# Are Green Bond and Carbon Markets in Europe complements or substitutes? Insights from the activity of power firms

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## Abstract

This paper studies the interactions between the European carbon and green bond markets from the lens of the European power firms' trading activity over an eight-year period (2013-2020). Those power firms have used two segments of carbon markets differently: one for short-term hedging and speculative purposes and one for long-term hedging needs. The second one is found to have an informational advantage over the other and complements it.

Interestingly, we show that power firms have used the green bond market as a complement to the carbon futures market used for their short-term hedging or speculative activities. Instead, they have employed the green bond market as a substitute for the carbon futures market used for their long-term hedging activities since 2018.

Taken together, our results shed light on a pivotal change in the behaviour of European power firms that progressively abandon the carbon market to issue more green bonds in order to finance their transition to clean energy production systems.



**Keywords**: Carbon Market; Futures Hedging; Green Bond Market; Power firms; Substitute; Complement



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## 1. Introduction

The electricity sector is the most concerned by the financing of energy transition in Europe because of stringent limits on greenhouse gas emissions (EU, 2019; Fatica et al., 2019). Against the backdrop of climate change, the European Union implemented its Emissions Trading System (EU ETS hereafter) fifteen years ago to cut greenhouse gases emissions to zero by 2050. The EU ETS has created the world's largest carbon market valued at 169 billion euros in 2019 (Refinitiv, 2020), where European Union Allowances (EUAs hereafter) can be traded.

Recent trends also point toward a rapid increase in the supply of green bonds especially in Europe (CBI, 2018; CBI, 2020a). Research has shown that green bonds have beneficial impacts on the reputation of firms (Flammer, 2020), on their cost of capital (Gianfrate and Peri, 2019), and also on their environmental footprints and financial performance (Flammer, 2020). In view of these benefits, the volume of green bonds issued by power firms that account for half of the emissions covered by the EU ETS (Schultz and Swieringa, 2018), has soared over the past few years in Europe (CBI, 2018; 2020b), highlighting their effort at mobilising debt to finance low carbon projects (Monk and Perkins, 2020). Since the environment surrounding carbon markets is volatile, they may also use green bonds as an efficient tool to manage their carbon risk exposure (Jin et al., 2020). Despite the growth in popularity of the green bond market among power firms, there is, however, a lack of understanding of its joint contribution with carbon markets in their transitions to carbon neutrality.

The purpose of this study is to better understand the different relationships between the European carbon and green bond markets from the lens of the trading activity of power firms. Our research exploits the idea that power firms can issue green bonds to reduce their carbon hedging needs rather than using EUA futures markets provided that they have the sufficient pipeline of low carbon and/or green projects to be financed. Issuing a new green bond is an information signal sent to investors on their willingness to switch from a carbon hedging policy to a long-term investment policy in sustainability (Flammer, 2020). In this respect, we acknowledge the importance of corporate green bonds because of their growing role in funding low carbon (or green) projects. Notably, the amount of green bonds issued by non-financial corporates has tripled between 2017 and 2019 (CBI, 2020a).

The originality of our paper consists of investigating the different volume-volatility interactions between the EUA carbon futures and green bonds markets from the lens of the activity of European power firms in order to test for substitutability/complementarity between those two markets. For that purpose, we take an informational perspective considering that the two markets are (information) complements (*resp.* substitutes) as those in which prices reflect information flows, with no significant (*resp.* significant) relationship between their trading volumes consistent with the definition of Holder et al. (2012) and Switzer and Fan (2008).

The issue of substitutability/complementarity between those markets is not new for power firms for two reasons at least. First, they could have invested in Clean Development Mechanism projects monetised in certified emission reductions (CERs). In Phase II of EU ETS (2008-12), they could convert up to 13.4% of their CERs in EUAs to offset their emissions while in Phase III (2013-2020) only CERs from the least developed regions could substitute for EUAs. Second, volatility transmissions from energy markets to the EUA carbon market are significant due to a prominent fuel switching relationship (Schultz and Swieringa, 2018). As a result, natural gas may serve as a substitute for coal in power generation in Europe in addition to complement renewable energy because it covers for the intermittency of power generated by renewables.

Understanding the interactions between those markets is not only important for power firms but also for investors, exchanges and policy makers. Since carbon prices are volatile, power firms and investors can include green bonds in their portfolio of energy and carbon assets to hedge against carbon price volatility (Jin et al., 2020). From the perspective of carbon exchanges, knowing that the two markets are either substitutes or complements is essential in terms of product design and marketing issues. In fact, the degree of competition may lead current carbon exchanges to launch (or not) green bond listings in view of the associated expenses. From a policy making perspective, if issuing green bonds is actually viewed as an alternative to carbon hedging by power firms, it may indicate that the carbon price signal operates so the EU may decide to adjust the emission cap for the power sector accordingly.

However, due to a lack of volume data, analysing the different interactions between carbon and green bond markets has been difficult, at best. To date, few papers have explored the volatility relationships between carbon and green bond markets. Using world S&P price indexes, Jin et al. (2020) found that the green bond market is more related to the carbon market than the energy market. Using US S&P price indexes, Hammoudeh et al. (2020) detected a significant time-varying causality running from the US carbon index to the US green bond market from 2013 to 2015. However, the price indexes used in those papers are not accountable for the European corporate green bond market performance and risk (Bachelet et al., 2019).

To the best of our knowledge, no attempts have been made to study the interactions between carbon and green bond markets using the different volume/volatility relationships. To bridge this gap, we extend the methodology of Rannou and Barneto (2016) to explore the interactions between volume and volatility of European carbon futures and green bond markets.

The primary emphasis of our study is to examine the interactions between the volumes of EUA carbon futures and their volatilities. The second emphasis of our study is to shed light on the complementarity and/or the substitutability relationships between the green bond and the EUA futures markets from the perspective of European power firms' trading (volume) activity.

Empirically, we consider monthly aggregate volumes of EUA futures and green bonds since the number of green bonds issued by power firms remains low making the daily frequency irrelevant. Next, we follow the recommendations of Lucia et al. (2015) to dissociate two EUA carbon futures markets: *i*) that related to the second-to-maturity EUA December futures, which concentrates long-term hedging positions notably those of power firms; *ii*) that related to the front EUA futures, which reflects the extent of short-term hedging or speculative positions.

We then perform a series of Granger causality tests and regression tests to assess causality between monthly volumes of EUA futures and green bonds issued by European power firms and volatility. In this regard, we develop a bivariate GJR GARCH model to study causality between volume and volatilities by capturing the asymmetric behaviour of volatility conditional to price variations after the arrival of positive or negative information (proxied by volume) as in Rannou and Barneto (2016). In addition, we consider three VAR model specifications to examine the relationships between the volumes of the two EUA carbon futures and green bond markets controlling for effects of their own volatility, of the macroeconomic environment (Broadstock and Cheng, 2019) and of energy sector performance (Liu et al., 2020). Finally, we employ a rolling VAR procedure to assess the time-varying influence of the green bond volumes on the activity of the two EUA futures markets.

Our study builds on the lessons of information theories connected to market microstructure research. The Sequential Arrival of Information Hypothesis (SIAH hereafter) developed by Copeland (1976) considers that information is disseminated sequentially from one group of informed traders (hedgers) to another group of uninformed traders (speculators). Since information arrives to the two groups at different rates, they react and trade at different times generating lagged relationships between volume and volatility *de facto*. The Dispersion of beliefs model (DBM) of Shalen (1993) is complementary to SIAH. DBM attributes unusual volumes and excess volatility to uninformed traders' dispersions of beliefs in the context of a futures market. Because uninformed traders are inclined to exaggerate price movements leading to increase volatility by their volumes, a positive volume-volatility relationship arises. Regarding EUA futures markets, Rannou and Barneto (2016) verified a lead-lag and positive relationship between volume and volatility, providing support for both SIAH and DBM. Bredin et al. (2014) also detected a lead-lag volume–volatility relation in the EUA futures markets after accounting duration effects as predicted by SIAH. Balietti (2016) found that the lead-lag and positive relation between volume and volatility in the EUA futures markets was mainly due to the trading activity of the power sector.

Apart from the case of EUA futures markets, the volume/volatility couple has also been explored to test the complementarity or substitutability nature of derivatives markets. Using the volumes of corn futures traded on U.S. and Japanese exchanges, Holder et al. (2002) showed that the two futures markets are complementary. By contrast, in the foreign exchange market, Switzer and Fan (2008) documented that futures and OTC forward markets are substitutes.

