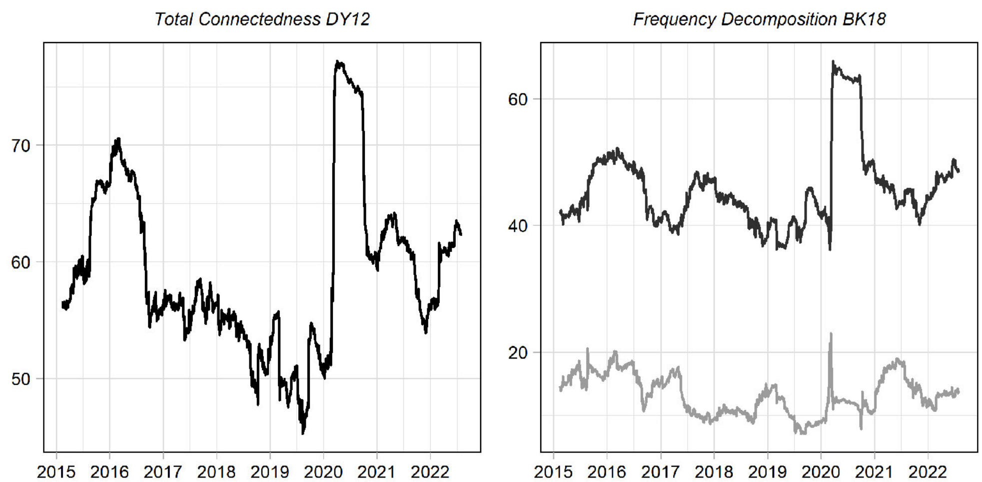

Figure 2. Total connectedness measured by DY12 framework and BK18 framework.

A noteworthy finding is that periods of severe economic events tend to be followed by periods where the connectedness in our system is driven by low frequency (long-term) transmission of shocks. In 2017 and 2021, we can observe in figure 2 a clear increase in long-term connectedness and a drop in short-term connectedness. Additionally, in the period around 2019 we can also notice that the overall connectedness is driven by the long-term rather than the short-term. In general, one could ask whether the severe economic shocks witnessed in 2015-2016 and 2020 cause investors to fear the consequences, resulting in extended periods of shock spillovers. In other words, after a severe negative shock, market participants expect that shocks in the market could have long-term impacts inducing uncertainty about the long-term stability of the market system.

Figure 2 reveals another intriguing observation - the total connectedness is not simultaneously driven by both frequencies at any particular time during the investigated period. This indicates that investors display heterogeneous responses to return shocks throughout the entire investigated period. The results clearly emphasize the importance of decomposing the system connectedness in different frequencies. In this way, we can gain a thorough understanding of the systematic risk between green financial markets, taking into account both the short-term and long-term perspectives. Therefore, we can conclude that utilizing both the DY12 and BK18 frameworks provides a more comprehensive view of the connectedness in our green financial system.

4.2 Net directional return connectedness

Figures 3 and 4 demonstrate the net directional spillovers of each variable in our system. First, figure 3 shows the DY12 results, while figure 4 shows the results from the BK18 framework. The net directional return connectedness allows us to identify net transmitters and receivers of spillovers in our green financial system. Figure 4 displays the breakdown of net return connectedness into short-term and long-term. The pink shade corresponds to the short-term component (high-frequency band), while the blue shade refers to the long-term component (low frequency band).

Figure 4 shows that the majority of the connectedness for our individual variables is driven by short-term connectedness. This finding corroborates the results in figure 2. Focusing on GB, we notice from figure 3 and figure 4 that based on both the DY12 and BK18 framework, GB is a net receiver of return spillovers from the other variables in the system. Additionally, the BK18 results reveal that GB is a net receiver of shocks in both the short-term and long-term, meaning across both frequencies. We also notice that the short-term component (high frequency) dominates the long-term (low frequency) component. Therefore, we could conclude that the short-term component drives the net directional spillover for GB. We detect a minor exception from this result in 2018, when GB acted as net transmitter of shocks in the long-term (low frequency). Some events that could be linked to this is the launch of the European Commission's sustainable finance action plan, the release of the IFC Guidance for Green Sovereign Issuers, and the issuing of the World Bank guide for public sector issuers on green bond proceeds (Richardson and Reichelt, 2018).

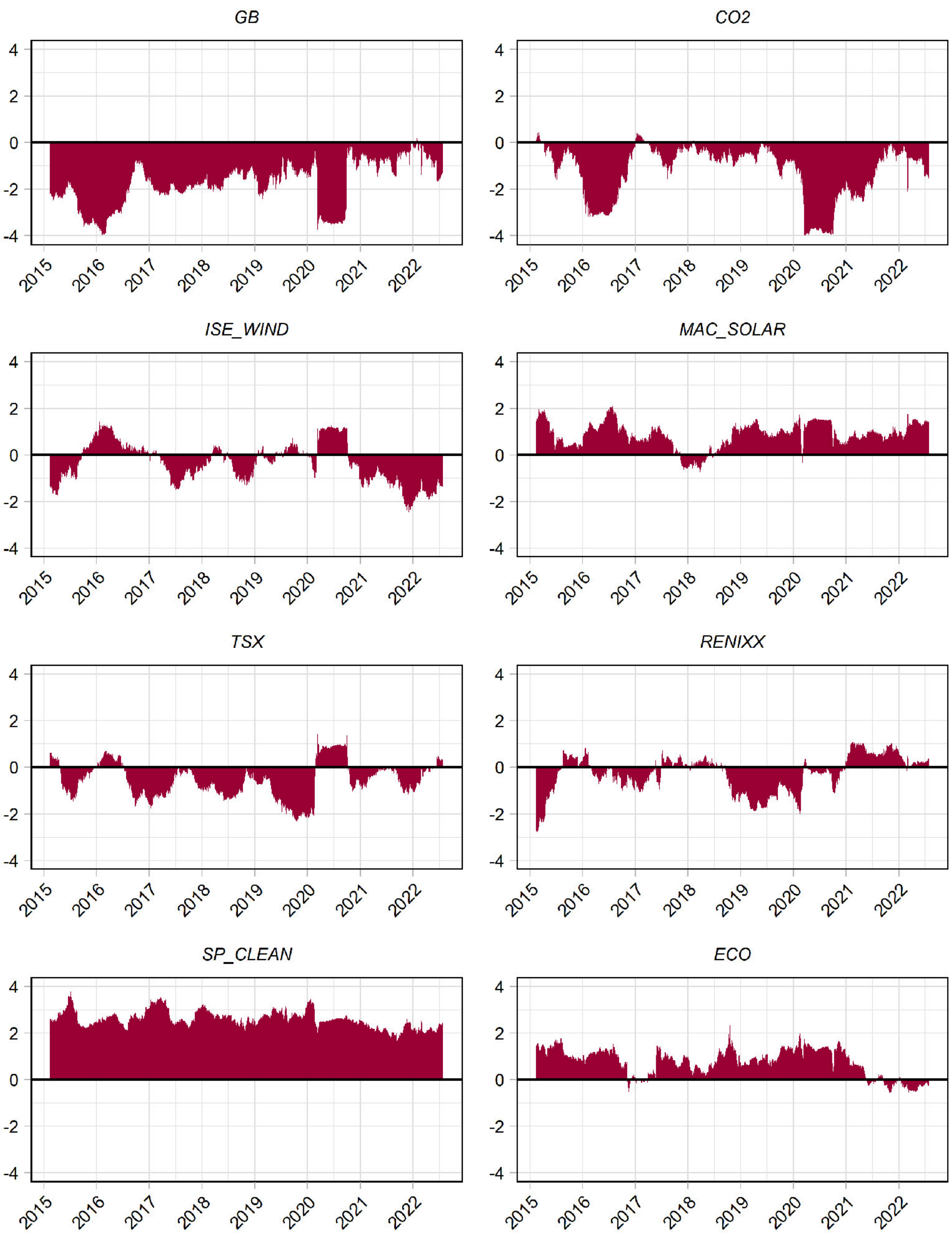

Figure 3. Net directional connectedness DY12.

In terms of market related events, it is noteworthy that in 2018 the cumulative green bond issuance reached \$500bn (Richardson and Reichelt, 2018). The findings also indicate that GB is receiving fewer shocks after the COVID-19 pandemic compared to pre-pandemic. Given the increased attention towards green bonds within academia and financial markets, we could speculate whether it is possible that GB's role may shift from being a net receiver to a net transmitter of shocks in the years to come. More importantly the results show that GB exhibit relatively lower connectedness in more recent periods, indicating that GB could serve as an effective diversification instrument for investors who operate in both the short-term and long-term green financial markets.

In figures 3 and 4, we can see similar patterns for CO2 quotas as we do for GB in both the DY12 and BK18 frameworks. CO2 emerges as a net receiver of shocks across frequencies for the majority of our investigated period. Additionally, the net connectedness is mainly driven by the short-term, which is the same case as for GB. CO2 diverges from the GB pattern during times of significant political and economic uncertainty, such as Brexit and the COVID-19 pandemic. In these periods, the net directional connectedness of CO2 to the rest of the system increases to a much greater extent compared to GB. On the other hand, during times of relative political and economic stability (2017-2019), CO2 shows only minimal connectedness with the rest of our green financial system. This finding may be of interest for both short-term and long-term oriented investors, as well as for policy makers working on carbon markets like the EU ETS. Overall, it can be observed that GB and CO2 are the primary net receivers of return spillovers in both the DY12 and BK18 frameworks, which is consistent with previous literature (Le et al., 2021).

Focusing on the clean energy markets, we observe some fluctuations in the net receiving and transmitting behavior for ISE_WIND, MAC_SOLAR, TSX and RENIXX in the DY12 framework. On the contrary, ECO displays less variability than the other indices, while SP_-CLEAN differs from the other variables by being a net transmitter rather than receiver of shocks. To better understand whether it is the short-term component or long-term component that drives the net directional spillovers for our clean energy assets we exploit the BK18 framework. Going into more detail regarding the clean energy variables, we can notice from figure 4 that MAC_-SOLAR, SP_CLEAN, and ECO generally act as net transmitters across both frequencies during the periods around the Greek debt crisis, the signing of Paris Agreement, Brexit and COVID-19 pandemic. Thus, we can deduce that during periods of political and economic uncertainty, the net return spillovers in the green financial system are driven by the general clean energy markets as well as the solar energy industry. At the same time, we notice that the connectedness for MAC_SOLAR, and ECO is estimated to be relatively low for the whole time period. Most of the return spillover transmission is driven by SP_CLEAN, and mostly driven by the high frequency band (short-term).

Figure 4. Net directional connectedness BK18.

A particularly interesting finding from the decomposed frequencies is that even though both SP_CLEAN and ECO emerge as net transmitters in the system, their connectedness to the system is driven by different frequencies and their connectedness displays different magnitudes. The net directional connectedness for SP_CLEAN is influenced by the high frequency band (short-term), whereas the connectedness for ECO seems to be mainly driven by the low frequency band (long-term). However, since the outbreak of the war in Ukraine and significant monetary policy tightening, especially from the Federal reserve system (FED), it seems that it is the short-term net spillovers that drive the net directional spillovers from ECO to our green finance system. This finding becomes clear when investigating both figures 3 and 4. From figure 3 ECO emerges as a net receiver of spillovers after mid-2021, and in figure 4 it is clear that it is the short-term (high frequency) spillover that dominates the long-term (low frequency) spillover.

