"My name is bond. Green bond." Informational Efficiency of Climate Finance Markets

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Abstract

This paper investigates the informational efficiency of green bond markets using a recently introduced quantitative measure for market inefficiency. The paper finds that, first, the degree of inefficiency of the green bond market is very similar to that of benchmark bond markets. Second, fundamental factors that drive bond prices in general also drive prices for green bonds. Third, the green bond market is less affected by challenging environments such as the COVID outbreak in 2020 and the inflation shock in 2022/2023 than the benchmark markets. The paper argues that the arrival of information not only leads to increased price volatility, but also deviation from random walk. To illustrate this, this paper uses data from the Philadelphia Fed Survey of Professional Forecasters to measure the degree of disagreement among market participants.
Keywords: Green Bonds, Efficient Market Hypothesis, Fractional Integration, Differences-of-opinion, Expectation Surveys
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1 Introduction

Climate finance is crucial for tackling climate change as it provides the necessary resources to support mitigation and adaptation efforts. With adequate funding, countries can invest in renewable energy projects, improve energy efficiency, develop climate-resilient infrastructure, and implement measures to mitigate the impacts of climate change on vulnerable communities. Additionally, climate finance facilitates technology transfer and capacity building in developing countries, enabling them to transition to low-carbon and climate-resilient pathways. By mobilising financial resources at both the domestic and international levels, climate finance plays a vital role in addressing the root causes of climate change while also building resilience to its impacts, ultimately contributing to a more sustainable and secure future for all.

Green bonds play a pivotal role in climate finance by channelling capital towards environmentally sustainable projects and initiatives. These bonds are specifically earmarked to finance projects that have positive environmental impacts, such as renewable energy development, energy efficiency improvements, sustainable agriculture, and climate adaptation measures. By providing investors with the opportunity to support projects that address climate change and promote sustainability, green bonds help mobilise private capital towards the transition to a low-carbon economy. Moreover, they enhance transparency and accountability in environmental investments by requiring issuers to disclose information on the environmental benefits of funded projects. Overall, green bonds serve as a critical financial instrument in accelerating global efforts to combat climate change and promote sustainable development.

In essence, the market for green bonds holds significant importance in light of the ongoing climate crisis. However, it ultimately remains just one market in the broader financial landscape. Therefore, conventional methodologies employed in financial market analysis are leveraged to scrutinise the market for green bonds as well. This paper delves into empirically assessing the informational inefficiency of green bond markets, a prominent research area within the area of empirical finance.

The empirical approach used in this paper is the quantitative measure for market inefficiency recently proposed by Duan, Li, Urquhart, and Ye (2021). The key idea of this approach is to measure market inefficiency through the extent to which the observed price behaviour deviates from the Random Walk benchmark. Duan et al. (2021) are similar in essence to Kristoufek and Vosvrda (2013, 2014) and Sattarhoff and Gronwald (2022). While the former base their measure on Hurst exponents, Sattarhoff and Gronwald (2022) use a multifractal approach. Duan et al.'s (2021) measure for market efficiency is based on the novel interpretation of fractional integration. In that approach, the order of integration d of a time series can be a fractional number between 0 and 1. This paper employs the so-called Feasible Exact Local Whittle estimator to estimate d. Duan et al. (2021) gauge the degree of inefficiency of a market using the absolute difference between the estimate of d and 1: $D = |1 - d|$. To measure dynamic efficiency, i.e. how efficiency is varying over time, this paper uses a rolling window approach.

It is essential for prices in a financial market to accurately reflect information because it ensures the efficient allocation of financial resources to investment projects. When prices accurately incorporate all available fundamental information about the supply and demand dynamics of goods, services, and assets, they provide reliable signals to investors and businesses. This allows market participants to make informed decisions about where to allocate their capital, directing investments towards projects that offer the highest returns and societal benefits. When prices fail to reflect information correctly, misallocations of resources can occur, leading to inefficiencies, market distortions, and ultimately sub-optimal economic outcomes. The approach employed in this paper not only allows one to analyse the development of the degree of inefficiency over time, but also across markets. Valuable insight emerges from a comparison of the degree of inefficiency of green bond markets to that of a number of benchmark markets such as aggregate, corporate and treasury bond markets as well as green energy stock markets.

The key results can be summarised as follows: first, the degree of inefficiency of the green bond market is generally found to be very similar to that of benchmark bond markets. Second, fundamental factors that drive bond prices in general also drive prices for green bonds. Third, the green bond market is less affected by challenging environments such as the COVID outbreak in 2020 and the inflation shock in 2022/2023 than the benchmark markets. A key fundamental factor of bond prices is inflation and monetary policy. Both factors have been much more difficult to predict during these two periods. Building on the so-called differences-of-opinion literature (Kandel & Person, 1995), the paper argues that the arrival of information not only leads to increased price volatility (Bollerslev, Li, & Xue, 2018), but also a deviation from random walk. To illustrate this, this paper uses data from the Philadelphia Fed Survey of Professional Forecasters to measure the degree of disagreement among market participants.