Our study brings three main novel contributions to the above-mentioned literature. First, we analyse the interactions between the volume and volatility of two EUA carbon futures markets used either for short-term hedging or speculation (i.e., EUA front futures) or long-term hedging needs (i.e., EUA second-to maturity futures) over an eight-year period (2013-2020) corresponding to the Phase III of EU ETS. Causality tests and regression results carried out in a bivariate GJR GARCH model clearly show that EUA futures trading activity in the second-to-maturity influence the trading activity in the front contract but not vice versa. This result provides evidence that the carbon market used by power firms for long-term hedging serves as a substitute to that used for short-term hedging and benefits from an informational advantage over the other since it is populated by hedgers (Bredin et al., 2014; Balcilar et al., 2016). Second, we find that European power firms consider the green bond market as a complement of the EUA carbon market used for short-term hedging. Third, we show that European power firms have begun to consider the green bond market as a substitute of the EUA carbon market used for long-term hedging from 2018, a period during which the EUA carbon price has soared. Our two latest results are insensitive to the variations of the economic context in Europe and of the equity market related to the energy sector. In practice, a European power firm who buys (*resp.*

sells) 1 ton of carbon dioxide with a front (*resp*. second-to maturity) EUA futures used for short- (*resp*. long-) term simultaneously issues 1 euro (*resp*. 0.15 euro) of green bonds, on average, according to our VAR model estimations. Overall, our findings highlight a pivotal change in the strategies of European power firms that progressively abandon the EUA carbon market and issue more green bonds to finance their transition to clean energy production systems.

The rest of the paper is organised as follows. The next section presents an overview of the European carbon and green bond markets. Section 3 discusses the related literature. This is followed by a presentation of the methodology and data used. Section 5 outlines the main empirical results. The final section offers concluding remarks and policy implications.

## 2. Institutional Background

The EU-ETS scheme has been rolled out in phases. The pilot Phase I started in 2005 and ended in 2007. As in Phase I, circa 90% of EUAs were allocated for free in Phase II that ran from 2008 to 2012. In Phase III (2013-2020), 12% were freely allocated implying that 88% of EUAs are auctioned, on average. In the power sector, 100% of EUAs were almost auctioned.[4] In theory, the EU ETS forces regulated firms to cover their carbon emissions by trading EUAs. In reality, the EU ETS is a financial market, which allows hedging and speculative positions.

The EU ETS covers applies to the power, industrial sectors and intra-EU flights. Almost 60% of the emissions covered by the EU ETS come from the electricity (or power) sector (EEA 2021). Consequently, it is the main EU ETS participant and the main buyer of EUA futures used for hedging purposes. According to the estimates of Schopp and Neuhoff (2013), European power firms hedge 46% of their output two years in advance, and 84% one year ahead, on average. In turn, they are continuously exposed to important electricity and EUA price

[4] In Phase III, a very low number of EUAs were freely allocated by certain Member States whose GDP per capita was below 60% of the EU average in 2013 in order to accelerate the modernisation of their electricity sector.

(volatility) risks (Balcilar et al., 2016) but also to volume risks such as demand for retail electricity suppliers and power output for renewable energy producers.

To reduce these two kinds of risk exposures, power firms are used to sell power several years ahead of production. To secure prices of their power generation inputs (e.g., coal, gas, fuels), they buy them in advance. In this respect, the carbon hedging schedule of a power firm is determined as a function of its volumes of power sold forward. Thus, when its expectations about future energy and EUA prices differ from futures prices, the power firm will adjust their EUA hedging volumes. More especially, Schopp and Neuhoff (2013) consider that they deviate from their hedging schedule because they contract greater (*resp*. lower) volumes of coal in year one (*resp*. year two) if expectations are higher (*resp*. lower). Mechanically, their carbon hedging demands tend to increase (*resp*. decrease) in year one but decrease (*resp*. increase) in year two.

Moreover, power firms can determine or adjust their carbon hedging demand on the basis of their calculated hedge ratios, which give the optimal amount of EUA futures that they must buy to reach a minimum level of unfavourable (spot) price variation (Balcilar and al., 2016).[5]

In Phase III of EU ETS (2013-2020), power firms are required to purchase a significant higher volume of EUA futures to be compliant because they have no longer received free EUAs and EUA auctions are also limited in number. In this context, hedging in the short term with EUA futures give power firms time to gradually make recourse less carbon intensive energy sources (Balcilar et al., 2016). Moreover, the fact that EUA futures are not always effective for hedging due to time-varying relationships between EUA spot and futures markets or between EUA and energy prices has stimulated the adoption of cleaner energy sources by power firms. Consequently, power firms have increasingly financed low-carbon technologies and cleaner energy productions to reduce their rising carbon hedging demand and their exposure to the EUA

[5] Using EUA December futures, Balcilar et al. (2016) find that the carbon hedging strategies based on the use of time-varying hedge ratios are more effective than those determined from static hedge ratios. Therefore, power firms may apply these time-varying hedge ratios to rebalance their EUA futures positions in a more profitable way.

(volatility) risk (Balcilar et al., 2016). For that purpose, they have issued green bonds that are debt instruments whose 'proceeds will be exclusively applied towards new and existing green projects' (Monk and Perkins, 2020) to finance or refinance investments in renewable energy and energy-efficiency projects (Bachelet et al., 2019; Liu et al., 2020).

Between 2017 and 2018, a period during which EUA carbon prices rose, the amount of green bonds issued by corporates took off in Europe. Thereafter, CBI estimated an added 50 billion dollars issuance value from non-financial corporates in 2019 vs. 2018 in Europe (CBI, 2020a). Among the 145 firms that issued green bonds in 2019, 48 belonged to the energy sector that uses about 90% of bond proceeds to finance low carbon energy investment (CBI, 2020a).[6] Energy sector issuance of green bonds is dominated by large and diversified power firms in Europe including EDF, Enel, Engie, Iberdrola, Ørsted (CBI, 2018; CBI, 2020b). Power firms continued their green bond issuance at an equivalent rate in 2020, notwithstanding the COVID-19 pandemic. For instance, the German electricity producer EON issued two green bonds with tranches ranging from 750 million euros to 2.25 billion euros. After a difficult second quarter in 2020, confidence returned in the next quarter resulting in the most prolific quarter in terms of issuance (World Bank, 2020a), supported by the EU plan to issue 225 billion euros in green bonds in the forthcoming years by the EU President von der Layen (CBI, 2020a; CBI, 2020b).

## 3. Literature Review

The interaction effect between the green bond market and the carbon market is twofold. First, if carbon emissions from power companies are capped, carbon emissions leakage can occur when those companies issued green bonds to finance climate change mitigation projects. This mitigation achieved reduces *de facto* the scarcity of EUAs below the cap, thereby allowing emissions to shift rather than their net reduction (Heine et al. 2019). Second, price volatility

[6] Among the top 10 issuers, we find five power firms: Iberdrola, Engie, TenneT, Enel, Innogy (CBI, 2020b).

explains the interaction between green bond and EUA markets. As the returns on investment for green projects depend on carbon prices, a more stable EUA price also creates a more stable return on investment and accordingly a greater demand for green bonds (Heine et al. 2019).

If the question about the complementarity between carbon pricing tools has been at the heart of debates in environmental theory (World Bank, 2020b), it has shown a resurgence of interest because of their potential link with green bonds. A survey made for the European Commission highlighted that the issuance of green bonds by non-financial corporates have led to a reduction in the firm level carbon emissions relative to total assets in Europe (Fatica et al., 2019). Moreover, Jin et al. (2020) verified that the green bond market offers the best hedge for the carbon market when studying causality between the S&P Energy, S&P Carbon and S&P Green Bond price indexes. In the US market, Hammoudeh et al. (2020) detected a time-varying causality from carbon prices to the green bond market from 2013 to 2015, a year during which carbon prices peaked. Using also price indexes, Reboredo et al. (2020) concluded that investors may use green bonds as an alternative to other fixed income securities in their portfolios.

To date, no studies, however, have investigated the substitutability/complementarity between carbon and green bond markets by studying their price–volume relationships i.e., how EUA carbon price volatility affects the volumes of EUA futures or green bonds and vice-versa.

Because traders cannot observe the information signal with only studying prices, volume may provide the required additional information for that signal to be captured. In this way, different categories of traders focus on the volatility–volume relationship in futures markets. Hedgers are prone to trade futures to smooth their future revenues or charges along a volume being determined according to their expectations about future price changes. As for speculators, they open a position in futures based on their forecasts of futures price volatility. Assessing precisely price volatility is therefore useful for hedgers and speculators in energy markets to assess margin requirements of their traded futures (Chevallier and Sévi, 2012).

From a theoretical perspective, a sizeable market microstructure literature has explored the linkages between price volatility and trading volumes in futures markets (Karpoff, 1987). Copeland (1976) built the SIAH model where information becomes known by distinct group of traders at different times, generating a positive and lead-lag relationship between volume and volatility. Hence, the rate by which information arrived and the level of information held by traders pilot their liquidity or hedging needs and drives the volume/volatility relation. The DBM of Shalen (1993) states that asymmetrically informed traders differ in the way they interpret incoming information and trade from their different beliefs. The dispersion (or variety) of their expectations involves a positive relation between volume and volatility. Those two main information theories: SIAH and DBM have been used to explain the volume/volatility relation on EUA futures markets. Bredin et al. (2014) document a positive and lead-lag relationship between volume and volatility of Phase II EUA futures providing support for the SIAH. Rannou and Barneto (2016) show that the volumes of nearby EUA futures affect volatility estimates but not vice-versa. Like Bredin et al. (2014), they report a significant lead–lag causal relation between volumes and volatility and conclude that both SIAH and DBM apply to EUA futures markets. Balietti (2016) attributes the positive and lead-lag volume–volatility relation in the EUA futures markets to the trading activity of energy producers including power firms.[7]

Outside the EUA futures markets, the volatility–volume relationship has been studied to test the complementarity or substitutability nature of derivatives markets. Holder et al. (2002) find a complementary relationship between U.S. and Japanese corn futures markets based on the quasi absence of volume interactions. In the foreign exchange market related to the Canadian Dollar, Switzer and Fan (2008) detect significant Granger causality from the futures

[7] Balietti (2016) uses the European Union Transactions Log to track permit transfers across the individual accounts of EU ETS installations in Phase I. Balietti (2016) estimates that accounts held by the power sector are responsible for almost 60% of the trading activity. However, the method developed by Balietti (2016) is not adapted to estimate the carbon hedging volumes. First, permit transfers are not priced and are not initiated on exchanges. Second, those transfers cannot be differentiated according to their objectives (hedging or speculating) and are not related to firms.

volume to OTC derivatives volume but not reciprocally. This result implies that futures markets have an informational advantage. Then, their regression tests provide evidence of substitutability between the foreign exchange futures market and the OTC derivatives market.