In figure 4, we also observe that the net directional connectedness for ISE_WIND and RENIXX is not dominated by one frequency but is equally affected by both frequencies in different time periods. For the case of ISE_WIND, which represents the wind energy market, the results demonstrate that the return transmission during the macroeconomic events of 2016 and during COVID-19 was mainly driven by the high frequency band, indicating that shocks are transmitted rapidly through the system. However, both during the time of the signing of the Paris Agreement and post-COVID-19 ISE_WIND seems to act as a net receiver of return spillover in our green financial system. On the other hand, RENIXX follows a different pattern than ISE_WIND, being a net transmitter of spillovers driven by the short-term in the post-COVID period while it appears to be a net receiver during the macroeconomic events of 2015-2016 switching between short-term and long-term connectedness. Lastly, TSX emerges as the most volatile variable switching multiple times between being a net transmitter and receiver of return spillovers at different frequencies.

Overall, our results suggest that GB, CO2, and clean energy markets react differently to market events and that return connectedeness varies depending on the frequency, especially among clean energy markets. Moreover, we observe that the connectedness of most clean energy markets remains considerably low throughout the entire analyzed period, as opposed to the high connectedness exhibited by SP_CLEAN and GB, as well as CO2 during times of economic and political instability. Consequently, our analysis suggests that SP_CLEAN is the primary net spillover transmitter within our green financial system, while GB serves as the primary receiver of return spillovers. Overall, the results provide interesting insights for investors that are seeking opportunities to explore green financial markets and identify potential diversification strategies for their portfolios.

4.3 Pairwise directional return connectedness

In this section, we shift our focus to the pairwise directional return spillovers to shed some light on the key transmitters and receivers of shocks in a bi-variate setting. First, we will provide an overview of the net receivers and transmitters between the variables in the system by presenting the static pairwise results from both the DY12 and BK18 frameworks. The results are shown in the network graph in figure 5. For comparison purposes, we have also included the DY12 results. Additionally, we have focused on the pairwise connectedness between GB and CO2 since we are particularly interested in the relationship of these two markets with the clean energy market. Nevertheless, we have provided a brief commentary of the results for the clean energy variables. The dynamic DY12 pairwise results and the clean energy pairwise results can be found in Appendix C.

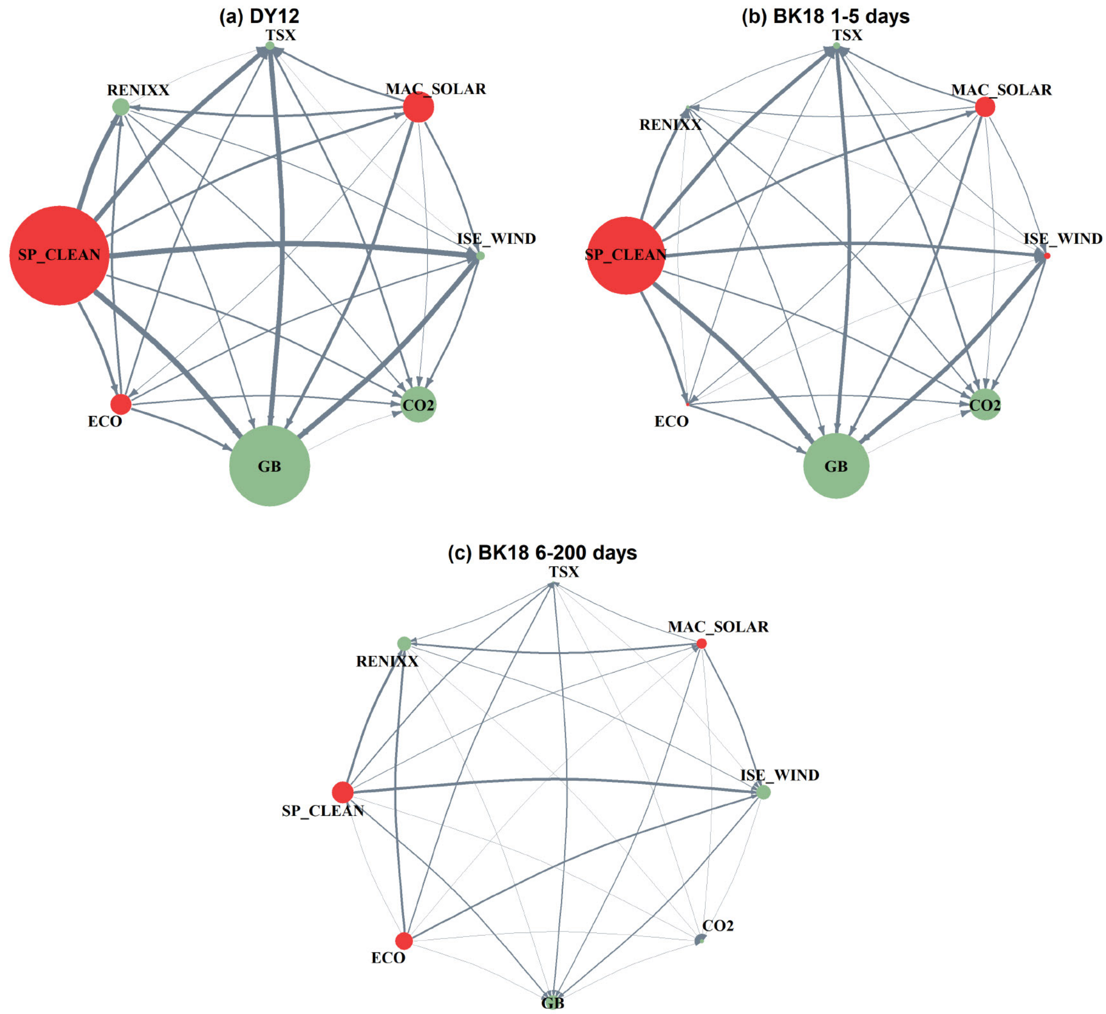

Figure 5. Net pairwise directional connectedness measured using both the DY12 and BK18 framework. *Note*: The size of the nodes is proportional to the magnitude of each variable as transmitter/receiver of return connectedness to/from each one of the remaining variables in our green financial system. Additionally, the color of the node indicates whether a variable is a net transmitter/receiver of connectedness to/from all the other variables. In this figure net transmitters are colored red and net receivers are colored green. Finally, the thickness of the line arrows reflects the strength of the connectedness between a pair of variables, which means that thicker edges represent stronger net pairwise connectedness.

From figure 5 we see that GB emerges as the largest net receiver of return shocks in our green financial system, followed by CO2. The only pairwise relationship where GB is a net transmitter of return spillovers is between GB and CO2, but the net transmission is marginal, which is made clear by the significantly weak line going between GB and CO2. Furthermore, from part (b) in figure 5, we observe that the magnitude of shocks received by GB is primarily in the high frequency band, corresponding to 1-5 days. Three variables stand out as the strongest transmitters of return spillovers to GB, namely SP_CLEAN, TSX and ISE_WIND, with SP_CLEAN having the most significant effect. Again, we observe that this relationship is predominantly driven by the high frequency band, suggesting that the return spillovers are rapidly processed, within a single work week. There is some evidence of long-term (low-frequency) connectedness that arises during periods of turbulence, such as the Greek debt crisis, Brexit and COVID-19.

The analysis of CO2 reveals that it is the second largest net receiver, both in the high and low frequency bands. However, the magnitude of the connectedness is rather weak and almost negligible in the long-term, as indicated by part (c) in figure 5 and figure 7 (also figure C.2 in Appendix C). In figure 7, we observe that this generated marginal connectedness is mostly driven by the short-term (high frequency), especially during the Brexit and COVID-19 pandemic. In addition, except for a few exceptions, there is barely any long-term connectedness during the investigated period. Generally, during times of political and economic instability, CO2 tends to be more strongly connected with the clean energy markets and GB market at the high frequency band. Overall, it appears that CO2 is quite decoupled from the other variables in our green financial system. Furthermore, some may argue that certain investors regard CO2 as a commodity that can be used as a financial speculative instrument, much like the financialization of crude oil (Ferrer et al., 2018). Thus, certain investors may own "brown" stocks associated with polluting industries such as steel companies, while simultaneously purchasing carbon quotas to offset the perceived adverse impact of owning these stocks. The use of carbon quotas as a speculative instrument could be the reason for the lack of connectedness between CO2 and clean energy markets, similar to what has been observed for conventional and renewable energy markets (Ferrer et al., 2018; Asl et al., 2021).

When investigating the pairwise directional connectedness of our clean energy market variables we come across several interesting findings. First, in our static model in figure 5, SP_CLEAN displays relatively strong transmission of return spillovers to GB, ISE_WIND, RENIXX and TSX. However, we notice a relatively weaker connectedness between SP_CLEAN and MAC_-SOLAR, as well as SP_CLEAN and ECO. Focusing on the dynamic model, results indicate that SP_CLEAN is the main driver of return spillovers in our green financial system, both in the DY12 framework and the BK18 framework. Moreover, most of the pairwise connectedness between SP_CLEAN and the rest of the variables in the system is generated in the short-term (high frequency band). This finding also corroborates the net directional results in figure 4, where SP_CLEAN is showed to generate most connectedness at the short-term (high frequency band).

Figure 6. Net directional pairwise connectedness between green bonds and the green financial system measured at high and low frequency.

A noteworthy finding is that although the ISE_WIND seems to be a net receiver of return spillovers in the dynamic DY12 framework, in the BK18 frequency framework it emerges as a net transmitter in the short-term, and switches to a net receiver in the long-term. These insights into the wind energy market in the context of our green financial market may also be of interest for various investors and policy makers, as wind energy is a popular investment option for investors interested in renewable energy. Overall, the wind industry exhibits rather low connectedness to the other green financial markets, rendering it an attractive diversification opportunity. Yet, it may be beneficial for short-term green investors to be aware of the potential spillover from the general clean energy market represented by SP_CLEAN, and the potential spillovers from ISE_WIND to GB, and from ISE_WIND to CO2 especially during highly turbulent times.

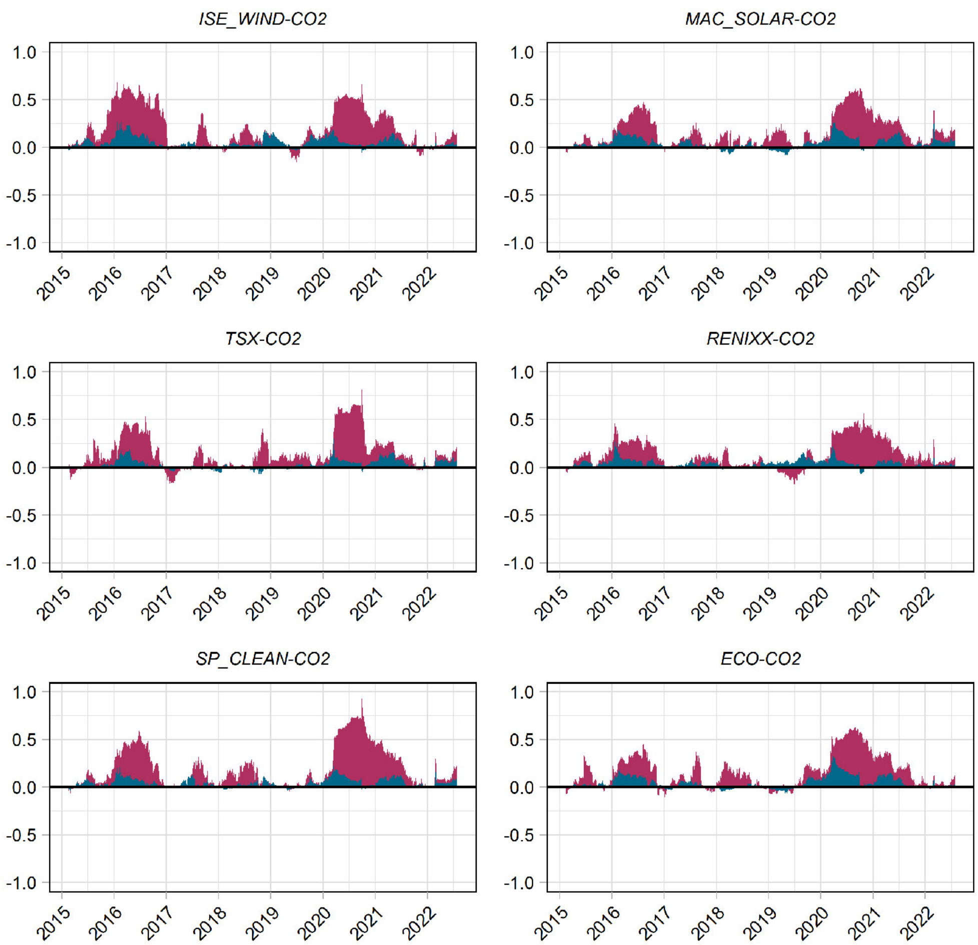

Figure 7. Net directional pairwise connectedness between carbon market returns and the clean energy markets at high and low frequency.