This paper contributes to three streams of literature. First, the vibrant literature on climate finance - given the role of green bonds in the context of climate finance and also the pressing nature of the climate crisis, all research efforts are more than justified. Among the closest related papers are Ren, Xiao, Duan, and Urquhart (2024) who look into the dynamic correlation of inefficiency between fossil energy and green markets, Adekoya, Oliyide, Asl, and Jalalifar (2021) who look into market efficiency and volatility persistence of green vs conventional bonds. The latter do not use the now common estimator FELW and the former do not consider conventional financial markets as benchmarks. In this sense, this paper is closer to Sattarhoff and Gronwald (2022) who compare the market efficiency of the EU ETS and compare it to that of the US stock market. Other issues studied in this literature are the connectedness between crude oil and green bond markets (Yousaf, Mensi, Vo, & Kang, 2024), volatility spillovers between green bond and new energy markets (Wu & Qin, 2024), the relationship between green bond issuance and stock price crash risk (Zhang, Li, & Chen, 2024), and the influence of climate policy uncertainty on volatility of new energy markets (Raza, Khan, Benkraiem, & Guesmi, 2024).

Second, the literature on how financial markets process information documents a strong relationship between the arrival of news and market activity;

see, e.g., Mitchell and Mulherin (1994) and Engle, Hansen, Karagozoglu, and Lunde (2021). Among the implications of this increased market activity is increased market volatility (Bollerslev et al., 2018; Engle et al., 2021). The views expressed in the so-called "differences-of-opinion" literature (Banerjee & Kremer, 2010; Kandel & Person, 1995) can explain this: disagreement among investors about how to interpret new information leads to increases in market activity and market volatility. In specific, Banerjee, Kaniel, and Kremer (2009) show that disagreement about higher-order beliefs can lead to asset price predictability. This paper's empirical findings empirically support this notion.

Third, this paper is also related to a literature that deals with disagreement of forecasters in specific; see, e.g., Mankiw, Reis, and Wolfers (2003), Patton, J, and Timmermann (2010), and Andrade and Bihan (2013). The objective of these papers is to explain why this disagreement exists. This type of analysis is relevant in the context of monetary policy analysis and anchoring of inflation expectations.

The remainder of the paper is organised as follows: Section 2 describes the data and method used in this paper. Section 3 presents the empirical results; Section 4 provides a discussion of these results. Section 5 offers some concluding remarks.

2 Data and Method

The dataset used in this paper is similar to the dataset used in Pham (2021). The analysis adopts the S&P Dow Jones Green Bond Index as a proxy for green bond pricing. Additional series employed in this research are detailed in Table 1. The data is at daily frequency, period of observation is October 2014 to February 2024. These datasets were accessed through the Bloomberg terminal. For forecast dispersion data, the dispersion of CPI and a 3-months treasury bill from the Federal Reserve Bank of Philadelphia is used.

Figure 1 displays key variables used in this paper: the green bond price index as well as the aggregate bond index on the one hand, and the MSCI World as broad stock market index as well as S&P Clean Energy on the

Table 1: Details of data

Index	Bloomberg Ticker	Benchmark
S&P Dow Jones Green Bond TR Index	SPUSGRN	Green bond
MSCI World	MXWO	General stock
S&P Global Clean Energy Index	SPGTCED	Clean energy stock
Bloomberg Global Aggregate Corporate	LGCPTRUU	Global bond
Bloomberg Global Aggregate Treasuries	LGTRTRUU	Global bond
Bloomberg Global Aggregate Index	LEGATRUU	Global bond
NASDAQ OMX Clean Energy-focused Index	GRNCLNFO	Green equity: Clean energy
NASDAQ OMX Wind	GRNWIND	Green equity: Wind energy
NASDAQ OMX Green Building	GRNGB	Green equity: Building
NASDAQ OMX Solar	GRNSOLAR	Green equity: Solar
NASDAQ OMX Green Transportation	GRNTRN	Green equity: Transportation
NASDAQ OMX Global Water	GWATERL	Green equity: Water

Source: MSCI, S&P, NASDAQ and Bloomberg terminal

other. The green bond price index largely moves sideways between the beginning of the sample and the end of 2019; on occasion, there is a sharper upward or downward movement. The second half of the sample contains turbulent periods: the outbreak of the COVID pandemic, the collapse of green bond prices in relation to the inflation shock in early 2022, and, finally, a generally more volatile movement in 2023. The development of the aggregate bond price series is overall similar to that of the green bond prices; only that overall fluctuation seems to be a bit higher than for the green bond price index. The development of the two stock price indices over time is, for obvious reasons, very different: the MSCI World index exhibits an upward trend throughout the sample period, with obvious deviations in 2020 and 2022. S&P Clean Energy moves more horizontally up until 2019, followed by a sharper increase which starts in 2020. Subsequently, there is a sharp decline in early 2021 and more of a downward trend in 2021-2023.