## 4. Methodology and data

### *4.1. Data selection*

We compile a first dataset from Datastream related to EUA December futures contracts traded on the European Climate Exchange (ECX). ECX has been the most liquid EUA futures exchange since the advent of EU ETS attracting many market participants and far greater trading volumes (Boutabba, 2009). For Boutabba (2009) and Stefan and Wellenreuther (2020), the quasi monopoly of ECX explains that it has led price discovery in Phases II and III.

This first dataset is composed of two EUA futures sliced series, namely the front December futures and the second-to-maturity futures starting from January 2013 until December 2020. Similar to Lucia et al. (2015) we consider the front EUA December futures as that concentrates the majority of the short-term hedging or speculative activity, whereas the hedging demand focuses on the second-to-maturity EUA December futures, as is the case in financial markets. We rely on splicing techniques to create two full time series: front and second-to maturity EUA December futures series. As in Rannou and Barneto (2016), we switched to the most liquid (front) contracts as evidence that the market's attention turns away as soon as the daily trading volume and open interest for the nearby December futures are lower than those for the next contract. We proceed similarly to form the second-to-maturity EUA December futures series.[8] As a result, this first dataset is made up of two full time series of ECX EUA futures cumulating 2020 observations (prices and volume) from 2013 to 2020: 1) front and 2) second-to maturity.

[8] Data related to the volumes traded by power firms on exchanges are not available because trading occurs on a limit order book that offers anonymity to traders (Rannou and Barneto, 2016). Further, in the event that identities of traders may be disclosed, the trading volumes of power firms should be underestimated since they will not include those of brokers who execute their large orders on their behalf. By contrast, our methodology allows us to estimate consistent hedging volumes since our two sliced series mimic the rollover strategies used by power firms or their brokers when they take short-term or long-term hedging positions with EUA December futures.

We build a second dataset of green bonds issued by power firms on European stock exchanges. Information related to green bonds is collected from Datastream and includes issuer name, issuance size, coupon rate, currency, rating, number of securities issued, use of proceeds. Also, we visited the websites of European exchanges where green bonds have been issued: the Luxembourg Green Exchange, Euronext, the London Stock Exchange, Deutsche Boerse, the Madrid Stock Exchange, Borsa Italiana, the Vienna Stock Exchange and the Nasdaq OMX to verify that the list of green bonds proposed by Datastream matches the compilation of the lists of green bonds displayed by those exchanges. This second dataset is composed of monthly aggregate volume of green bonds because green bond issues are not sufficient in number to form a daily volume series.[9] We consider green bonds issued by power companies covered by EU ETS with carbon emissions that exceed an annual total of emissions of 1 $MtC0_2eq$, which corresponds to an annual carbon hedging exposure of 12 million euros considering the average EUA price in Phase III (12 €/$tCO_2eq$). For the purposes of clarity and consistency with previous studies (Bachelet et al., 2019; Broadstock and Cheng, 2019; Flammer, 2020), we decided to exclude sustainability linked bonds and transition bonds from our sample of green bonds.[10]

Table 1 outlines the characteristics of the 86 sampled green bonds issued by power firms over the period January 2013 - December 2020. Two preliminary findings emerge from our interpretation of the Table 1 statistics. First, there is no apparent association between the level of the bond credit risk (measured by the rating) and the number or the size of the green bonds

[9] We compute the volume by dividing the notional amount of green bond issued by the value of securities issued.
[10] Green Bonds are bonds where the proceeds are exclusively used to finance green and low carbon projects with clear environmental benefits, which are aligned with the EU Taxonomy. However, there are firms that cannot issue green bonds today, due to a lack of sufficiently green projects. This is the reason why investment banks have proposed transition bonds to provide financing for these firms, which are 'brown' today but target a transition to green in future. However, no uniformly accepted definition or standards of transition bonds clearly exists today. By contrast, ICMA (2020) defined Sustainability-Linked bonds as bonds for which the financial and/or structural features (e.g., coupon, maturity, repayment amount) can vary depending on whether the issuer respects predefined Environmental and/or Social and/or Governance (ESG) goals within a predefined timeline.

issued. Second, the more that the level of annual carbon emissions of a power firm is important, the shorter is the maturity of green bond it issued is and the greater is its number of bond issues.

[INSERT TABLE 1 HERE]

Figure 1 plots the number of those sampled green bonds issued annually and the evolution of the front EUA futures. Interestingly, when the EUA carbon price averaged €24.7/t$CO_2$eq. between 2019 and 2020, i.e., more than three times higher than over the period 2013-2018, we observe that the number of green bonds issued has taken off from 15 green bonds in 2018 to 27 two years after. If this result suggests that an increasing EUA price may boost green bond issuance of power firms, it also indicates a negative inter-market price/volume relationship.

[INSERT FIGURE 1]

In addition, we observe from Figure 2 that the annual volume of the sampled green bonds issued by power firms is a negative function of their aggregate annual level of carbon emissions. If the volume of their green bond issuances has significantly increased from 2017-2018, this of carbon emissions plummeted to a third indicating that power firms have progressively switched to cleaner and low carbon technologies as underlined by Hammoudeh et al. (2020).

In fact, most of the proceeds from green bonds issued by power firms tend to be geared towards renewable energy projects including wind farms, solar energy and photovoltaic facilities, hydro-power and biomass generation. Also, they may be allocated to energy efficiency projects like renovation of buildings, low-carbon transportation and infrastructure. A small share of proceeds may also be used to finance biodiversity projects (CBI, 2019).

[INSERT FIGURE 2]

These two results underscore that the power firms' supply of green bonds is negatively related to their carbon hedging demand as seen in Table 1 but also to the cost of their hedging (i.e., the price of EUA futures). Ultimately, these negative relationships raise the question of substitutability between the EUA and the green bond market for the case of power firms.

*4.2. Causality tests*

To assess causality between returns and volume, we model the conditional mean equations:

$$RET_{EUA,t} = \alpha_{RET_{EUA}0} + \sum_{i=1}^{p} \beta_{RET_{EUA},i} RET_{EUA,t-p} + \sum_{j=1}^{q} \kappa_{RET_{EUA},j} VOL_{t-q} + \varepsilon_{RET_{EUA},t} \tag{1}$$

$$VOL_t = \alpha_{VOL,0} + \sum_{a=1}^{a} \beta_{VOL,a} RET_{EUA,t-a} + \sum_{b=1}^{b} \kappa_{VOL,b} VOL_{t-b} + \sum_{c=1}^{c} \omega_{VOL,c} \varepsilon^2_{RET_{EUA},t-c} + \varepsilon_{VOL,t} \tag{2}$$

Where: $RET_{EUA,t}$ is the EUA futures return at month t, $VOL_t$ the corresponding monthly volume of EUA futures (or green bonds). Eq. (1) includes $\varepsilon^2_{RET}$ lagged squared errors to measure return volatility to test whether in this specification lagged return volatility causes volume. Although Eqs. (1) and (2) are not written in a conventional VAR form, the rationale of running causality tests between volatility and volume series is analogous to this of linear Granger causality tests (Rannou and Barneto, 2016).[11] Significance of the causality results are based on F-statistics. Chevallier et Sévi (2012) find a positive but asymmetric for crude oil and natural gas futures. Using a bivariate GJR GARCH model, Rannou and Barneto (2016) also detect an asymmetric relationship between volume and volatility of EUA futures in Phase II of EU ETS. To estimate conditional variance modelled by an asymmetric impact of prior positive and negative volume (information) shocks, we write a GJR-GARCH (Glosten et al, 1993) process such that:[12]

$$\sigma^2_{RET_{EUA},t} = \delta_{RET_{EUA}} + \sum_{m=1}^{M} \beta_{m,p} \sigma^2_{RET_{EUA},t-m} + \sum_{n=1}^{N} \kappa_{RET_{EUA},n} \left[\varepsilon_{RET_{EUA},t-n}\right]^2 + \lambda_{RET_{EUA}} I^-_{RET_{EUA},t-1} \left[\varepsilon_{RET_{EUA},t-1}\right]^2 + \sum_{o=1}^{O} \theta_{RET_{EUA},o} VOL_{t-o} \tag{3}$$

$$\sigma^2_{VOL,t} = \delta_{VOL} + \sum_{p=1}^{P} \theta_{VOL,p} \sigma^2_{VOL,t-p} + \sum_{q=1}^{Q} \kappa_{RET_{EUA},q} \left[\varepsilon_{VOL,t-q}\right]^2 + \lambda_{VOL} I^-_{VOL,t-1} \left[\varepsilon_{VOL,t-1}\right]^2 \tag{4}$$

Where: $\sigma^2_{RET_{EUA},t}$ and $\sigma^2_{VOL,t}$ are the conditional variances of returns and volume at time t, the dummy variables $I^-_{RET,t-1}$ et $I^-_{VOL,t-1}$ are equal to 1 (otherwise equal to 0) if respectively $\varepsilon_{RET_{EUA},t-1}$ <0 or if $\varepsilon_{VOL,t-1}$ <0. The asymmetric effect of information on volatility is captured by $\lambda_{RET_{EUA}}$ and $\lambda_{VOL}$ in Eqs. (3) and (4), respectively. To examine the relation between volatility and volume,

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[11] We proceed to pair wise causality tests following the Toda and Yamamoto (1995) approach, which allows the fitting of volume and volatility variables into a VAR in levels without considering cointegration testing procedure.