Another interesting result associated with the clean energy markets is that ECO, which is identified as a net receiver at both frequency bands is mainly influenced by the long-term component. Additionally, as depicted in figure 5, ECO is the only variable that increases in magnitude at the long-term (6-200 days). A potential answer to this result may be that ECO could be constructed from stocks that tend to be more have investors who scrutinize information more thoroughly after a shock, resulting in a larger spillover magnitude in the long-term (low frequency band). We notice that the pairwise directional spillover between ECO and GB, and ECO and CO2 is rather low and mostly driven by the short-term in figures 6 and figure 7, indicating that most of the low frequency (long-term) return spillover transmission occurs between ECO and other clean energy markets. This can also be seen in figure 5 part (c), where the return spillover from ECO at the low frequency band is transmitted mainly to RENIXX, ISE_WIND and TSX.

5 Discussion

Our results show that connectedness in the green financial system is both time and frequency dependent. In line with previous studies (Diebold and Yilmaz, 2009; Albulescu et al., 2019; Naeem et al., 2020), we find that periods of political and economic uncertainty tend to increase connectedness between the assets under examination.

An interesting finding is that periods of severe economic events tend to be followed by periods where the connectedness in our system is driven by long-term (low frequency) transmission of shocks. This prompt us to question whether investors fear the aftermath and the uncertainty surrounding the resolution of these severe economic shocks. Thus, new information is examined with greater scrutiny, which translates into shock spillovers being transmitted over longer periods. Following a serious shock, market participants anticipate that disruptions in the market may have lasting impacts, including uncertainty about the long-term stability of the market. Such a finding can be of great interest for both investors and policy makers in planning and portfolio management.

Following the COVID-19 pandemic, from early 2020 until today, the total return connectedness has continued to remain at higher levels than those observed before the pandemic. This connectedness is likely linked to the energy crisis in Europe, the war in Ukraine and tightening monetary policies across Europe and the US. Nevertheless, the relatively low connectedness between our green assets indicates prospects for diversification in the long-run, as well as among specific assets in the short-term. Numerous financial market leaders suggest investing in climate-aligned assets, which as demonstrated, can be advantageous for investors. Among the most famous is BlackRock CEO Larry Fink, emphasizing the importance of aligning the financial markets and climate efforts in his letters to CEOs in 2021 and 2022. Moreover, the World Bank has faced increasing pressure to tackle climate change[8], and to quickly ramp up efforts to allocate more money to finance climate initiatives.

Overall, our results show that the system connectedness is mainly created at the high frequency band. Consequently, most of the return spillovers between our green assets are transmitted through the system within a week. Thus, investors in climate finance can find it easier to construct a diversified green portfolio in the long-run than in the short-run. One may assume

[8]Article from Financial Times (2023).

that this finding might stimulate or attract a long-term perspective towards green investments rather than prompting short-term speculation. This is particularly crucial for a successful green transition and can motivate policy makers to design policies that encourage investors with long-term investment preferences to invest in the green financial market. Simultaneously, the world is lagging in terms of financing the green transition. Therefore, we can argue that it is also essential to motivate short-term investors to secure a rapid influx of capital. Policy makers can enhance the attractiveness of the green financial market for short-term investors by designing policies that target reducing the short-term connectedness.

GB and CO2 are estimated as net receivers of shocks, with most of the return spillovers occurring at the high frequency (short-term) band. Furthermore, since 2021, there has been a significant decrease in net connectedness across the different frequency bands for GB. The fact that GB and CO2 are net receivers implies that they are not key determinants of the performance of clean energy and clean technology stocks. Consequently, we can assume that GB, CO2 prices and clean energy stocks can be utilized by investors for portfolio diversification. Importantly, both GB and CO2 exhibit relatively low connectedness at the low frequency band. Thus, these assets could provide an interesting avenue for long-term investors who focus on green financial markets. Our findings can encourage long-term investors such as pension funds and sovereign funds to consider creating fully climate-aligned portfolios.

Our findings indicate a low level of connectedness of CO2 prices with the other green assets in our system during periods of stability. The level of connectedness, however, increases significantly during highly turbulent periods, specifically in 2016 and 2020. CO2 quotas can be perceived as a commodity used as a speculative instrument by certain investors, such as short-term traders and hedge funds, similar to the financialization of crude oil discussed by Ferrer et al. (2018). For instance, some investors may purchase carbon quotas as a potential hedge against climate risk in their portfolios when owning "brown" stocks. This may affect the lack of connectedness between CO2 and the clean energy market, similar to the documented decoupling of traditional and new renewable energy markets (Ferrer et al., 2018; Asl et al., 2021). Consequently, CO2 has the potential to act as an interesting diversification tool for portfolios that include clean energy stocks and/or green bonds.

Our findings also suggest that SP_CLEAN is a main driver of the high frequency return spillovers, while the connectedness associated with the other clean energy markets is relatively low across both frequencies. There are prolonged periods where the net connectedness of the clean energy assets is primarily driven by the low frequency (the long-term). Upon analyzing the pairwise connectedness results, it becomes apparent that the primary contributor to long-term connectedness is the transmission of spillovers among the various clean energy indices, rather than the relationship between GB-CO2 and clean energy markets[9] Therefore, the clean energy assets could be used as diversification tools for short-term portfolios. This finding could be valuable for short-term investors, including day traders and hedge funds, who are seeking diversification opportunities within the green financial markets.

6 Conclusion

In recent years, the world has witnessed a significant surge in the awareness and need for finance that aligns with climate goals. This trend can be attributed to the need for green transition investment in response to the pressing challenge of climate change. Green bonds and carbon markets along with clean energy markets can be seen as the most important financial building blocks for a successful green transition in line with the Paris Agreement, the EU Green Deal and other global and regional climate initiatives.

This paper investigates the time and frequency dynamics of connectedness among green bonds, carbon prices, and clean energy markets, using the novel connectedness framework by Baruník and Krehlík (2018), regarded as an extension to the spillover index approach by Diebold and Yilmaz (2012). The BK18 framework allows us to explore the connectedness between our chosen green assets in both the time and frequency domain simultaneously. Therefore, we can decompose the total and directional connectedness, found by the DY12 framework, to different frequencies and discover short and long-term connectedness between our chosen assets. The BK18 connectedness results can facilitate portfolio diversification for investors operating in different time horizons, eventually increasing funding for environmentally friendly projects. This can cultivate positive change towards a sustainable future and assist into achieving the global sustainability goals. We selected two frequency bands that represent the short-term and long-term horizon. The high frequency band comprising 1-5 days (equivalent to a working week) represents a short-term horizon, while the low frequency band of 6-200 days refers to a long-term horizon[10].

Our empirical results provide insights into the green financial market, where SP_CLEAN generally transmits return spillovers, while GB and carbon prices act as net receivers, and the other clean energy markets display a rather low net connectedness. We find that generally, high frequency band (short-term) return spillovers dominate low frequency band (long-term)

[9]In the preceding paragraph, we noted that connectedness is mainly driven by the short-term spillovers among GB-CO2, and clean energy markets.

[10]While we have also used three frequency bands (see Appendix B), the medium-term horizon has not yielded significant insights. Furthermore, aligning our frequency bands with those used in previous studies has made it easier to compare our results with the existing literature.

spillovers in magnitude. This means that, as per today, the green financial market benefits the long-term investors who operate at the low frequency band, even more in turbulent periods, as most return spillover connectedness is found in the short-term. Thus, it appears that generally the green financial market is quite efficient in rapidly processing information, resulting in shock transmissions mainly occurring within one working week. Moreover, discovering rather low connectedness in the long-term implies that these markets appear to be primarily driven by their own fundamentals and the overall economic standing. Our analysis also reveals that several of our clean energy indices exhibit low connectedness, even at at the high frequency band (short-term). This finding may interest short-term investors and incentivize increased capital in these markets.

Our results regarding CO2 quota prices reveal low connectedness with the rest of the system during periods of stability, with a notable increase only during highly uncertain political and economic periods. CO2 prices display an increased connectedness during the Brexit crisis and the COVID-19 pandemic, while for the remainder of the time period, CO2 appears to be weakly connected both with green bonds and clean energy markets. This finding may present opportunities for short-term investors who wish to diversify their green portfolio by including CO2 as a potential option. However, short-term investors should be aware of considerable return spillovers during extremely turbulent periods, which can make portfolio diversification more difficult, or less reliable. Overall, our results provide evidence of diversification prospects in green financial markets. This underscores the potential for investors to take advantage of these prospects and further promote the green financial transition.

Concerning policy makers, we would suggest that they pursue policy mixes that encourage greater investments from long-term investors, while also providing incentives for short-term investors to facilitate essential short-term climate capital. Policies can also enhance the attractiveness of the green financial market for short-term investors by designing policies that target reducing the short-term connectedness, especially aimed at GB. Moreover, providing insights into the connectedness between various clean energy markets in both the short-term and long-term could aid in designing and revising policies for an efficient and fair green transition.

An interesting next step for researchers and investors would be to compare minimum connectedness portfolios created at different frequencies to investigate short-term and long-term hedging opportunities in line with Tiwari et al. (2022). Lastly, it would be interesting to explore the possibilities of estimating which return spillovers are positive or negative in nature. These are important future research agendas, not accomplished using the DY12 and BK18 frameworks.

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A Appendix

Table A1. Summary Statistics and Tests.