Having briefly described the data used in this paper, attention is now directed towards the method. Processes characterised by fractional integration $I(d)$ have garnered increasing interest among empirical researchers in the fields of economics and finance. This is because $I(d)$ processes can effectively capture specific long-term features within economic and financial data (for details, see Zaffaroni and Henry (2003)). This paper employs the methodology introduced by Duan et al. (2021), which utilises a framework based on fractional integration, particularly using Shimotsu's (2010)

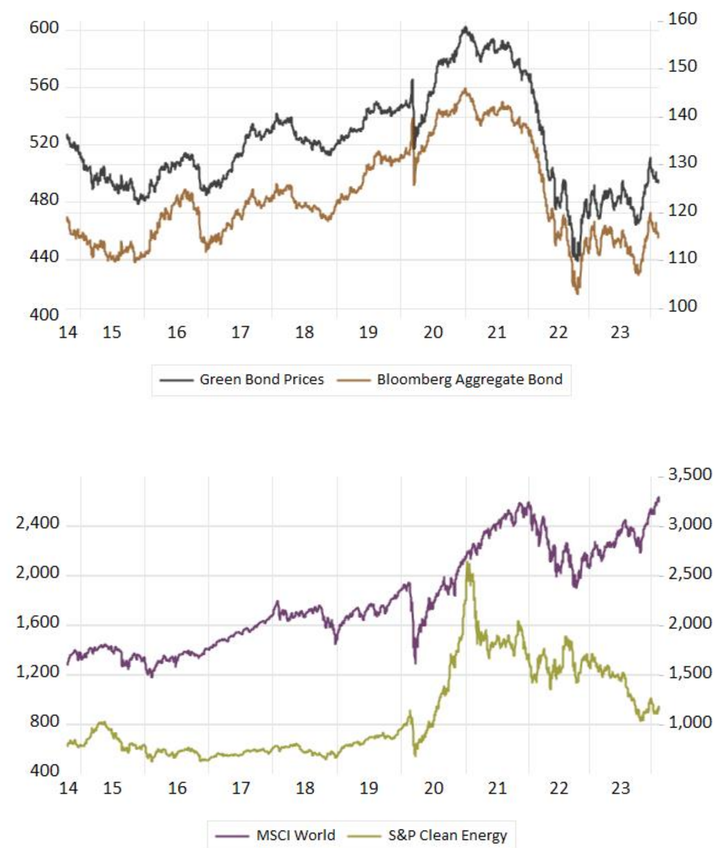

Figure 1: Selected time series used in this paper.

semiparametric Feasible Exact Local Whittle (FELW) estimator. Shimotsu (2010) introduce a modified (two-step) ELW estimator, tailored for economic data analysis, to account for an unspecified mean (which needs to be estimated) and a polynomial time trend. This estimation approach complements the fully extended local Whittle estimator introduced by Abadir, Distaso, and Giraitis (2007), which uses a fully extended discrete Fourier transform. A fully extended local Whittle is based on the Type I process, whereas FELW is founded on the Type II process.[1]

[1]See Shimotsu and Phillips (2006) for further details on the Type I and Type II process.

Table 2: Memory properties of a given price series (y_t) with different d values.

d **Value**	**Persistence of shocks**	**Market efficiency**	**Information transmission**	**The close degree to an efficient market**
$d > 1$	Expansionary memory, explosive over time	Inefficiency	Excessive transmission	-
$d = 1$	Permanent memory	Efficiency	Complete transmission	Efficient Market
$0.5 \leq d < 1$	Long memory	Inefficiency	Partial transmission	High degree
$0 < d < 0.5$	Long memory	Inefficiency	Partial transmission	Lower degree
$d = 0$	Short memory	Inefficiency	None	Zero degree
$d < 0$	Long memory	Inefficiency	Reverse transmission	-

Note: This table provides information on the memory properties of a given price series (y_t) across different integration orders (d) and outlines their corresponding effects on market efficiency. Adapted from "Dynamic efficiency and arbitrage potential in Bitcoin: A long-memory approach," by K. Duan, Z. Li, A. Urquhart, and J. Ye, 2021, *International Review of Financial Analysis*, 75, p. 4, (`https://doi.org/10.1016/j.irfa.2021.101725`). Copyright 2021 by Elsevier Inc.