[12] We obtain a GJR GARCH (1,1) optimal model for return variance after having estimated alternative specification including more lags in the asymmetry terms, which are not statistically significant at all levels.

we introduce lagged volume $VOL_{t-o}$ given $\theta_{RET_{EUA},o}$ that tests its impact on current volatility. Finally, we estimate a constant bivariate GJR-GARCH model using the Berndt–Hall–Hall–Hausman (BHHH) algorithm in all scenarios as in Rannou and Barneto (2016).

*4.3. VAR analysis*

We examine the connectedness between green bond and carbon markets but also with other financial markets in a flexible VAR framework. As a matter of fact, Liu et al. (2020) document a positive price relationship between the green bond and (clean) energy stock markets. Specifically, we develop three VAR model specifications with two lags and FUT1 and FUT2 volume as endogenous variables. In Model 1, the green bond volume is an exogenous variable providing an insightful base from which to study our subsequent Models 2 and 3. Given volatility is likely to affect EUA futures volume (see Table 4), Model 2 includes the volatility of the two EUA futures markets as exogeneous variables. Model 3 adds two exogeneous variables to Model 2: *i*) the monthly return of MSCI Energy index (*EnergyRet*) to control for the influence of the stock market performance of the European energy sector (Broadstock and Cheng, 2019; Liu et al., 2020) and *ii*) the OECD Composite Leading Indicator (*CLI Europe*) for the EU to control for changes in business activity in Europe (Broadstock and Cheng, 2019).

## 5. Empirical Results

*5.1. Descriptive statistics of the two EUA futures and Green Bond markets*

Panels A and B of Table 2 provide summary statistics on the mean, standard deviation, skewness, excess kurtosis, the Jarque–Bera test for normality and ARCH test of the two EUA futures volatility series as well as the two EUA futures and green bonds volume series respectively. The front EUA futures (FUT1) exhibits higher mean monthly volume and volatility than the second-to-maturity EUA futures (FUT2) signalling a positive volume/volatility relationship in EUA futures markets consistent with the findings of previous studies (Bredin et al., 2014; Rannou and Barneto, 2016). Since the two EUA futures volatility series have significant skewness, and excess kurtosis, normality is rejected given the Jarque Bera test. If the ARCH (2) statistic of the EUA futures volatility and volume series are significant, it is, however, insignificant for the case of the GB volume series, that would offer lower predictability perspective. Given the ARCH (2) tests, we suspect the existence of a time-varying second moment in EUA futures. Therefore, we then adopt GJR-GARCH asymmetric specification when regressing volatility in order to capture dependence structures in mean and conditional variance equations. Moreover, we conduct ADF tests, which confirm that all volume and volatility series are stationary. Besides, ADF tests can be unreliable in the presence of structural breaks. Instead, we test for an unknown structural break in the intercept and level and unit root simultaneously using the Zivot and Andrews (ZA) test as in Boutabba (2009). ZA tests also attest that all series are stationary.

[INSERT TABLE 2 HERE]

The contemporaneous correlations between the volatility and volume series of the two EUA futures and the green bond markets are reported in Table 3. As shown by Lucia et al. (2015), the front EUA futures (FUT1) volatility is almost perfectly correlated with that of the second-to-maturity EUA futures (FUT2), while their volumes are significantly less positively related, suggesting that the two EUA futures markets are complementary and used for different purposes: short-term hedging or speculative for FUT1 and long-term hedging for FUT2.

On the one hand, we can argue that if FUT2 contracts are not considered as an alternative to FUT1 contracts by power firms, the two futures markets are indeed complements. This implies that an increase in the volume of FUT2 would cause an increase in the FUT1 volume, as power firms prefer using FUT1 to hedge instead of speculating or arbitraging. On the other hand, we can argue that the two carbon markets share information unlike Holder et al. (2002). In this way, power firms view these markets as informationally complements. In case when

EUA prices react to the same informational factors, no relationship in volumes would be detected. Thus, the two EUA futures markets also appear to have a complementary relationship.

Also, we note that the correlation between the FUT1 futures and the green bond volumes is significantly positive while this between the FUT2 futures and the green bond volumes is negative. Taken together, these two results suggest a complementary (*resp*. substitutability) relationship between the green bond market and EUA futures markets used for short-term hedging or speculation (*resp*. long-term hedging) purposes by European power firms.

[INSERT TABLE 3 HERE]

*5.2. Causality tests results*

Table 4 presents Granger causality tests with 2 and 3 lags used to study lead-lag relationships. Panel A results indicate a unidirectional causality running from the volatility of the two EUA futures to their corresponding volumes significant at all lags and a unidirectional causality from their own volatilities to the volumes of the other one, which is only significant with 3 lags. These results suggest that the nature of price risks hedged in the two EUA futures markets by power firms (through their trading volumes) may be not identical. Further, an absence of causality from the EUA futures volume and their volatilities is reported implying that these volumes have no explanatory power for volatility changes in the EUA futures markets in contrast with the findings of Switzer and Fan (2008) related to the foreign derivatives market.

Besides, we can see from Panel B the absence of inter-market causal relations between the volume of green bonds and the volatility of the two EUA futures. Accordingly, higher EUA volatility risks do not necessarily cause a large number of green bond issuances by European power firms instead of a significant increasing trend of EUA prices observed from 2017 (see Figure 1). This latest result is in line with that of Hammoudeh et al. (2020), who detect causality running from US carbon prices to the US green bond market over the period 2013-2015.

Interestingly, Panel C shows that the green bond volume causes the two EUA futures volume with 2 and 3 lagged months, which corresponds to the time necessary to issue a green bond (Monk and Perkins, 2020) but not vice-versa. Also, a unidirectional causality from the second-to-maturity EUA futures (FUT2) volume to the front EUA futures (FUT1) volume is observable at all lags. This result can be interpreted in two ways. First, since FUT2 trading activity is found to lead FUT1 trading activity, the EUA carbon market used for long-term hedging appears to have an informational advantage consistent with the findings of Lucia et al. (2015). This is due to the fact that this FUT 2 market is largely dominated by hedgers such as power firms that are privately informed traders (Bredin et al., 2014; Rannou and Barneto, 2016). Second, considering the definition of complementary markets of Holder et al. (2002), we can argue that the two EUA futures markets have a complementary relationship because of an absence of a significant bidirectional causality between their respective trading volumes.

[INSERT TABLE 4 HERE]

To verify that the aforementioned causal relations between those EUA futures markets persist, we regress their contemporaneous trading volumes on lagged values of the volumes of the two EUA futures in a similar manner as Rannou and Barneto (2016). We determine two lags as optimal autoregressive lags with the AIC benchmark for volume variables in Table 5.

On the left column (*resp*. right column) of Table 5, we show the results with the FUT 1 (*resp*. FUT2) EUA volume as the dependent variable. From Panel A of Table 5, we report a significant unidirectional causality running from the second-to maturity EUA futures (FUT2) volume to the EUA front futures (FUT1) volume. Enhanced trading volumes in the FUT2 market therefore increase the trading volume in the FUT1 market, confirming that the FUT2 market complements FUT 1 and benefits from an informational advantage over FUT1.

Panel B includes the contemporaneous volume of green bonds as a regressor in the mean equations. We observe a significant positive causality running from green bond volume to the volume of the two EUA futures markets as seen in Table 4. Compared to Panel A, the magnitude of asymmetric GARCH coefficient (δ) is reinforced. The leverage effect parameter in the GJR–GARCH (1,1) model (α) remains statistically significant and negative implying that positive shocks (market advances) lead to increase the EUA futures volume more than negative shocks (market retreats) of the same magnitude. Besides, the Wald test statistic for the green bond volume coefficient is significant at the 5% level, which is not the case of FUT2.[13]

In addition to the above tests, we conduct similar regression with the green volume as a dependent variable. We note the absence of significant causality from lagged volumes of the two EUA futures markets on the green bond volume (See Appendix (Table A.1)).

Taken together, Table 5 results confirm those of Table 4 in a sense that they clearly indicate that power firms use the green bond market as a complement to the EUA carbon market used for their short-term hedging. Instead, they consider the green bond market as a substitute for the EUA market used for their long-term hedging, but this inter-market linkage appears to be unstable. Further investigation on this instable relationship will be carried out in §5.4.