	GB	CO2	ISE_WIND	MAC_SOLAR	TSX	RENIXX	SP_CLEAN	ECO
Mean	0.006	0.088	0.024	0.032	0.026	0.048	0.036	0.027
Std. Dev.	0.269	2.413	0.954	1.805	1.235	1.538	1.31	1.882
Min	-2.403	-19.453	-11.708	-14.854	-14.617	-16.343	-12.507	-16.952
Max	1.447	16.191	9.835	11.264	10.834	17.246	10.979	13.338
Skewness	-0.441	-0.433	-0.88	-0.534	-1.266	-0.174	-0.586	-0.498
Kurtosis	6.399	7.855	18.192	7.78	22.414	15.751	13.398	8.867
Jarque-Bera	5075.7***	7597.7***	40642***	7502.9***	61902***	30198***	22007***	9686.7***
ADF	-13.621***	-14.309***	-13.72***	-13.188***	-12.969***	-13.323***	-12.525***	-12.974***
KPSS	0.074	0.06	0.032	0.06	0.043	0.068	0.047	0.088
Observations	2920	2920	2920	2920	2920	2920	2920	2920

Notes: i) *, ** and ***, respectively denote rejection of the null hypothesis at 1%, 5% and 10% significance levels. ii) ADF: Augmented Dickey-Fuller, KPSS: Kwiatkowski-Phillips-Schmidt-Shin

B Appendix

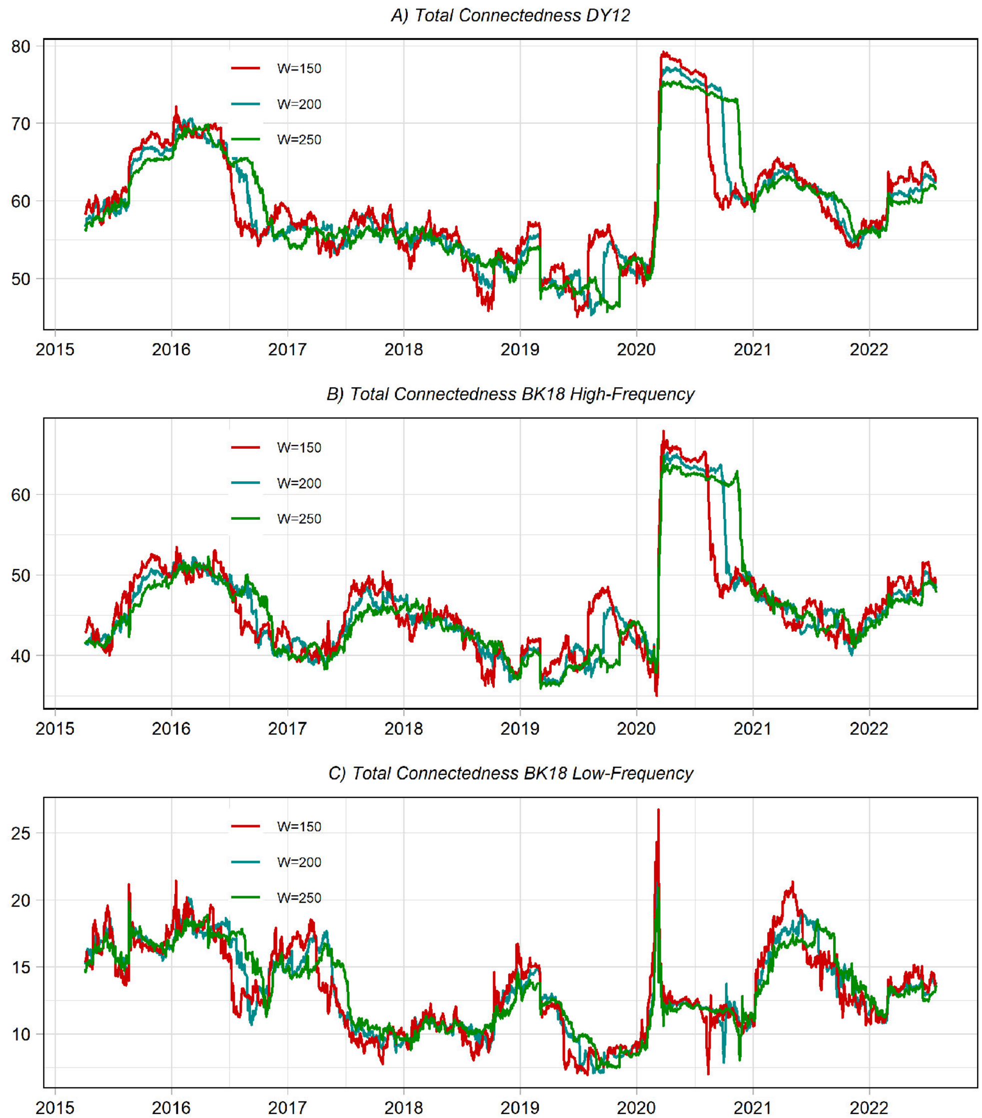

Figure B.1. Robustness check using different rolling window sizes (150, 200 and 250 days). *Notes*: i) The rolling window of 200 days represents our main results in the paper, ii) This figure displays the overall time-varying connectedness of DY12 and the time-frequency connectedness of BK18 for two frequency bands (low and high).

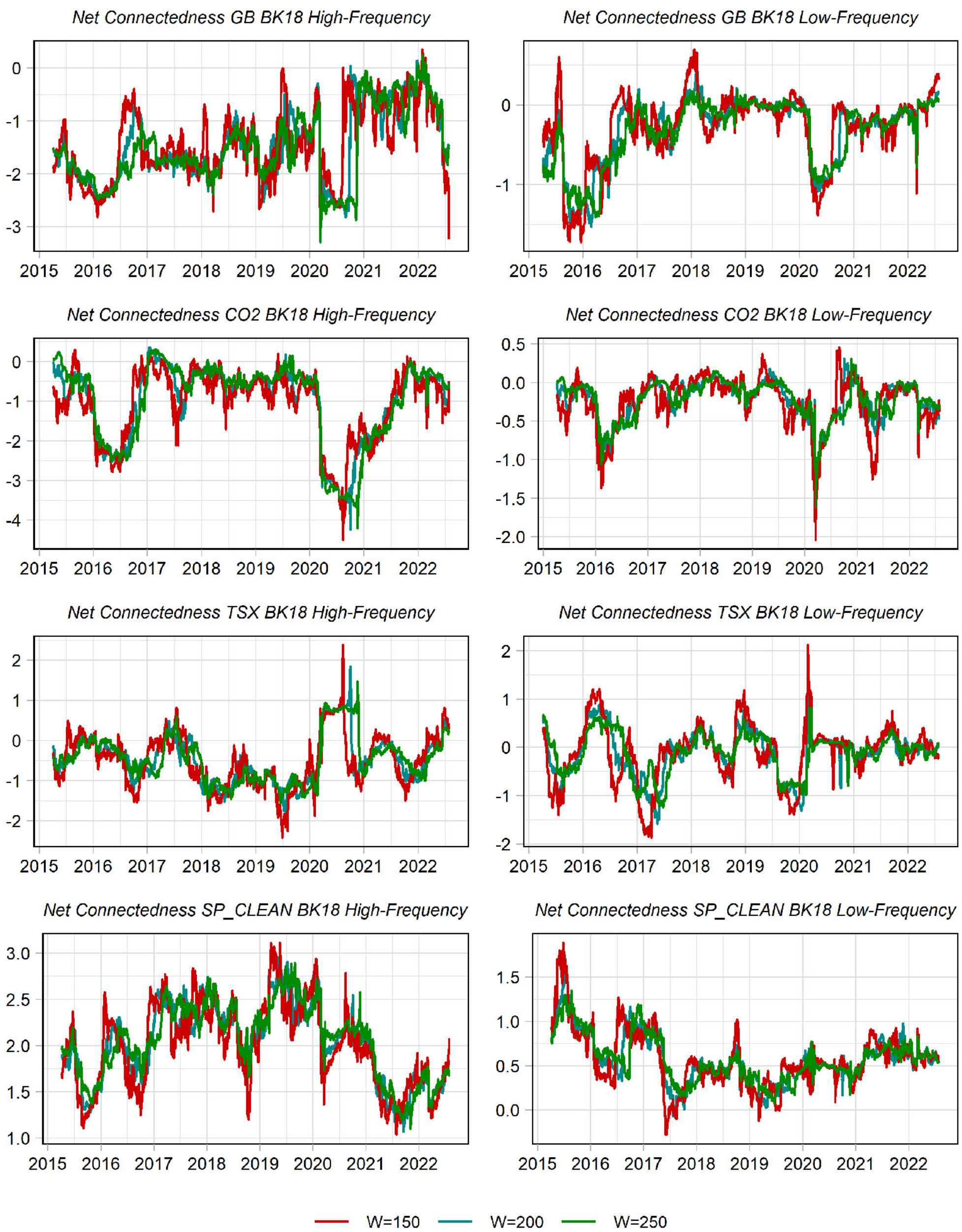

Figure B.2. Robustness check using different rolling window sizes (150, 200 and 250 days). *Notes*: i) The rolling window of 200 days represents our main results in the paper, ii) This figure displays the net time-frequency connectedness of BK18 for two frequency bands (low and high). For simplicity, we split the indices in two graphs.

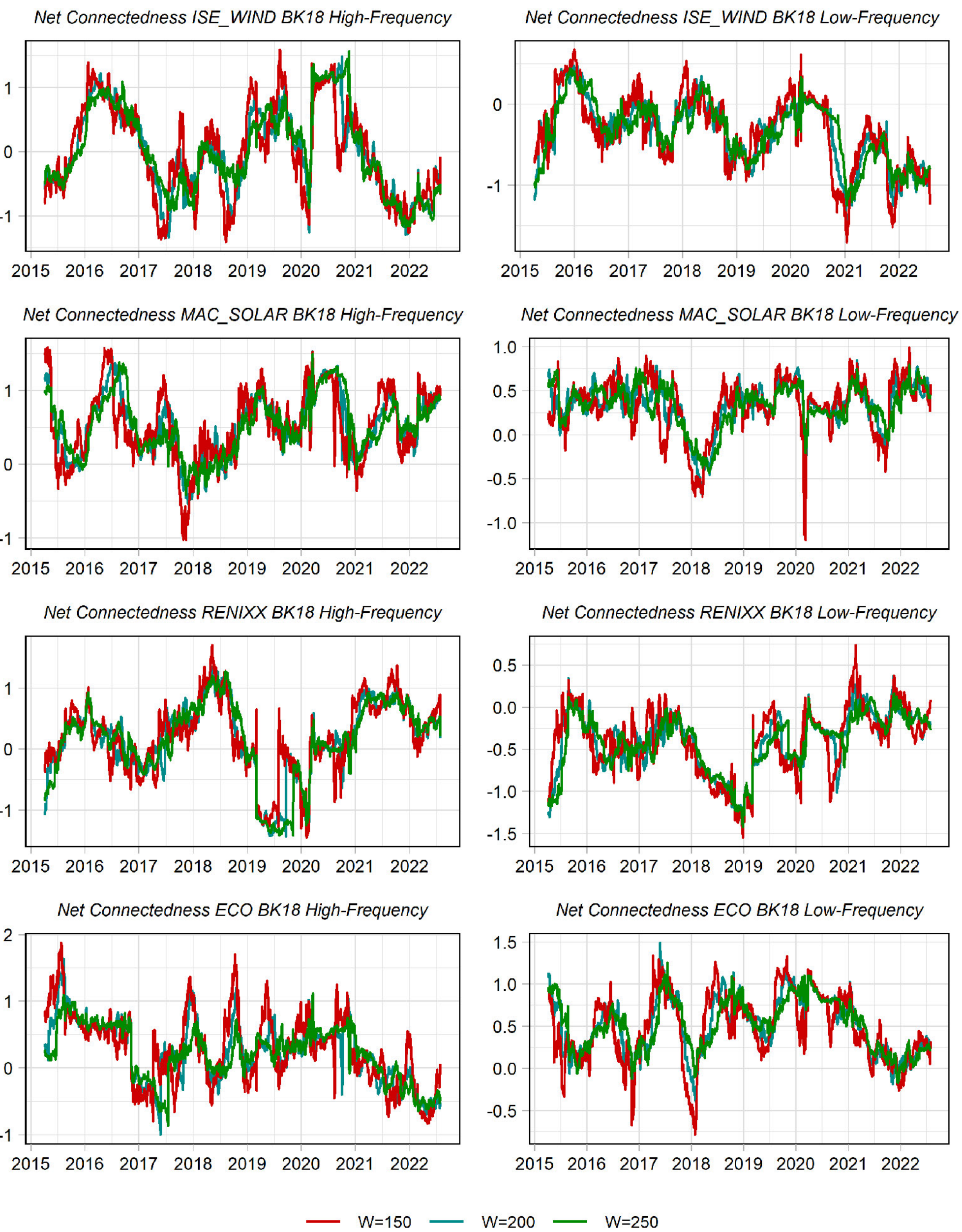

Figure B.3. Robustness check using different rolling window sizes (150, 200 and 250 days). *Notes*: i) The rolling window of 200 days represents our main results in the paper, ii) This figure displays the net time-frequency connectedness of BK18 for two frequency bands (low and high). For simplicity, we split the indices in two graphs.