Duan et al. (2021) follows Hamilton (1994) to explain different forms of "memory" within a given time series to identify potentially existing fractional integration order that is a crucial metric for quantifying the level of market informational efficiency.[2] Moreover, this accommodates the fractional integration order by incorporating the concept of "long-memory" within the model system.

The empirical analysis is initiated by estimating d-value i.e. fractional integration order of green bond price series as well as benchmark series (y_t) by using the Feasible Exact Local Whittle estimator (FELW) introduced by Shimotsu (2010). Considering that overly high or low bandwidths can result in a reduced or increased number of valid observations utilised in the

[2]Later, they adopt the Fractionally Cointegrated Vector Autoregressive (FCVAR) model introduced by Johansen (2008) and Johansen and Nielsen (2012) that accounts for both short-run error corrections and long-term links among the target variables. For the details of the model see Section 3.1 of Duan et al. (2021)

estimation of d using the FELW methods (Shimotsu, 2010), causing unstable outcomes, a moderate bandwidth of 0.6 is chosen to generate the time series for d. Later, the d-value is used to gauge the degree of market efficiency. Table 2 (Duan et al., 2021) show the statistical (memory) properties of y_t at varying values of d, along with the corresponding indications of market efficiency.

To examine how the informational efficiency of the markets under consideration evolves over time, market efficiency is assessed by using a self-derived index D in this study. This D index is created by computing the absolute difference between 1 and the fractional integration order that provides insights into the bond market's evolving nature of efficiency.

$$D_t = |1 - d_t|$$

where d_t is the estimated fractional integration order at time t. A 1-year rolling window is used to estimate the d-value. The index D, determined by the disparity between d values and 1, inversely signifies the level of market efficiency. In other words, a higher D indicates a larger absolute gap, reflecting a more inefficient market and a lower degree of market efficiency. Hence, D can also be seen as a representation of the degree of market inefficiency.

3 Results

The upper panel of Figure 2 shows the green bond price index along with the estimate of the degree of inefficiency, D, of the green bond market. The degree of inefficiency is mostly fluctuating between 0 and 0.2; however, it exceeds 0.1 only in certain periods. Often, the degree of inefficiency is found to be close to 0. This is the random walk benchmark; the market is close to being fully efficient. Increases in the degree of inefficiency in the first half of the sample are related to sharp increases or decreases in the green bond price index: end of 2016, mid 2017 as well as mid 2018. During the period COVID became a pandemic in early 2020, green bond prices exhibit drastic movements. As a result, the degree of inefficiency jumps up to around 0.2.

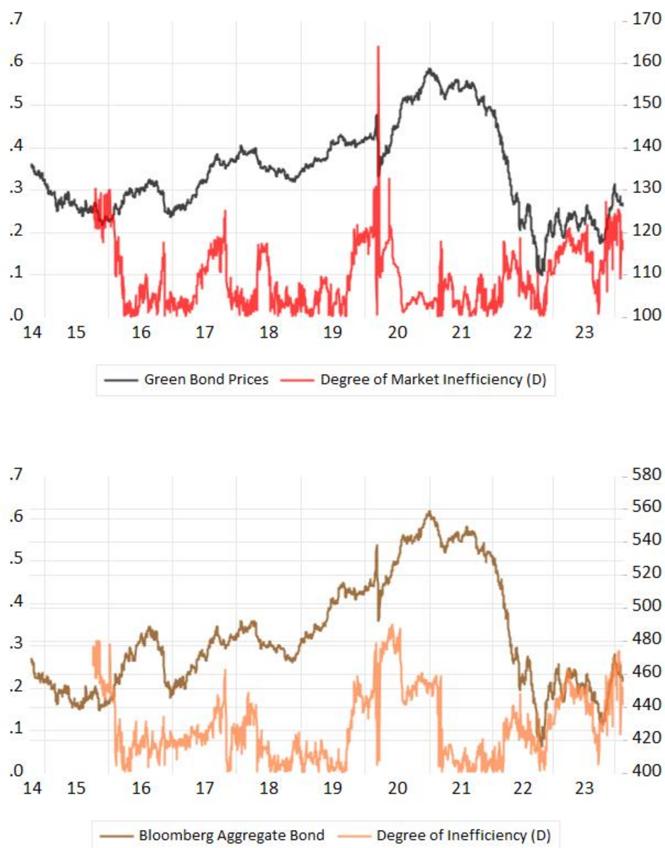

Figure 2: Inefficiency of green bond as well as aggregate bond markets.