[INSERT TABLE 5 HERE]
[INSERT TABLE A1 HERE]

*5.3. VAR analysis*

Panels A and B show the results of the VAR models for the front EUA futures (FUT1) and the second-to-maturity futures (FUT2) volumes as the dependent variable respectively. In Model 1, the coefficient of the lagged FUT2 volume is significant validating its impact on the FUT1 volume seen in Tables 4 and 5. Also, we verify that the green bond volume influences negatively (*resp*. positively) the FUT2 (*resp*. FUT1) volume confirming the results of Table 5. This second result is in line with those of Jin et al. (2020) and Hammoudeh et al. (2020) who both detect a unidirectional (price) causality from the green bond market to the carbon market.

[13] We also applied Wald tests on the lagged coefficients of FUT1 and FUT2. All tests reject the null hypothesis that those coefficients are equal to 0, giving evidence that they are stable.

From Model 2, we observe a significant positive relation between the two EUA futures market volatility and their respective volume as shown by previous studies (Lucia et al., 2015; Balietti, 2016; Balcilar et al., 2016; Rannou and Barneto, 2016). As explained by Balietti (2016), this positive relation is mainly attributed to energy providers.

Looking at the Model 3 results, the coefficients of *CLI Europe* and *Energy Ret* are insignificant at 1% and 5% levels. This third important result suggests that the hedging activities but also green bond financing strategies are insensitive to the business climate fluctuations and to the energy sector (returns) performance in Europe as shown by Reboredo et al. (2020).

Overall, Models 1, 2 and 3 confirm our two previous findings. The green bond market serves as a substitute (*resp*. complement) of the EUA carbon markets used for long-term hedging (*resp*. short-term hedging and speculation) for European power firms while these two carbon markets are complementary for their hedging activity.

[INSERT TABLE 6 HERE]

*5.4. Robustness tests*

The Wald test performed in Table 5 indicates that the impact of green bond volume on EUA futures volume may be time-varying and even unstable. To control for instability, we use a rolling procedure to assess the time-varying behaviour of green bond volume coefficients through the VAR Model 1. We employ a window size of 18 months to estimate this rolling VAR, a period consistent with the hedging horizon of power firms (Schopp and Neuhoff, 2013).

Figure 3 plots the evolution of rolling coefficients for the green bond volume estimated in the front EUA futures (FUT1) equation along with their t-tests to assess simultaneously their sign and their significance. Coefficients are found to be positive and significant from February 2016 (i.e., the sub-period from February 2016 until July 2017) to March 2017 (i.e., the sub-period from March 2017 until July 2018) but has become insignificant afterwards.

This important finding implies that the green bond market is used as a complement of the EUA carbon market used for short-term hedging or speculation by power firms but less and less.

[INSERT FIGURE 3]

In the same vein, Figure 4 outlines the evolution of rolling green bond volume in the second-to maturity EUA futures (FUT2) equation along with their corresponding t-tests. With the volume of the second-to-maturity EUA futures, the estimated coefficient of the green bond volume is positive and statistically significant from May 2016 (i.e., the sub-period from May 2016 until October 2017) to March 2017 (i.e., the sub-period from March 2017 until August 2018) but it is negative and significant for the rest of the sub-periods.

[INSERT FIGURE 4]

According to our model inferences, an increase (*resp*. a decrease) of 1 ton in the front EUA futures (*resp*. second-to-maturity EUA futures) volume induces a green bond issue of 1 euro (*resp*. 0.15 euro) by European power firms, on average. In practice, it implies that a European power firm that buys (*resp*. sells) 1 ton of carbon dioxide with a front (*resp*. second-to maturity) EUA futures used for short- (*resp*. long-) term hedging simultaneously issues 1 euro (*resp*. 0.15 euro) of green bonds, on average. As a result, we conclude that the relationship between the front EUA futures and green bonds volumes is much stronger than that existing for the second-to-maturity EUA futures.

Quite importantly, we also notice a more pronounced negative relationship between the volume of green bonds and that of second-to-maturity EUA futures from 2018 where EUA prices have dramatically increased, indicating that the green bond market has become a substitute of the EUA market used for long-term hedging in the case of power firms.

## 6. Conclusion

This study is, to our knowledge, the first to examine the interactions between the European carbon and green bond markets from the perspective of the European power firms' activity. Since the advent of EU ETS in 2005, European power firms have been indeed the most concerned by hedging their carbon risk exposure and financing green technologies to reduce it. We proceed in two steps. First, using volume to proxy information, we study the causal relations between the volume and volatility of two EUA carbon markets used either (1) for short-term hedging and speculating or (2) long-term hedging over an eight-year period (2013-2020) corresponding to the Phase III of EU ETS. Second, we examine the relationships between the volume of these two carbon markets and that of green bonds issued by European power firms.

Three new key findings emerge from our study. First, the EUA carbon market used by power firms for long-term hedging serves a substitute of the EUA carbon market used for short-term hedging or speculating. Second, the first aforementioned carbon market has an informational advantage over the other because it is dominated by hedgers like power firms that are informed (Bredin et al., 2014; Rannou and Barneto, 2016). Third, we show that the green bond market acts as a complement of the EUA carbon market used for short-term hedging, while it has become a substitute of that used for long-term hedging since 2018. In practice, a European power firm that buys (*resp*. sells) 1 ton of carbon dioxide with a front (*resp*. second-to maturity) EUA futures used for short- (*resp*. long-) term simultaneously issues 1 euro (*resp*. 0.15 euro) of green bonds, on average. This result relates to the fact that the carbon price signal begins to operate in Europe, which has bolstered the green bond issuance programs of European power firms. But it is unlikely to be the main driving force (Bachelet et al., 2019; Zerbib, 2019; Flammer, 2020). Taken together, our results underscore a recent pivotal change in the strategies of European power firms that progressively abandon the EUA carbon market used for long-term hedging and issue more green bonds to finance their transition to clean energy systems.

Our findings have major implications for power firms, investors, policy makers, and exchanges alike. Since the green bond market may serve as a substitute for the carbon market used for their long-term hedging, power firms or investors can include green bonds in their portfolio of energy and carbon assets as an hedging instrument (Jin et al., 2020). From a policy making perspective, if issuing green bonds is an alternative to long-term carbon hedging strategies of power firms, it also signals that the carbon price signal operates in Europe so the EU can decide to decrease the emission cap accordingly. To compensate for this decrease, corporate green bond issuers like power firms may claim fiscal incentives to the EU when issuing green bonds. In this way, they might issue more and sizeable green bonds (Zerbib, 2019) in order to reduce their carbon hedging demand more quickly. This measure may also contribute to reduce two disadvantages that they face simultaneously: high due diligence costs (Gianfrate and Peri, 2019) and increased carbon hedging costs that renewable energy producers for instance do not really support.  Finally, knowing that the green bond market is viewed as a substitute for the carbon market by power firms is essential for the two main European carbon exchanges: ECX and EEX since power firms represent their most active and largest investor community. Possibly, these exchanges can launch their own green bond listings to develop their services to power firms in order to keep them captive and to broaden their investor clienteles.

We must admit that our work has one shortcoming, which lies in the assumption that the EUA carbon futures market used for long-term hedging is dominated by power firms that anticipate their emission levels and their hedging demand with certainty. Aside from addressing this limitation, future research may be carried out according to two directions. First, our study may be extended to the case of U.S. or Chinese environmental markets. Second, the comparison between the strategies of industrial actors, who are also important carbon emitters and those of power firms in the European carbon and green bond markets is left for future research.

## Inclusion and Diversity statement

While citing references scientifically relevant for this work, we also actively worked to promote gender balance in our reference list.

## Declaration of Competing Interest

No potential conflict of interest was reported by the authors.


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Any remaining errors or omissions are solely the responsibility of the authors.