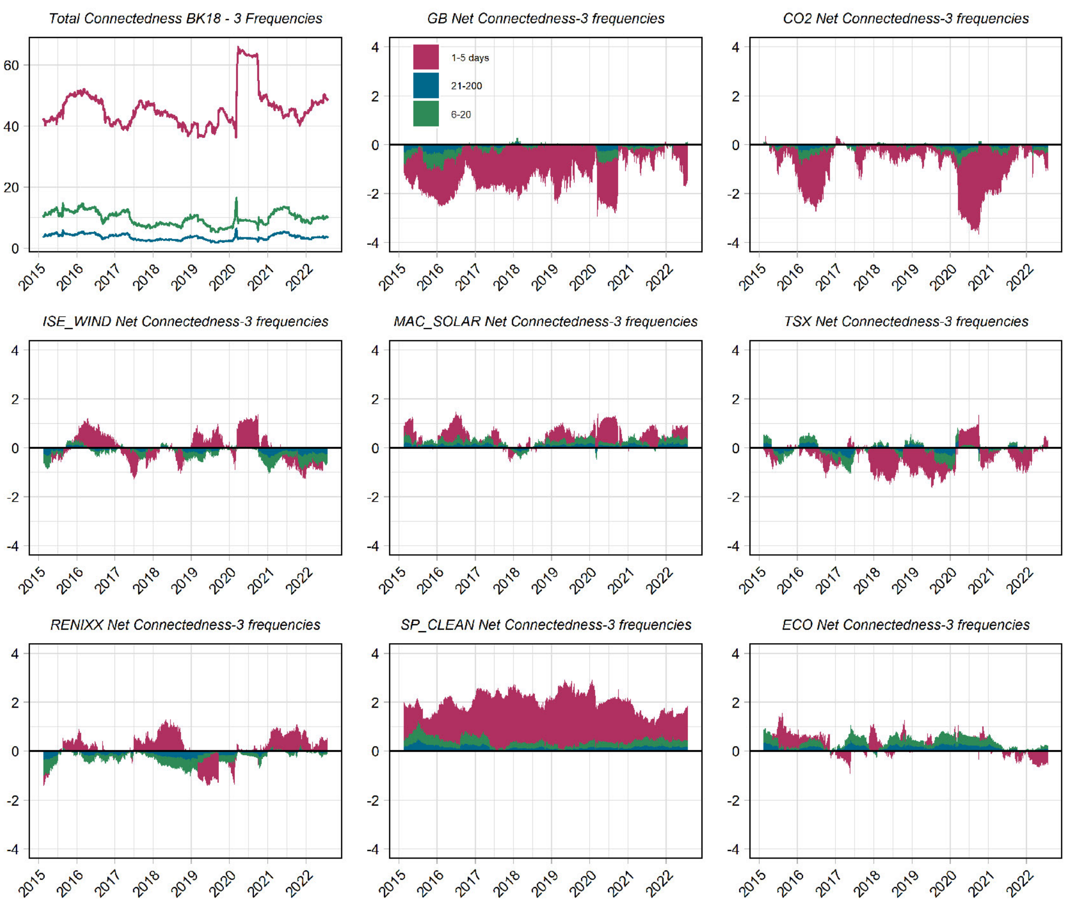

Figure B.4. Robustness check using three frequency bands. *Note*: i) This figure displays the total connectedness of our system, but also the net connectedness for each index in three frequencies.

C Appendix

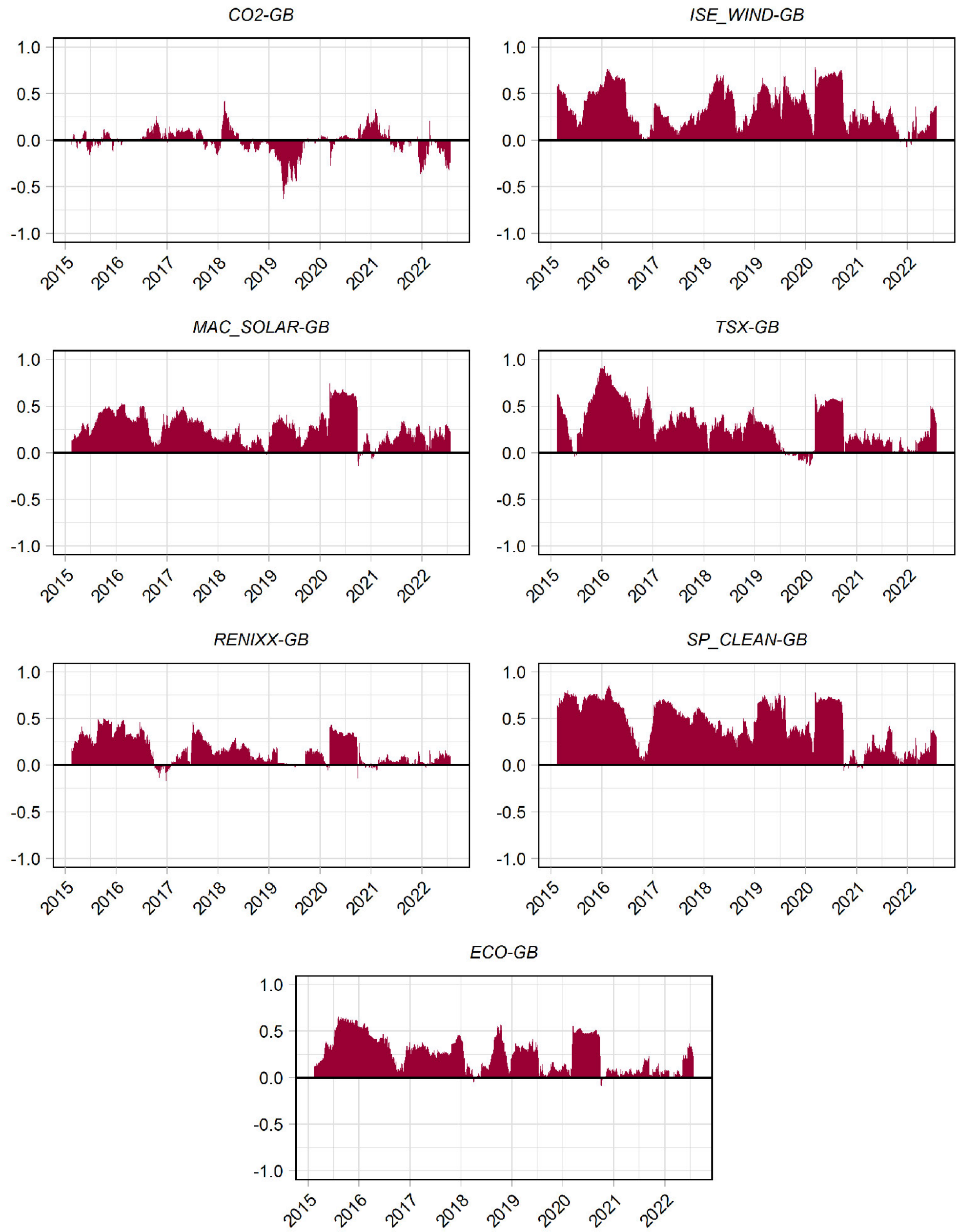

Figure C.1. Net directional pairwise connectedness between green bonds and the green financial measured by the DY12.

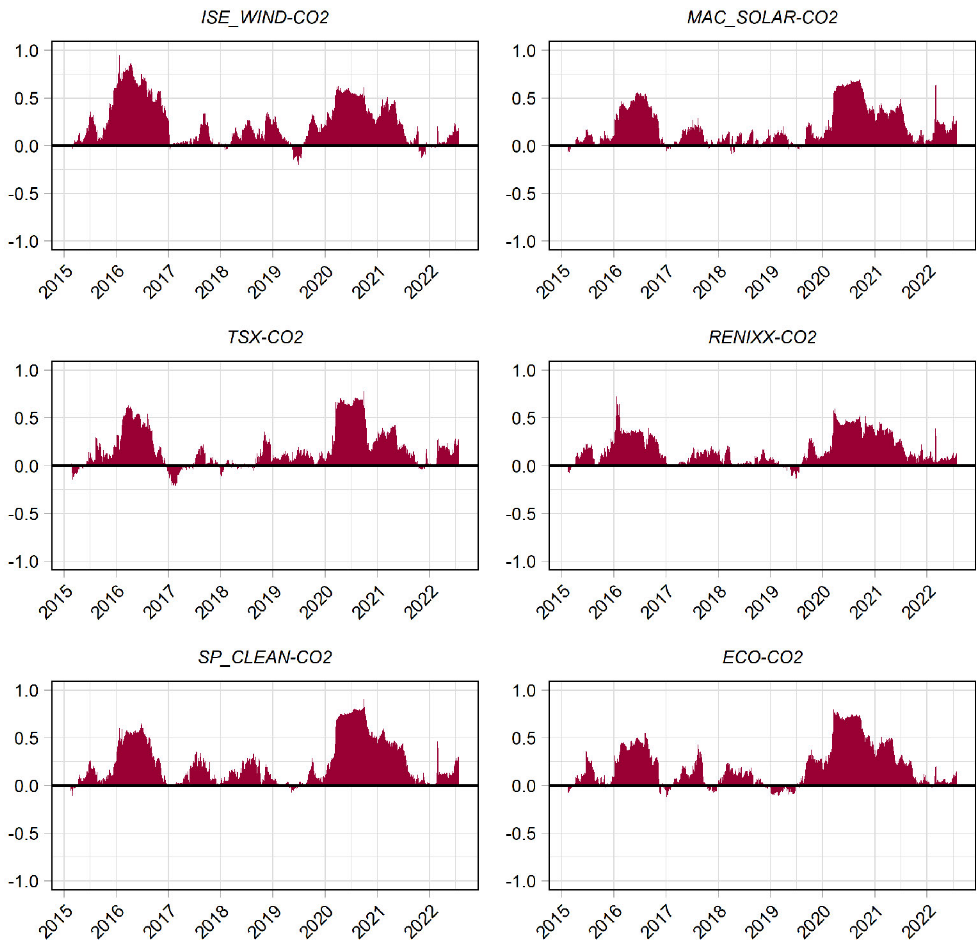

Figure C.2. Net directional pairwise connectedness between CO2 and the green financial measured by the DY12.