There is an increase in the degree of inefficiency also during 2022 following the invasion of the Ukraine. Green bond prices collapsed during this period. Noteworthy is the larger degree of inefficiency in 2023; this period is certainly challenging because of the enormous increases in inflation rates as well as the resulting monetary policy responses.

The lower panel of Figure 2 shows Bloomberg's Aggregate Bond Price index. This is a useful benchmark as it measures performance in global bond markets. As described above, the development of the aggregate bond price series is overall similar to that of the green bond prices; only that overall fluctuation seems to be a bit higher than for the green bond price index. The degree of inefficiency overall follows the same pattern as that of the green bond market; however, there are a few noteworthy differences: in the first half of the sample, the degree of inefficiency is not found to be as close to 0 as that for the green bond market; this applies in particular to 2016 and 2017. Also, the period with high degree of inefficiency in 2019 and 2020 is found to last longer. Similar again is the development of the degree of market inefficiency in 2023. One way to summarise this: changes in green bond prices can be largely attributed to challenges the aggregate bond market as a whole has to deal with. It is nevertheless noteworthy that the degree of inefficiency of the green bond market is slightly lower than that of the aggregate bond market. One possible reason might be that the aggregate bond market has to process a larger quantity of information compared to the green bond market: not all information the aggregate bond market responds to is equally relevant for the green bond market.

Insightful is also the comparison of degree of inefficiency of the green bond market and two major stock indices: the MSCI World as a broad stock market index and S&P Clean Energy; see Figure 3. The degree of inefficiency of these two stock markets is largely similar; it mostly fluctuates around 0.1; deviations from that are found for the obvious periods. What stands out is that the degree of inefficiency during the extreme periods in 2020 and also 2022/2023 is smaller than for both the aggregate bond market and the green bond market. This is not surprising insofar as the inflation shock and the resulting monetary policy responses are of much greater relevance for the bond market than for the stock markets in general. Thus, it is a challenge for the market to process the information; the result is a higher degree of inefficiency.

Figure 4 show the results of the analysis of broader green stock markets, NASDAQ OMX Green Economy: Clean Energy, on the one hand, and a number of submarkets on the other. The stock indices in all these markets exhibit their own idiosyncratic movement. Some are more similar to the broad market, e.g. NASDAQ OMX Wind energy, some develop in a very different manner, in particular NASDAQ OMX Buildings. The degree of

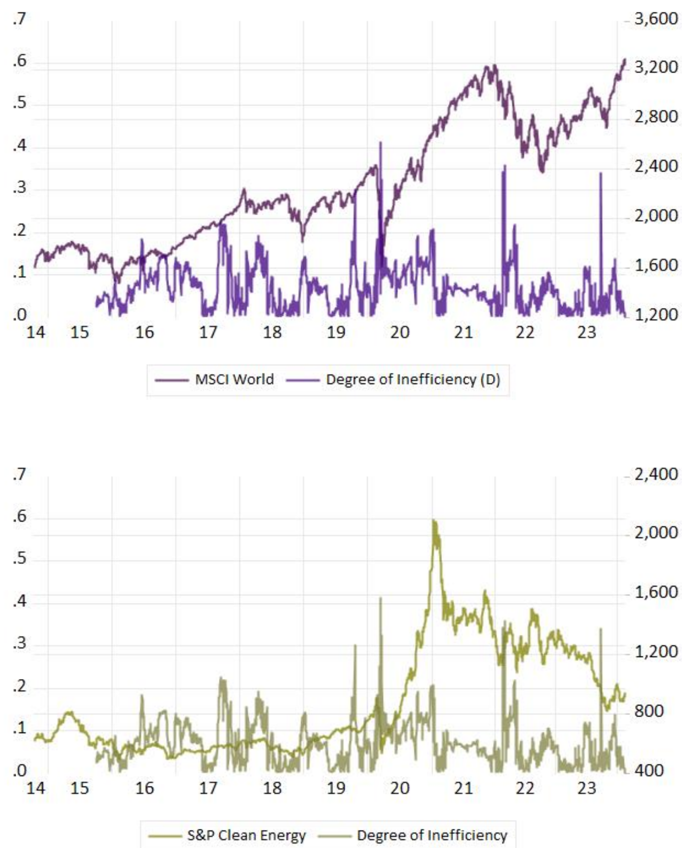

Figure 3: Inefficiency of MSCI World as well as S&P Clean Energy

inefficiency of the broad market is found to fluctuate between 0 and 0.1; on certain occasions, this value exceeds 0.1. Consistent with the findings for the stock markets discussed above, the monetary policy responses during the COVID period and the inflation shock bother this market to a lesser extent. The fluctuation of the degree of inefficiency is found to vary across these sub-markets: it is lower than the broad market for the solar energy-focused as well as transport-focused, but higher for the buildings-focused. The degree of inefficiency of the green bond market does not differ substantially from that of these markets. Noteworthy is also that the degree of inefficiency