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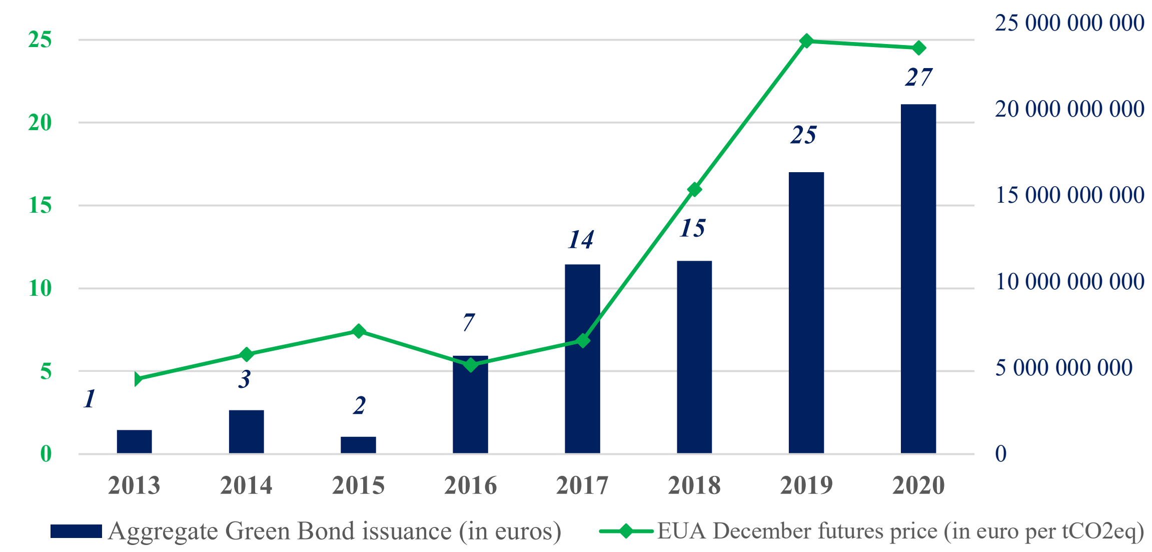
## List of Tables and Figures

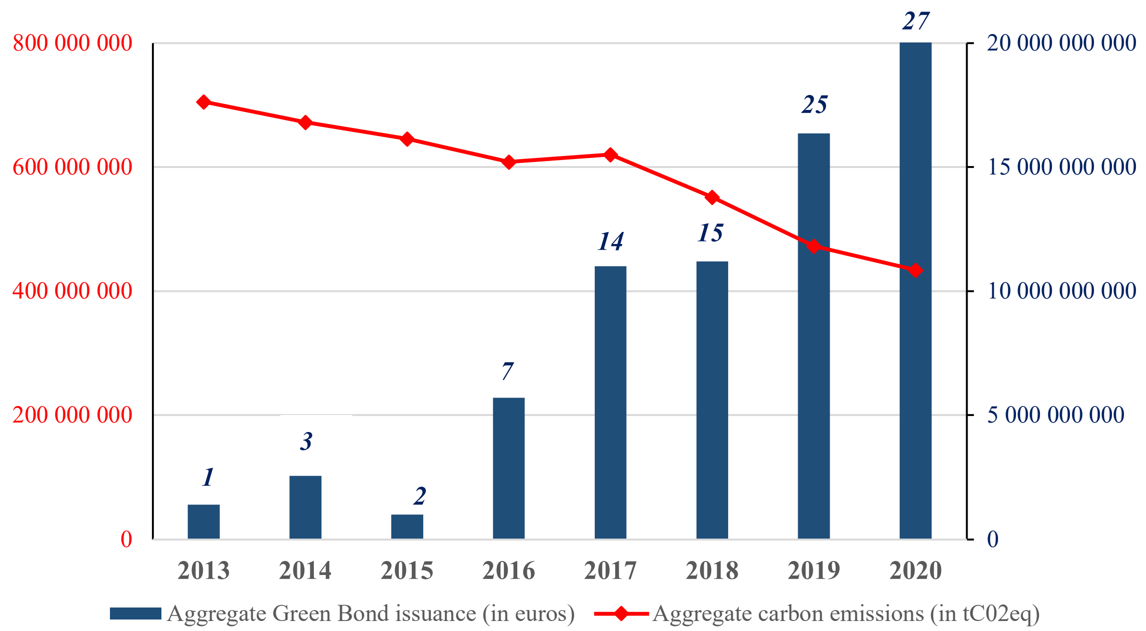
**Figure 1.** Large power firms: Carbon price trajectory vs. green bond issuance




*Source*: Refinitiv, Point Carbon

*Note*: The numbers in italics correspond to the annual number of green bonds issued by European power firms.

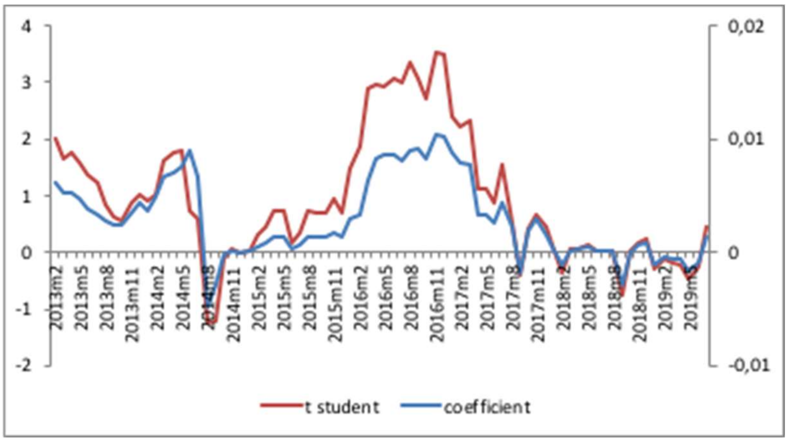
**Figure 2.** Power firms: Carbon emissions trajectory vs. green bond issuance




*Source*: Refinitiv, Point Carbon

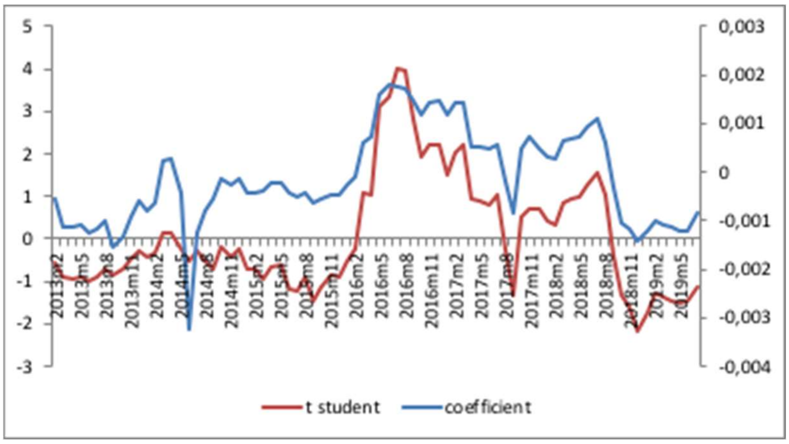
*Note*: The numbers in italics correspond to the annual number of green bonds issued by European power firms.

**Figure 3**. Rolling estimates of the green bond volume coefficient in the front EUA carbon futures equation (**FUT1**)




*Note*: The blue curve represents the evolution of the green bond coefficient in the rolling VAR written in Eq. (5) (*see right axis*) while the red curve graphs the evolution of its corresponding t-test (*see left axis*). Dates on the x-axis are those of the start of each rolling window.

**Figure 4.** Rolling estimates of the green bond volume coefficient in the second-to-maturity EUA carbon futures equation **(FUT2)**




*Note*: The blue curve depicts the evolution of the green bond coefficient in the rolling VAR written in Eq. (5) (*see right axis*) while the red curve highlights the evolution of its corresponding t-test (*see left axis*). Dates on the x-axis are those of the start of each rolling window.

**Table 1**. Summary characteristics of the green bond sample

| *Power firms (Issuers)* | Number of issues | Average issuance amount (*in M€*) | Average maturity (*in years*) | Average issue rating | Annual carbon exposure (*annual verified emissions*) in MtCO2eq |
|---|---|---|---|---|---|
| ***A2A*** | 1 | 400 | 10 | Baa2 | 7 105 |
| ***E.ON*** | 6 | 766.667 | 8 | A3 | 86 966 |
| ***EDF*** | 4 | 1 850 | 7 | A3 | 87 823 |
| ***EDP*** | 3 | 833.333 | 20 | Baa2 | 19 477 |
| ***EnBW*** | 4 | 833.333 | 42 | Baa2 | 20 148 |
| ***ENEL*** | 9 | 1 111.111 | 7 | A3 | 106 767 |
| ***Enexis*** | 1 | 500 | 12 | Aa3 | 1 657 |
| ***Engie*** | 10 | 800 | 11 | Baa1 | 113 418 |
| ***Eurogrid (Elia Group)*** | 1 | 750 | 12 | Baa1 | 1 318 |
| ***Iberdrola*** | 9 | 744.444 | 8 | A3 | 26 070 |
| ***Ignitis*** | 2 | 300 | 10 | Baa1 | 1 206 |
| ***National Grid*** | 2 | 300 | 12.5 | A2 | 8 724 |
| ***Naturgy*** | 1 | 800 | 3 | Baa1 | 22 322 |
| ***Orsted*** | 4 | 435.535 | 12 | Baa1 | 4 456 |
| ***Stedin*** | 1 | 500 | 10 | A3 | 1 870 |
| ***Scottish & Southern Energy*** | 2 | 625 | 8.5 | Baa1 | 14 860 |
| ***Stockholm Exergi*** | 5 | 37.719 | 5.8 | Baa1 | 8 234 |
| ***TenneT*** | 15 | 623.333 | 12 | A3 | 3 640 |
| ***Terna*** | 2 | 330.526 | 8.5 | A3 | 1 380 |
| ***Vattenfall*** | 3 | 500 | 6.5 | Baa1 | 74 621 |
| ***Verbund*** | 1 | 500 | 10 | A3 | 2 040 |
| ***TOTAL*** | **86** | **645** | **12** | **A3** | **20 192** |

*Notes*: The average issuance amount is expressed in millions of euros. For issuance denominated in a currency other than the euro, the amount is translated into euros with the exchange rate prevailing at the issuance date.
The displayed average rating by firm is an arithmetic mean of the rating obtained for all bond issued. For comparison purposes, we use the corresponding Moody's rating.
The carbon exposure is the annual level of Scope 1 emissions verified to be covered by power firms for compliance purposes that we averaged between 2013 and 2020. This information is provided by Datastream on an annual basis. When it is not available (case of unlisted companies: EnBW and Vattenfall), the volume of verified emissions disclosed in the annual report of the firm is used.
The row ***TOTAL*** displays the sample average of the different variables except for the column "Number of Issues" that reports the aggregate volume of green bond issuances.