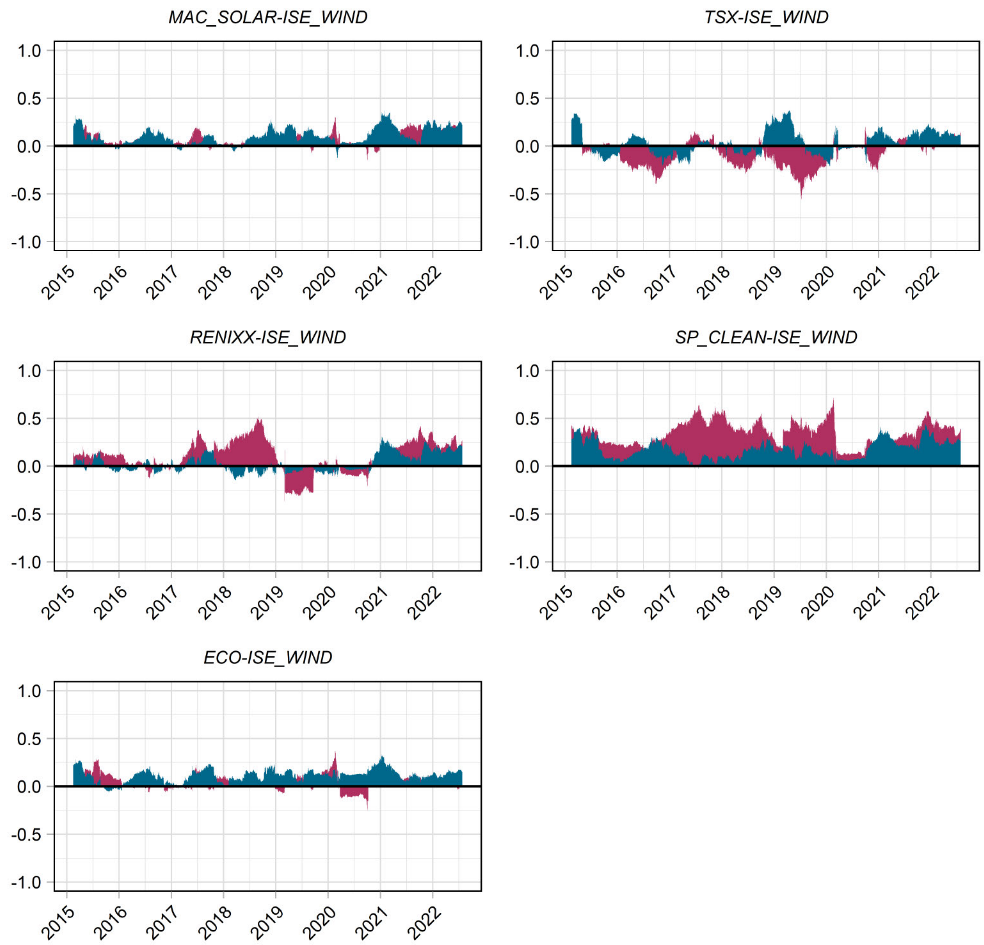

Figure C.3. Net directional pairwise connectedness between ISE_WIND and other clean energy markets using the BK18 framework.

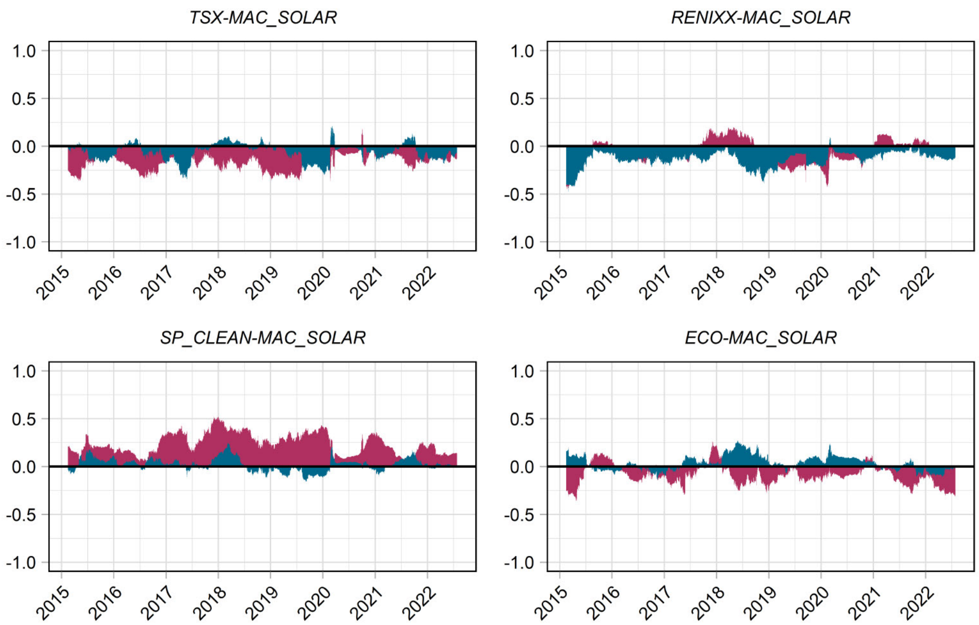

Figure C.4. Net directional pairwise connectedness between MAC_SOLAR and other clean energy markets using the BK18 framework.

Figure C.5. Net directional pairwise connectedness between TSX and other clean energy markets using the BK18 framework.

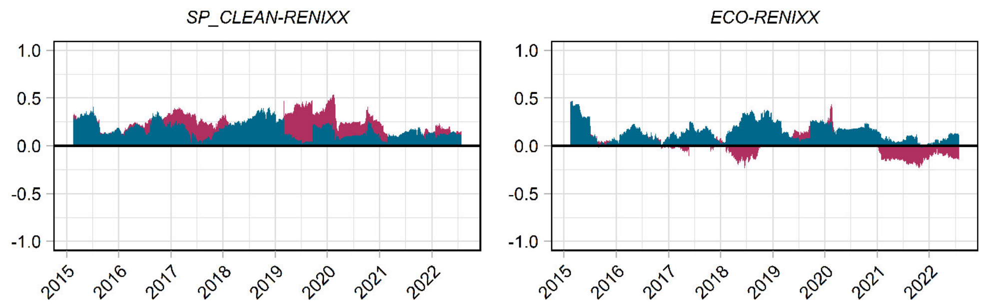

Figure C.6. Net directional pairwise connectedness between RENIXX and other clean energy markets using the BK18 framework.

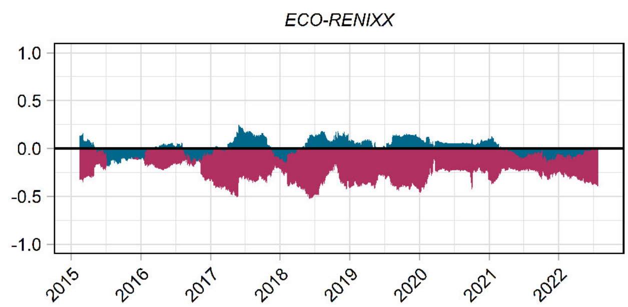

Figure C.7. Net directional pairwise connectedness between ECO and RENIXX using the BK18 framework.

D Appendix

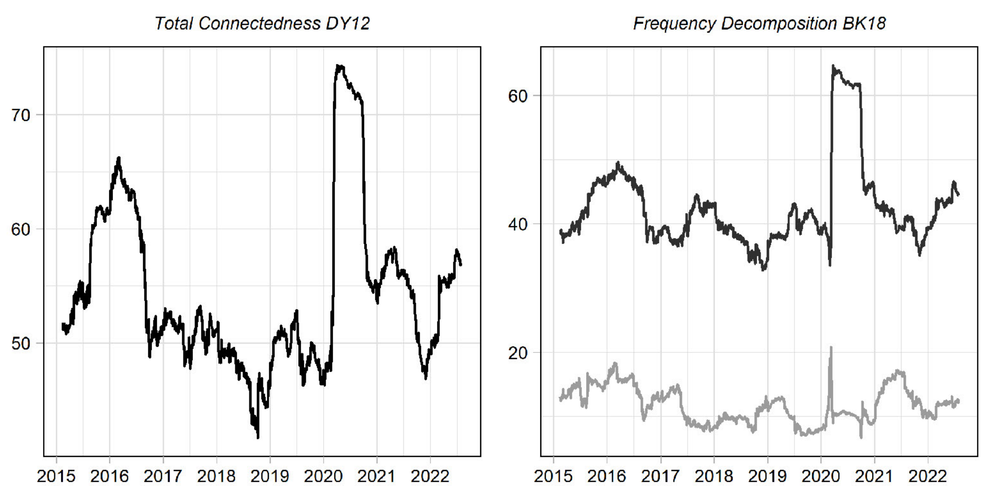

Figure D.1. Total connectedness measured by DY12 framework and BK18 framework without RENIXX.

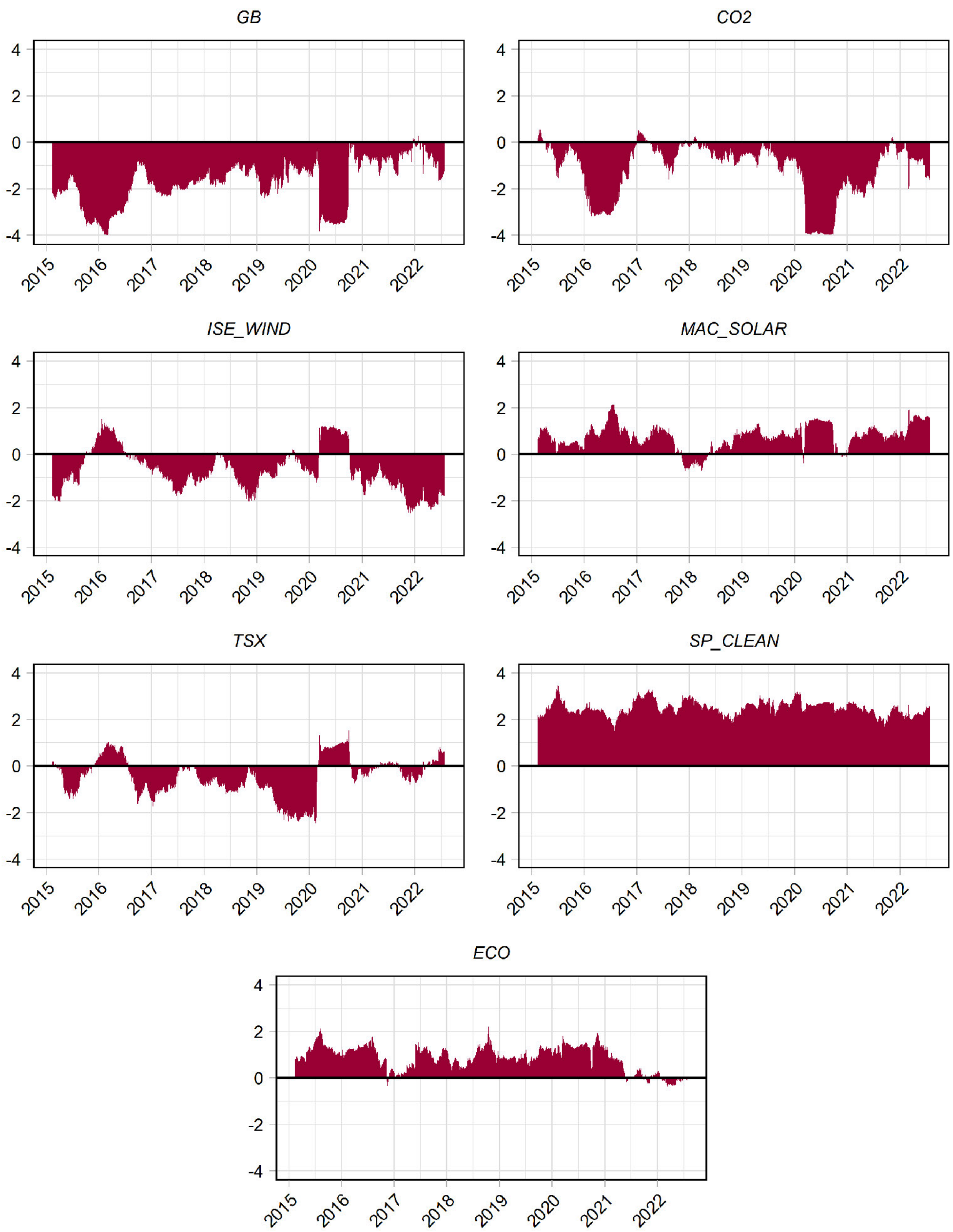

Figure D.2. Net directional connectedness DY12 without RENIXX.