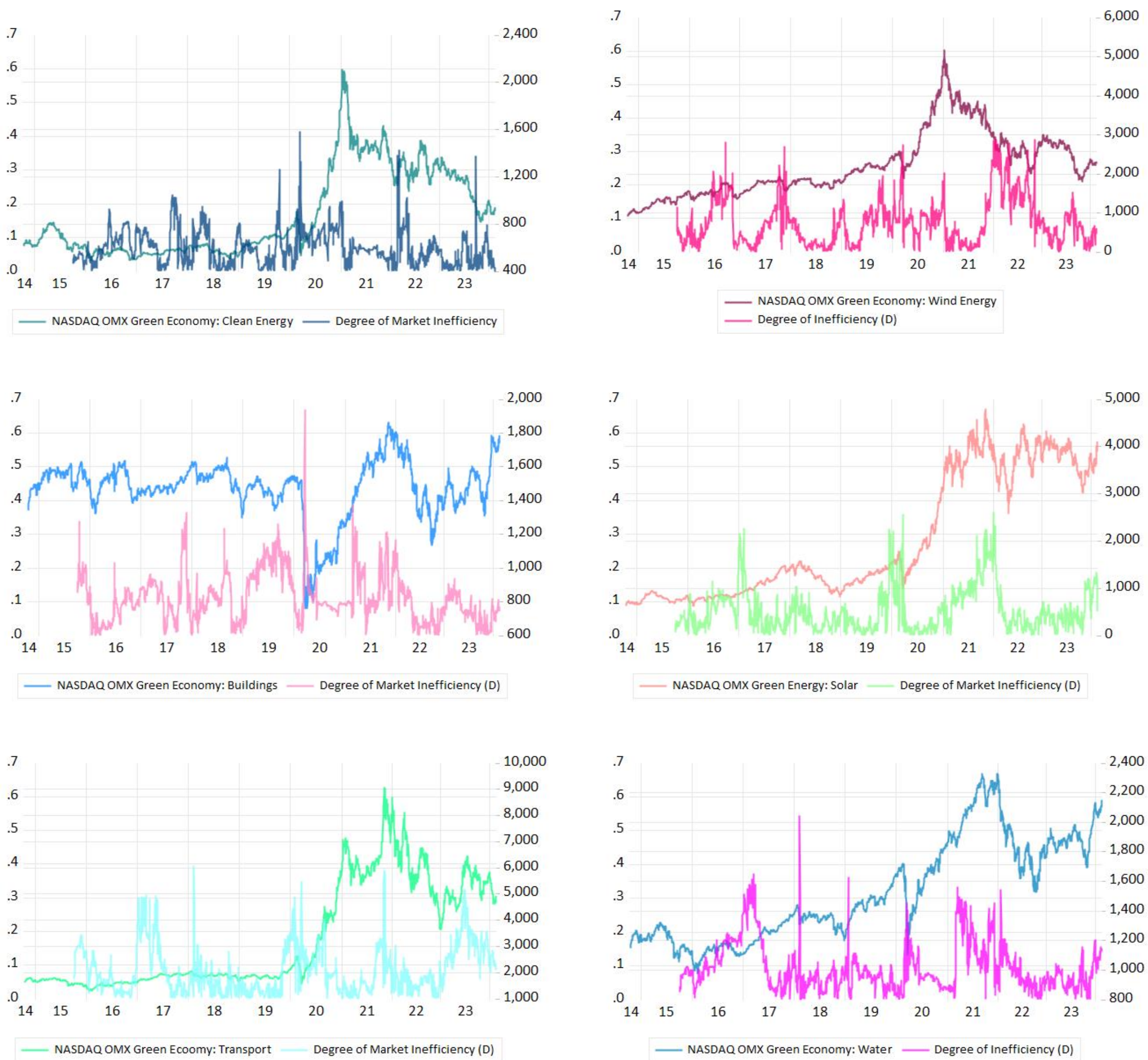

Figure 4: Inefficiency of other benchmark markets

of green bond markets drops to close to 0 frequently which is the Random Walk benchmark of an efficient market. This is not the case for all green energy stock markets, but for some; e.g. solar and transport.