**Table 2.** Descriptive monthly statistics for EUA futures and Green Bonds (GB)

*Panel A: Volatility of EUA Futures*

| | VOLATFUT1 | VOLATFUT2 |
|---|---|---|
| **Mean** | 0.4674 | 0.4547 |
| **Median** | 0.4045 | 0.3927 |
| **Max.** | 1.0972 | 1.0351 |
| **Min.** | 0.1446 | 0.1430 |
| **Std. Dev.** | 0.2081 | 0.2048 |
| **Skewness** | 2.1894 | 2.1748 |
| **Kurtosis** | 10.09 | 9.43 |
| **Normality (JB)** | 278.24** | 268.14** |
| **ARCH (2)** | 10.12** | 10.40** |
| **ADF** | - 4.95** | - 4.93** |
| **ZA** | - 5.85* | - 5.89** |

*Panel B: Volume of EUA futures and Green Bonds (GB)*

| | VOLUMEFUT1 | VOLUMEFUT2 | VOLUMEGB |
|---|---|---|---|
| **Mean** | 394 192 | 194 347 | 6 819 543 |
| **Median** | 373 482 | 171 492 | 6 786 555 |
| **Maximum** | 884 692 | 380 696 | 40 000 000 |
| **Minimum** | 170 002 | 21 441 | 0 |
| **Std. Dev.** | 143 433 | 53 119 | 8 064 440 |
| **Skewness** | 0.86 | 2.27 | 1.51 |
| **Kurtosis** | 3.60 | 9.78 | 4.47 |
| **Normality (JB)** | 13.29** | 39.37** | 45.32** |
| **ARCH (2)** | 6.04* | 14.77** | 1.76 |
| **ADF** | - 3.92** | - 3.81** | - 4.96** |
| **ZA** | - 6.36** | - 4.98* | - 13.4** |

*Notes*: *Panel A* reports monthly statistics for volatility of the front EUA futures (**VOLATFUT1**) and of the second-to-maturity EUA futures (**VOLATFUT2**) observed along the period January 2013 to December 2020. Volatility represents a 20 moving average business days volatility.
*Panel B* displays monthly statistics for aggregated volumes of the front EUA futures (**VOLUMEFUT1**) and of the second-to-maturity EUA futures (**VOLUMEFUT2**) respectively as well as the volume of green bond issued by power firms (**VOLUMEGB**) along the period January 2013 to December 2020.
Normality tests are carried out based on Jarque-Bera (JB) tests. ARCH (2) is a $\chi^2$ statistic of Lagrange Multiplier (LM) used to test autoregressive conditional heteroscedasticity effects with 2 lags.
Both the Augmented Dickey and Fuller (ADF) and Zivot and Andrews (ZA) unit root tests are performed under the specification: intercept and without trend.
** Indicates significance at 1% level.
* Indicates significance at 5% level.

**Table 3.** Pairwise correlation tests

| | VOLUMEFUT1 | VOLUMEFUT2 | VOLUMEGB | VOLATFUT1 | VOLATFUT2 |
|---|---|---|---|---|---|
| **VOLUMEFUT1** | 1 | | | | |
| **VOLUMEFUT2** | 0.396 | 1 | | | |
| **VOLUMEGB** | 0.207 | -0.135 | 1 | | |
| **VOLATFUT1** | 0.387 | 0.046 | -0.095 | 1 | |
| **VOLATFUT2** | 0.383 | 0.05 | -0.041 | 0.998 | 1 |

*Note*: ** and * denote significance at 1% and 5% levels respectively.

**Table 4.** Pair-wise causality between volume and volatility in a bivariate GJR GARCH model

*Panel A*. **Volume/Volatility** of EUA Carbon Futures (**FUT1 & FUT2**)

| | **Lag = 2** | | **Lag = 3** | |
|---:|---|---|---|---|
| **Null Hypothesis** | F-Stat | *Prob.* | F-Stat | *Prob.* |
| **VolatilityFUT1 does not Granger Cause VolumeFUT1** | 3.049* | *0.033* | 6.05* | *0.000* |
| **VolumeFUT1 does not Granger Cause VolatilityFUT1** | 0.868 | *0.461* | 1.091 | *0.367* |
| **VolatilityFUT2 does not Granger Cause VolumeFUT2** | 5.6** | *0.001* | 5.22** | *0.001* |
| **VolumeFUT2 does not Granger Cause VolatilityFUT2** | 0.425 | *0.654* | 1.584 | *0.191* |
| **VolatilityFUT1 does not Granger Cause VolatilityFUT2** | 1.034 | *0.287* | 0.055 | *0.994* |
| **VolatilityFUT2 does not Granger Cause VolatilityFUT1** | 1.449 | *0.234* | 1.893 | *0.12* |
| **VolatilityFUT2 does not Granger Cause VolumeFUT1** | 1.856 | *0.143* | 2.536* | *0.046* |
| **VolumeFUT1 does not Granger Cause VolatilityFUT2** | 0.539 | *0.657* | 1.18 | *0.326* |
| **VolatilityFUT1 does not Granger Cause VolumeFUT2** | 1.874 | *0.14* | 3.034* | *0.033* |
| **VolumeFUT2 does not Granger Cause VolatilityFUT1** | 0.592 | *0.622* | 1.161 | *0.334* |

*Panel B*. **Volatility** of EUA Carbon Futures (**FUT1 & FUT2**) and **Volume GB**

| | **Lag = 2** | | **Lag = 3** | |
|---:|---|---|---|---|
| **Null Hypothesis** | F-Stat | *Prob.* | F-Stat | *Prob.* |
| **VolatilityFUT1 does not Granger Cause VolumeGB** | 0.384 | *0.764* | 0.269 | *0.896* |
| **VolumeGB does not Granger Cause VolatilityFUT1** | 0.050 | *0.985* | 0.221 | *0.926* |
| **VolatilityFUT2 does not Granger Cause VolumeGB** | 0.399 | *0.754* | 0.280 | *0.890* |
| **VolumeGB does not Granger Cause VolatilityFUT2** | 0.046 | *0.987* | 0.206 | *0.934* |

*Panel C*. **Volume** EUA Carbon Futures (**FUT1 & FUT2**) and **Volume GB**

| | **Lag = 2** | | **Lag = 3** | |
|---:|---|---|---|---|
| **Null Hypothesis** | F-Stat | *Prob.* | F-Stat | *Prob.* |
| **VolumeFUT2 does not Granger Cause VolumeFUT1** | 3.049* | *0.033* | 2.496* | *0.049* |
| **VolumeFUT1 does not Granger Cause VolumeFUT2** | 0.868 | *0.461* | 1.135 | *0.346* |
| **VolumeFUT1 does not Granger Cause VolumeGB** | 1.813 | *0.19* | 1.648 | *0.240* |
| **VolumeGB does not Granger Cause VolumeFUT1** | 3.034* | *0.03* | 2.509** | *0.046* |
| **VolumeFUT2 does not Granger Cause VolumeGB** | 1.449 | *0.234* | 1.161 | *0.334* |
| **VolumeGB does not Granger Cause VolumeFUT2** | 3.032* | *0.032* | 2.536* | *0.044* |

*Note*: Causality tests are performed on a full time period basis (January 2013 to December 2020). We employ the Toda and Yamamoto (1995) procedure to test causal relations.
We estimate F-Stats to assess the significance of Granger causality tests given the following null hypothesis:
$B_1 = B_2 = \ldots = B_M = 0$ from Eq. (3) or $\theta_1 = \theta_2 = \ldots = \theta_M = 0$ from Eq. (4).
If this null hypothesis is rejected in the first (second) case, volatility (volume) is said to Granger-cause volume (volatility). The corresponding *p-values* of F-Stats are expressed in italics.
** and * denote, respectively, statistical significance at 1% and 5% levels.