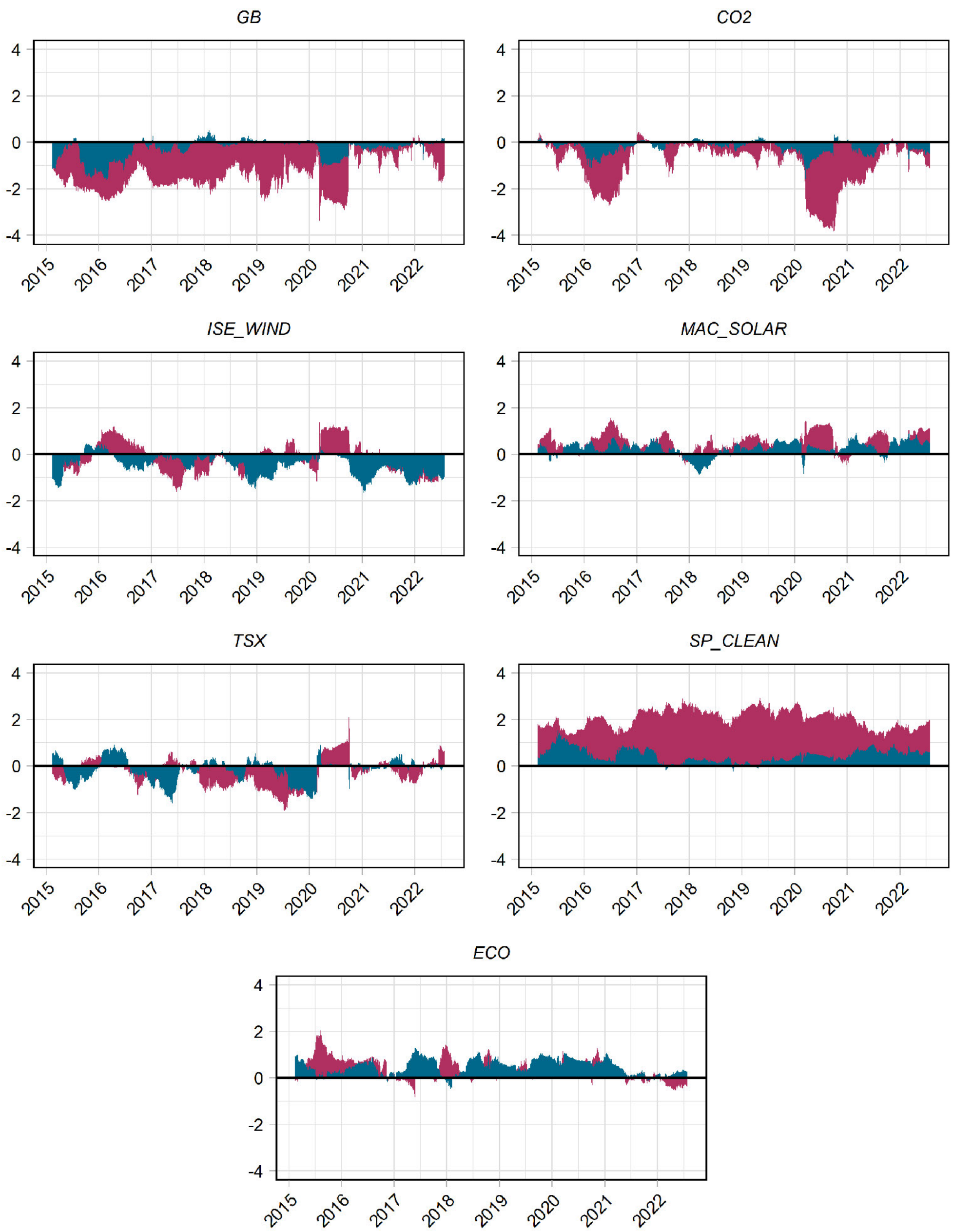

Figure D.3. Net directional connectedness BK18 without RENIXX.

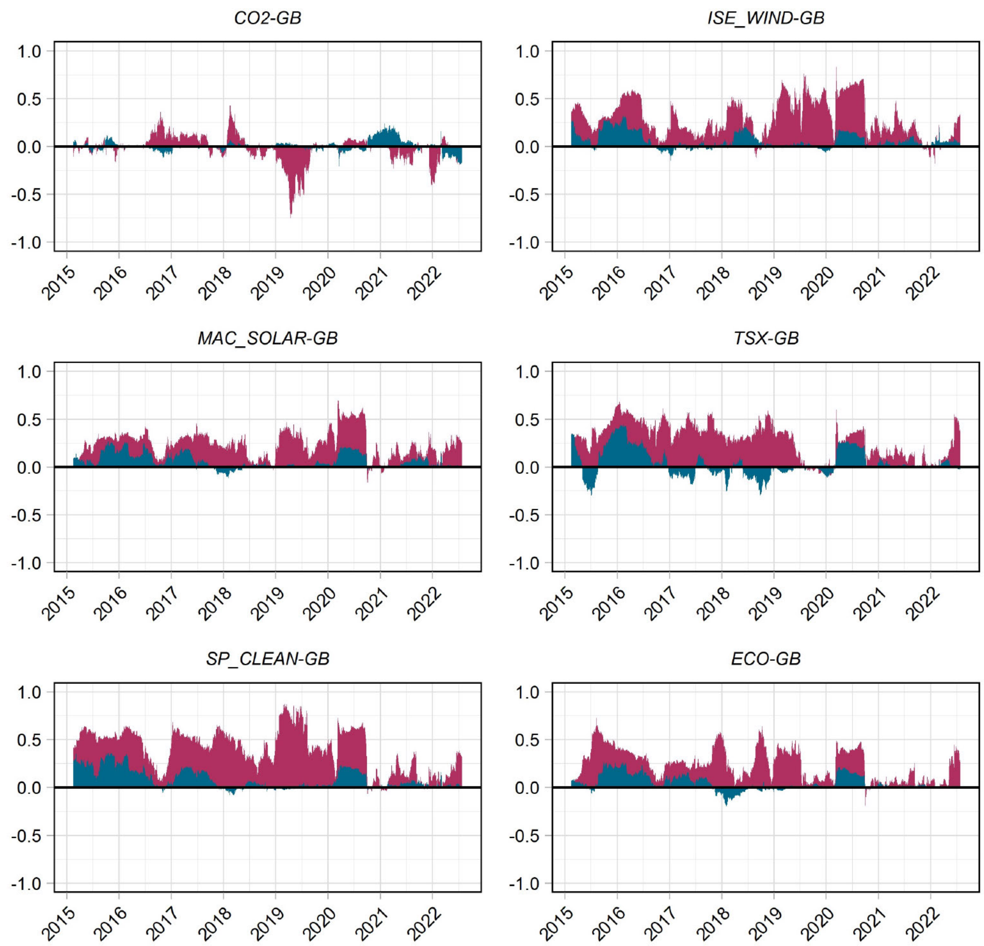

Figure D.4. Net directional pairwise connectedness between green bonds and the green financial system without RENIXX.

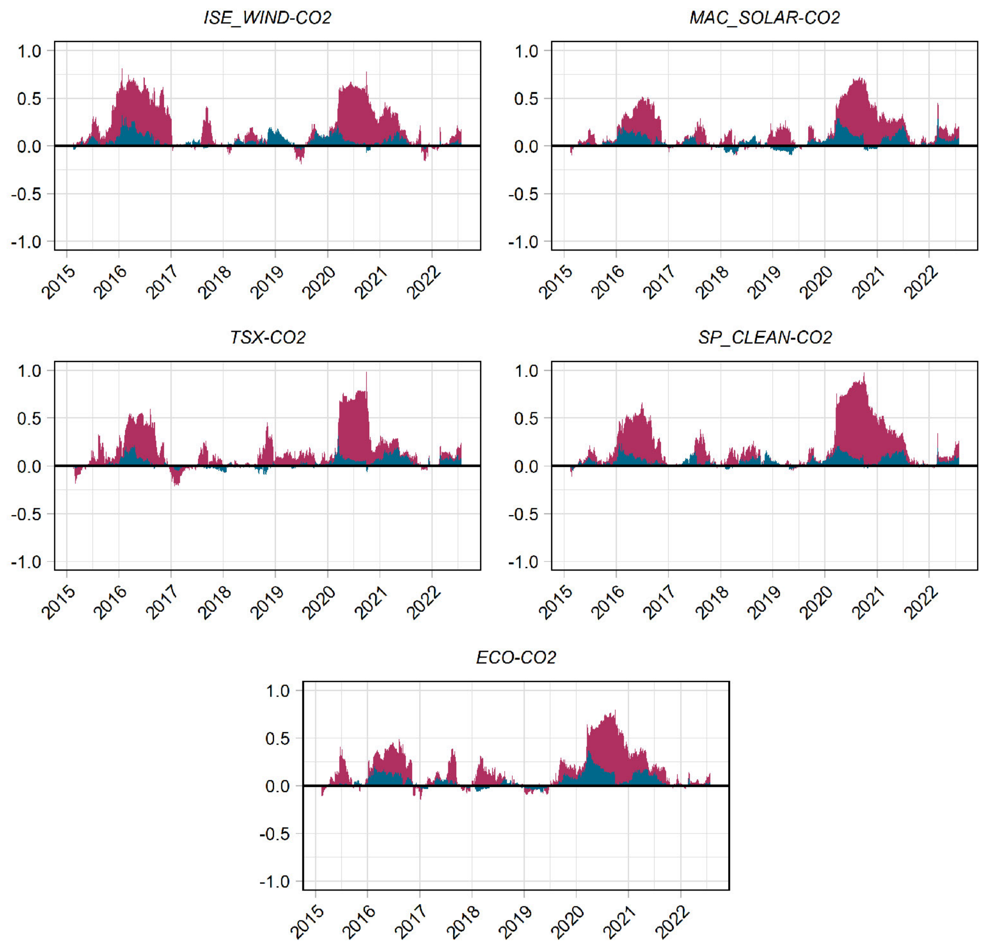

Figure D.5. Net directional pairwise connectedness between carbon market returns and the green financial system without RENIXX.

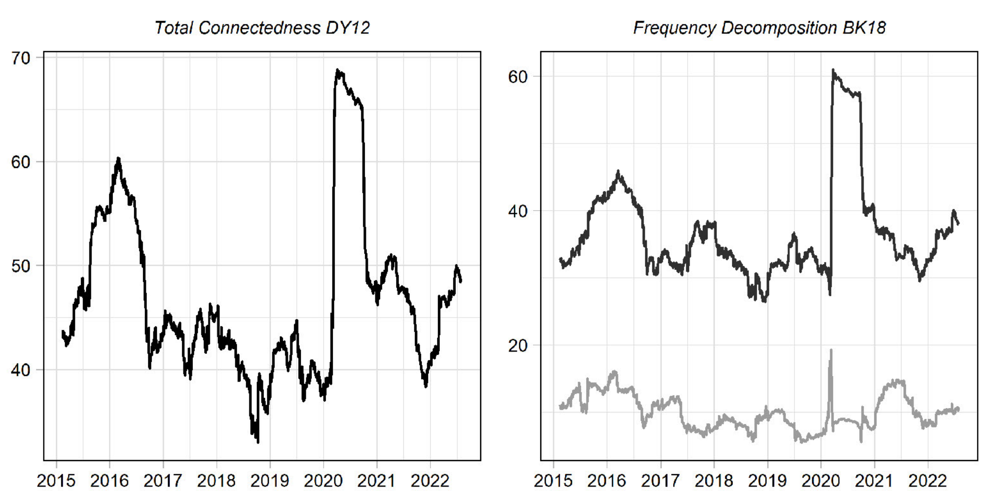

Figure D.6. Total connectedness measured by DY12 framework and BK18 framework without RENIXX and MAC_SOLAR.