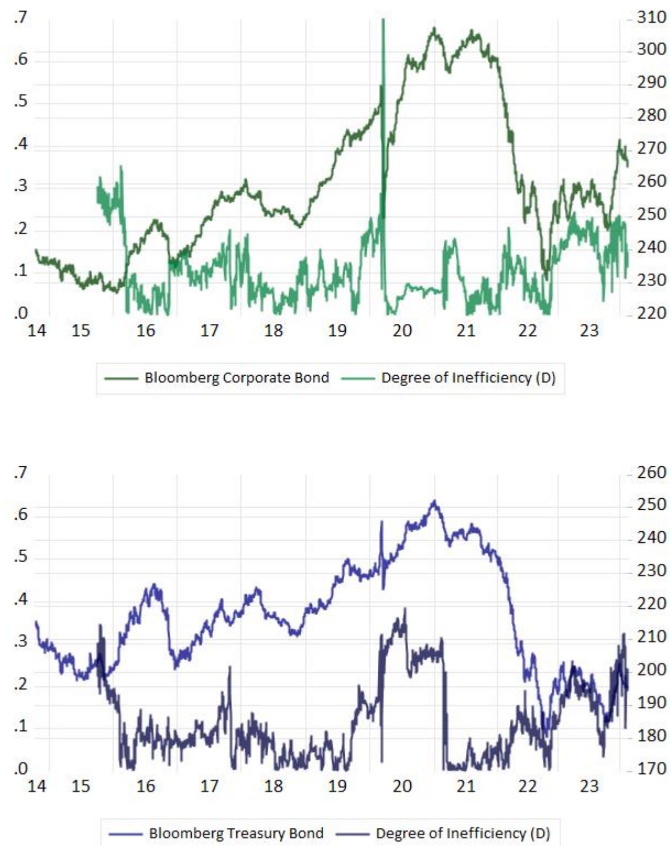

Figure 5: Inefficiency of corporate as well as treasury bond markets

Having presented the results for these green stock markets, attention is now directed towards additional benchmark bond markets. Figure 5 shows the results of the analysis of the corporate bond market as well as the treasury bond market. The development of prices in these two markets is overall similar; a difference is that the level of the corporate bond price index after the 2022 decline is approximately at the level where it was in 2017; the treasury bond prices drop to a much larger extent to a level that clearly below the levels in the first half of the sample. The degree of inefficiency for these two bond markets is found to fluctuate around 0.1 in the first half of the sample. The degree of inefficiency of the corporate bond market fluctuates to a larger extent, however. A major difference is the degree of inefficiency during the 2019-2020 period: the degree of inefficiency of the treasury bond market is not only found to be much higher, it also remains high for a much longer period. In addition, the degree of inefficiency of both markets is found to increase throughout 2023. The following section discusses this finding in more detail.

4 Discussion

Recall that assessments of the degree of inefficiency are based on the deviation of observed price movements from a random walk benchmark. Expressed in more general terms, it is based on the statistical behaviour of price series. It is well-documented that the arrival of new information in a financial market leads to increased market activity as well as volatility (Bollerslev et al., 2018; Engle et al., 2021). To explain this, these authors cite the so-called "differences-of-opinion" literature: investors do not necessarily agree on how to interpret new information and what the updated evaluation of the asset would be. This creates additional trading incentives and, thus, market activity. This paper argues that increased volatility is not the only reflection of this; this also results in price behaviour that deviates further from a random walk.

To provide empirical support for this assertion, Figure 6 displays the degrees of inefficiency of the green bond market, the three bond benchmarks along with the dispersion of CPI (left panel) as well as 3-months treasury bill (right panel) forecasts.[3] These dispersion measures are used to capture

[3] Data source: Cross-Sectional Forecast Dispersion: Survey of Professional Forecasters, Federal Reserve Bank of Philadelphia. Dispersion is measured as the difference between the 75th and the 25th percentile of the forecast for the variable of interest. Note that the original data is available at a quarterly frequency. Thus, the frequency of the degree of inefficiency measure has been converted from daily to quarterly.