**Table 5.** Trading volume regression for the two EUA carbon futures markets (**FUT1 & FUT2**)

*Panel A*. Cross regression with front (FUT1) and second-to-maturity (FUT2) futures volume

| **Dependant Variable** | **Volume FUT1** | | **Volume FUT2** | |
|---|---|---|---|---|
| | Coeff. [SE] | z-Stat (*Prob.*) | Coeff. [SE] | z-Stat (*Prob.*) |
| ***1. Conditional Mean Equation of Trading Volume*** | | | | |
| **Intercept** | **30607**** [13698] | 2.234 *0.000* | **110435**** [36382] | 3.035 *0.002* |
| **Volume FUT1 (-1)** | **0.598**** [0.091] | 6.593 *0.000* | **0.36** [0.219] | 1.644 *0.1* |
| **Volume FUT1 (-2)** | **-0.081** [0.071] | *-1.136* *0.256* | **-0.207** [0.219] | -0.947 *0.344* |
| **Volume FUT2 (-1)** | **0.044*** [0.021] | 2.09 *0.04* | **0.47**** [0.1] | 4.715 *0.000* |
| **Volume FUT2 (-2)** | **-0.031** [0.041] | -0.767 *0.443* | **0.208*** [0.099] | 2.101 *0.036* |
| ***2. Conditional Variance Equation*** | | | | |
| **ω** | **4.74E+08*** [2.32E+08] | 2.041 *0.04* | **8.08E+08** [4.54E+08] | 1.781 *0.075* |
| **δ** | **0.126*** [0.062] | 2.026 *0.042* | **0.106** [0.091] | 1.174 *0.241* |
| **α** | **-0.416**** [0.113] | -3.282 *0.001* | **-0.273*** [0.119] | -2.296 *0.022* |
| **β** | **0.774**** [0.124] | 6.241 *0.000* | **0.748**** [0.158] | 4.734 *0.000* |
| ***3. Diagnostic Tests*** | | | | |
| **$R^2$** | 0.415 | | 0.456 | |
| **Adj. $R^2$** | 0.380 | | 0.431 | |

*Panel B*. Cross regression with front (FUT1), second-to-maturity (FUT2) futures volume and green bond (GB) volume

| **Dependent Variable** | **Volume FUT1** | | **Volume FUT2** | |
|---|---|---|---|---|
| | Coeff. [SE] | z-Stat (*Prob.*) | Coeff. [SE] | z-Stat (*Prob.*) |
| ***1. Conditional Mean Equation of Trading Volume*** | | | | |
| **Intercept** | **78125** [45478] | 1.717 *0.085* | **46408**** [16059] | 2.889 *0.004* |
| **Volume FUT1 (-1)** | **0.694**** [0.137] | 5.073 *0.000* | **0.01** [0.053] | 0.842 *0.093* |
| **Volume FUT1 (-2)** | **0.066** [0.125] | 0.526 *0.599* | **-0.075** [0.053] | -1.415 *0.157* |
| **Volume FUT2 (-1)** | **0.086*** [0.39] | 2.205 *0.029* | **0.373**** [0.127] | 2.927 *0.003* |
| **Volume FUT2 (-2)** | **-0.159** [0.330] | -0.484 *0.629* | **0.125*** [0.058] | 2.155 *0.037* |
| ***Volume GB*** | **0.028*** [0.013] | 2.152 *0.031* | **-0.016*** [0.008] | -2.021 *0.048* |
| ***W-1 (Volume GB)*** | ***1.97**** | *0.05* | ***1.81*** | *0.074* |
| ***2. Conditional Variance Equation*** | | | | |
| **ω** | **3.23E+08** 2.02E+08 | 0.537 *0.591* | **5.22E+08** [3.81E+08] | 1.371 *0.170* |
| **δ** | **0.205** [0.443] | 0.462 *0.644* | **0.135** [0.114] | 1.706 *0.254* |
| **α** | **-0.536*** [0.268] | -2.002 *0.049* | **-0.560**** [0.193] | -2.901 *0.004* |
| **β** | **0.597*** [0.265] | 2.251 *0.026* | **0.673*** [0.328] | 2.050 *0.040* |
| ***3. Diagnostic Tests*** | | | | |
| **$R^2$** | 0.481 | | 0.410 | |
| **Adj. $R^2$** | 0.432 | | 0.351 | |

*Note*: We employ z-statistic to test the significance of estimated coefficients. Their values and their corresponding *p-values* are reported in the right columns. The Bollerslev and Wooldridge (1992) robust standard errors are shown in square brackets beneath the coefficients.
Adj. $R^2$ is the $R^2$ adjusted for degree of freedom.
** and * indicates respectively statistical significance at 1% and 5% levels.

**Table 6.** VAR analysis

*Panel A*. VAR (2) with **FUT1** (front EUA futures) volume as dependent variable

| | ***Regression Model*** | | |
|---|---|---|---|
| **Variables** | ***(1)*** | ***(2)*** | ***(3)*** |
| **Volume FUT1(-1)** | **0.6****<br>[0.107] | **0.54****<br>[0.107] | **0.564****<br>[0.112] |
| **Volume FUT1(-2)** | **0.092**<br>[0.111] | **0.061**<br>[0.109] | **0.08**<br>[0.112] |
| **Volume FUT2(-1)** | **0.151***<br>[0.074] | **0.141***<br>[0.072] | **0.139**<br>[0.084] |
| **Volume FUT2(-2)** | **-0.074**<br>[0.299] | **-0.017**<br>[0.293] | **-0.07**<br>[0.299] |
| ***Intercept*** | **99256****<br>[37892] | **72418***<br>[38481] | **-560352**<br>[944036] |
| ***Volume GB*** | **0.003***<br>[0.001] | **0.002****<br>[0.001] | **0.002***<br>[0.001] |
| ***Volatility FUT1*** | | **2869.7***<br>[1440.6] | **2510.3***<br>[1270.8] |
| ***Volatility FUT2*** | | **-2580.6**<br>[1854.4] | **-2413.4**<br>[1634.1] |
| ***CLI Europe*** | | | **6179.1**<br>[9211.7] |
| ***EnergyRet*** | | | **-1735**<br>[1288] |
| **$R^2$** | **0.507** | **0.534** | **0.541** |
| **Adj. $R^2$** | **0.479** | **0.497** | **0.491** |
| F-stat | 16.723 | 14.104 | 10.982 |
| *Prob. (F-stat)* | *0.000* | *0.000* | *0.000* |

*Panel B*. VAR (2) with **FUT2** (second-to-maturity EUA futures) volume as dependent variable

| | ***Regression Model*** | | |
|---|---|---|---|
| **Variables** | ***(1)*** | ***(2)*** | ***(3)*** |
| **Volume FUT1(-1)** | **0.038***<br>[0.048] | **0.037**<br>[0.05] | **0.04**<br>[0.053] |
| **Volume FUT1(-2)** | **0.033**<br>[0.05] | **0.036**<br>[0.051] | **0.039**<br>[0.053] |
| **Volume FUT2(-1)** | **0.595****<br>[0.132] | **0.584****<br>[0.138] | **0.584****<br>[0.14] |
| **Volume FUT2(-2)** | **-0.154**<br>[0.135] | **-0.164**<br>[0.138] | **- 0.135**<br>[0.18] |
| ***Intercept*** | **25087**<br>[17048.7] | **24427**<br>[18155] | **-68028**<br>[448244] |
| ***Volume GB*** | **-0.001***<br>[0.000] | **-0.001***<br>[0.001] | **-0.001***<br>[0.001] |
| ***Volatility FUT1*** | | **-2695.7**<br>[2068.7] | **-2361.8**<br>[1869.6] |
| ***Volatility FUT2*** | | **2736.3**<br>[1933.7] | **2407.7**<br>[1759] |
| ***CLI Europe*** | | | **902.9**<br>[4373.9] |
| ***EnergyRet*** | | | **780.4**<br>[896.3] |
| **$R^2$** | **0.445** | **0.497** | **0.407** |
| **Adj. $R^2$** | **0.403** | **0.437** | **0.328** |
| F-stat<br>*Prob. (F-stat)* | 12.053<br>*0.000* | 13.253<br>*0.000* | 10.238<br>*0.000* |

*Note:* We apply the Akaike Information criteria to determine the number of appropriate lags, which is equal to 2 for both FUT1 and FUT2 volume.
Adj. $R^2$ is the $R^2$ adjusted for degree of freedom.
** and * indicates respectively statistical significance at 1% and 5% levels.

# Appendix

**A1.** Trading volume regression for the green bond market as the two EUA futures markets as regressors (**FUT1 & FUT2**)

| **Dependant Variable** | **Volume GB** | |
|---|---|---|
| | Coeff.<br>[SE] | z-Stat<br>(*Prob.*) |
| ***1. Conditional Mean Equation of Trading Volume*** | | |
| **Intercept** | **-5382761****<br>[13698] | -1.044<br>*0.297* |
| **Volume FUT1 (-1)** | **2.595**<br>[12.64] | 0.205<br>*0.837* |
| **Volume FUT1 (-2)** | **22.17**<br>[17.90] | *1.239*<br>*0.215* |
| **Volume FUT2 (-1)** | **-16.61**<br>[35.09] | -0.473<br>*0.636* |
| **Volume FUT2 (-2)** | **-24.72**<br>[27.19] | -0.909<br>*0.363* |
| ***2. Conditional Variance Equation*** | | |
| **ω** | **7.74E+13**<br>[4.22E+13] | 1.835<br>*0.067* |
| **δ** | **0.051**<br>[1.103] | 0.046<br>*0.963* |
| **α** | **-0.118****<br>[0.024] | -4.832<br>*0.000* |
| **β** | **0.598***<br>[0.230] | 2.138<br>*0.032* |
| ***3. Diagnostic Tests*** | | |
| **$R^2$** | 0.211 | |
| **Adj. $R^2$** | 0.165 | |

*Note*: We employ z-statistic to test the significance of estimated coefficients. Their values and their corresponding *p-values* are reported in the right columns. The Bollerslev and Wooldridge (1992) robust standard errors are shown in square brackets beneath the coefficients.
Adj. $R^2$ is the $R^2$ adjusted for degree of freedom.
** and * indicates respectively statistical significance at 1% and 5% levels.