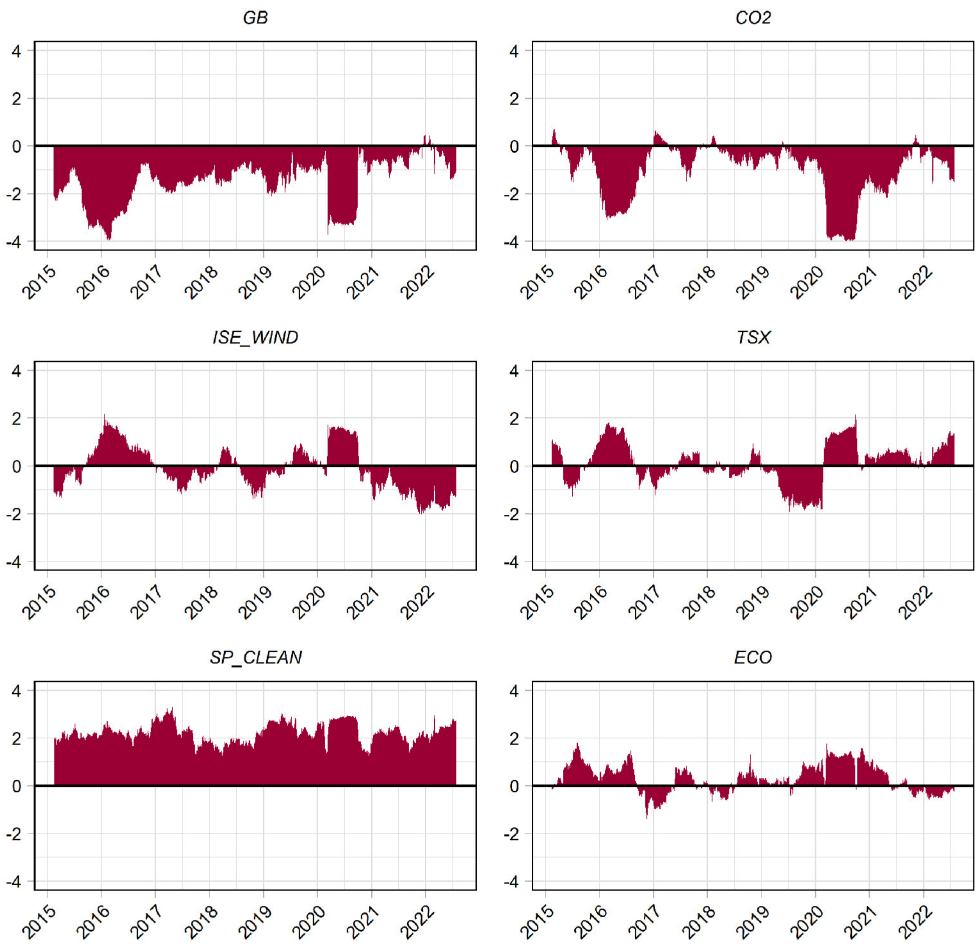

Figure D.7. Net directional connectedness DY12 without RENIXX and MAC_-SOLAR.

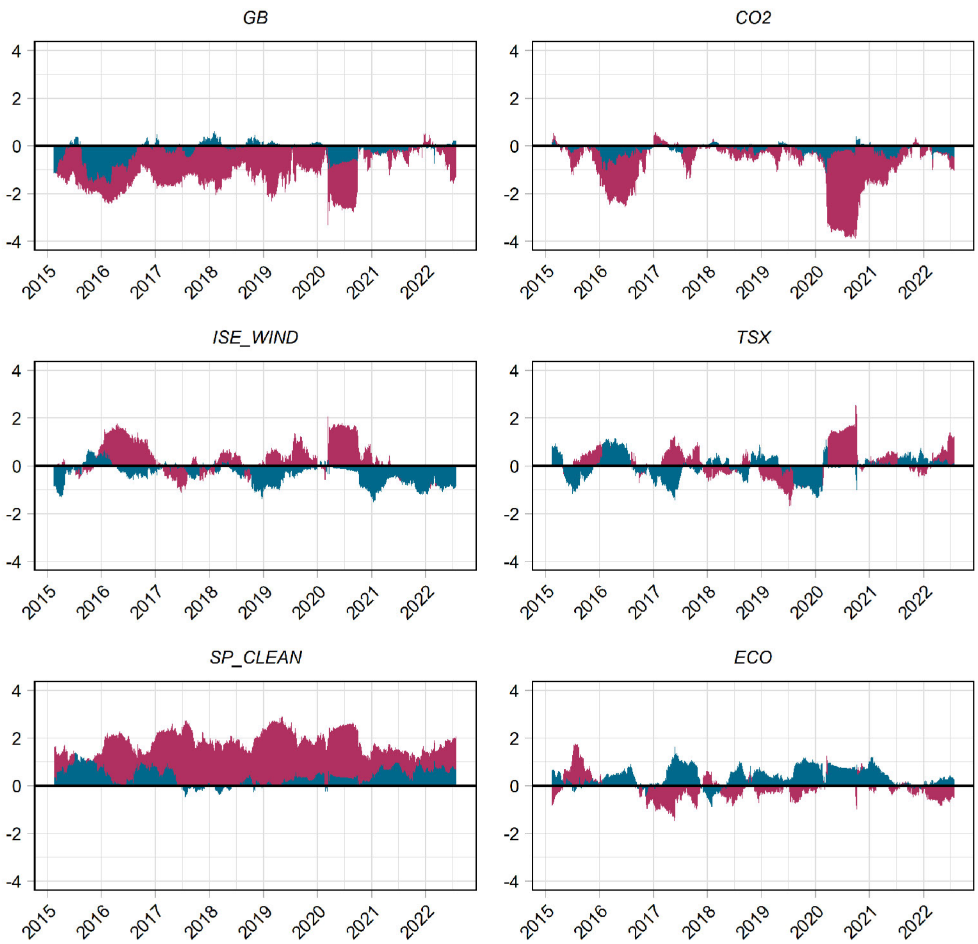

Figure D.8. Net directional connectedness BK18 without RENIXX and MAC_-SOLAR.

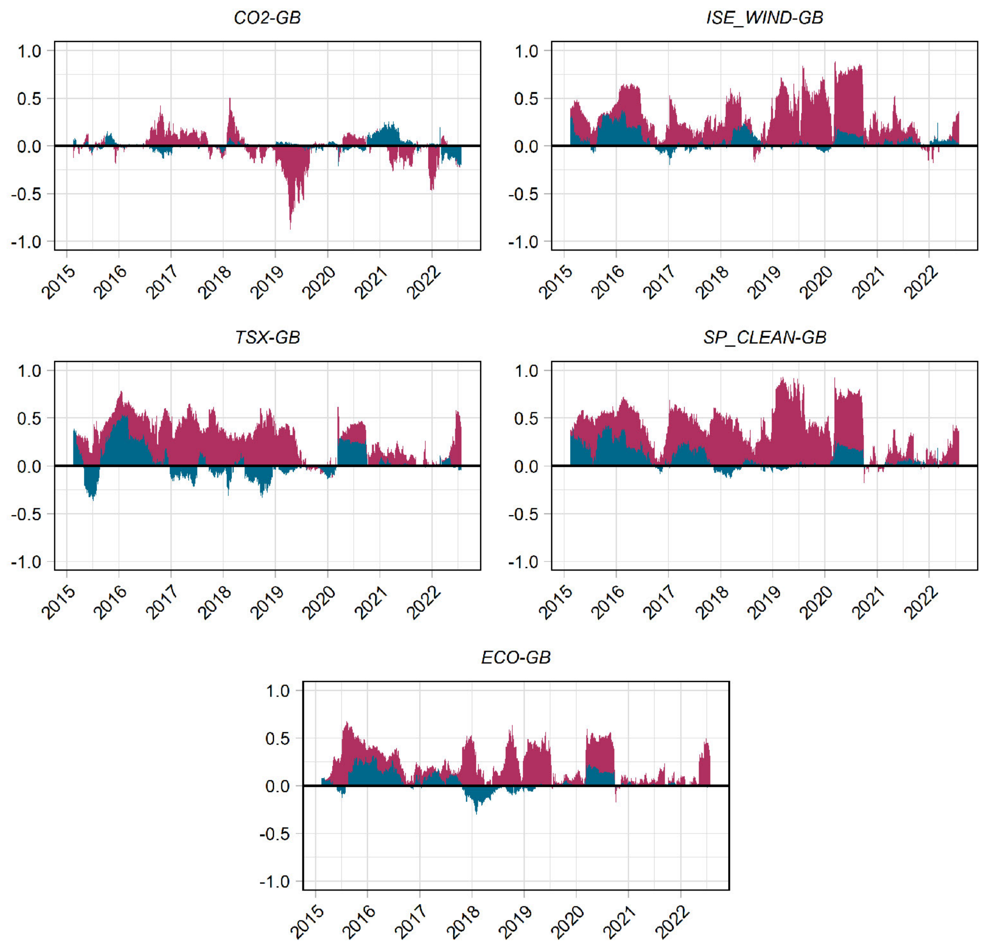

Figure D.9. Net directional pairwise connectedness between green bonds and the green financial system without RENIXX and MAC_SOLAR.

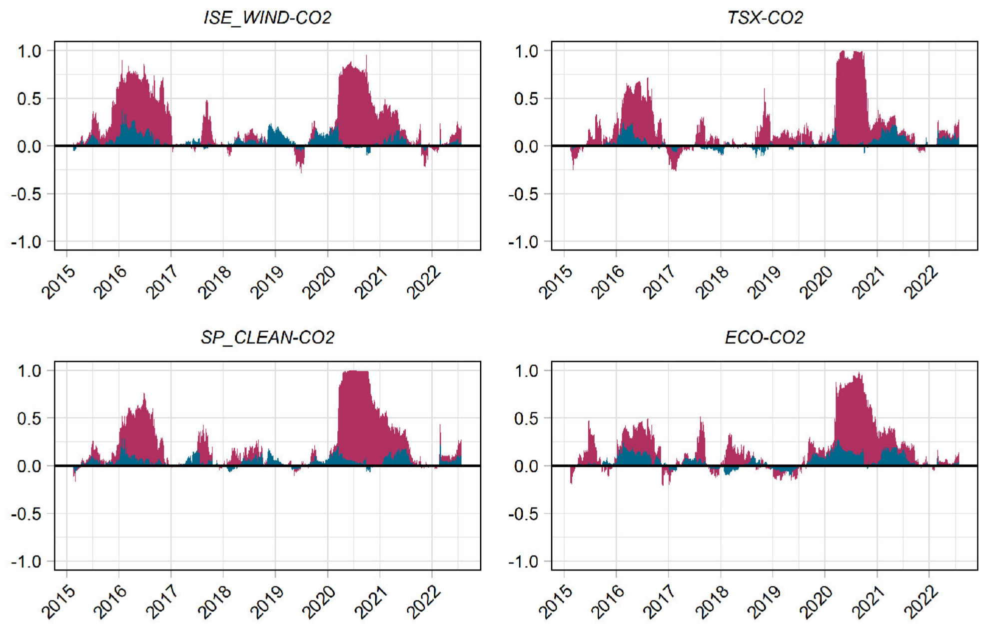

Figure D.10. Net directional pairwise connectedness between carbon market returns and the green financial system without RENIXX and MAC_SOLAR.