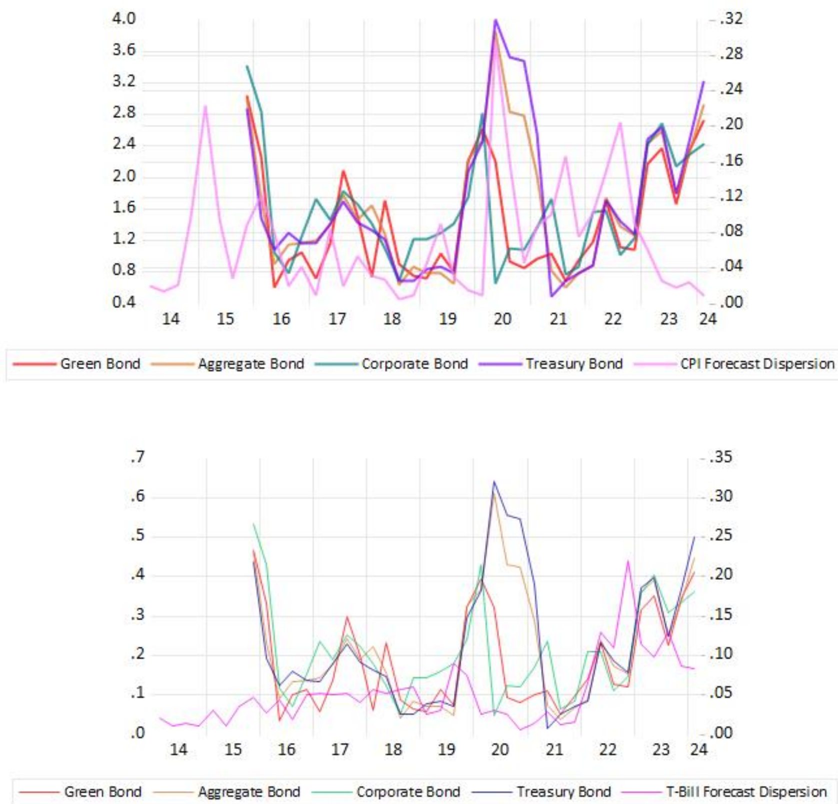

Figure 6: Bond market inefficiency and forecast dispersion

the extent to which market participants disagree - in short, it is a measure for "differences-of-opinion". It is evident that CPI forecast dispersion sharply increase in 2020; this coincides with the increase in the degree of inefficiency of the aggregate bond market. What is more, treasury bill forecast dispersion experiences an upward shift in 2022; the measure remains at a higher level until the end of the sample period. During this period, the degree of inefficiency of all benchmark bond markets increases. The degree of inefficiency of the green bond market is overall lower than that of the two benchmark bond markets; also there is not such a strong increase in 2020.

5 Conclusions

This paper analyses informational inefficiency of green bond markets. The key finding is that the main drivers of green bond prices are general factors that drive aggregate bond markets. This finding is based on the similarity of price movements as well as how the degree of inefficiency develops over time. This paper also shows that the degree of inefficiency of green bond market is slightly lower than that of the aggregate bond market. The market is less affected by extreme periods such as the Covid period as well as the inflation period in 2022. On both these occasions, monetary policy responses heavily affect treasury bond markets.

This paper's findings and interpretations are consistent with the discussions of Gronwald, Wadud, and Dogah's (2024) analysis of informational inefficiency of global crude oil markets. It follows the same notion: periods with higher degrees of inefficiency are turbulent periods; it is more challenging for markets to process information in difficult times. This interpretation is based on predictions of the so-called differences-of-opinion models (Kandel & Person, 1995). It is also consistent with Sattarhoff and Gronwald (2022) who find that the European Union Emissions Trading Scheme is informationally more efficient than the US stock market: the quantity of information that has to be processed is much larger for the US stock market. Finally, it is also consistent with Ren et al.'s (2024) analysis of spillover effects from fossil energy and green energy markets. These authors show that international crude oil benchmarks are the most significant information transmitter and receiver in the spillover network of market inefficiency. They also find that the green bond market is vulnerable mostly to its own shocks; in other words, there is no strong interaction with fossil energy markets and other green energy markets. This paper, in addition, interprets data from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters in a novel way. Finally, the paper also argues that the arrival of information not only leads to increased price volatility, but also deviation from random walk.

Treasury bond prices mirror essential factors pertinent to treasury bond ownership, while corporate bond prices similarly reflect fundamental considerations specific to holding corporate bonds. Both treasury and corporate bonds serve as critical financing mechanisms for governments and corporations, respectively. However, the distinctive purpose of green bonds lies in financing efforts to combat climate change, rendering this market exceptionally crucial given the pressing nature of the climate crisis. The results obtained in this paper are encouraging. Green bond prices generally align with broader bond risk trends, without exhibiting unjustified deviations from fundamental perspectives. Notably, inflation risk predominantly impacts treasury bonds, highlighting market dynamics. Despite its recent emergence and niche status, the informational inefficiency of the green bond market appears comparable to that of well-established, broad, and mature markets.

The efficient market hypothesis holds significant relevance due to its assertion that asset prices incorporate all available information, rendering prediction based on historical price movements impossible. This mechanism ensures the efficient allocation of capital to investment projects. While it would be unreasonable to expect any market to be perfectly efficient, the green bond market is, compared to other markets, relatively efficient. This implies that funds are allocated not less efficiently than through other markets. Ultimately, inefficient allocations of funds to investment projects is never a welcome outcome, but given the role climate finance plays in tackling climate change, this is of particular importance.

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