“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; in addition, fundamental factors that drive bond prices in general also drive prices for green bonds. The green bond market, however, is less affected by challenging environments such as the COVID outbreak in 2020 and the inflation shock in 2022/2023 than the benchmark markets. Second, the paper argues that the arrival of information in a market not only leads to increased price volatility, but also to a larger deviation from the random walk. To illustrate this, the 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. By mobilizing financial resources at both 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 channeling capital toward environmentally sustainable projects and initiatives. These bonds are specifically earmarked to finance projects with 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 mobilize private capital toward the transition to a low-carbon economy. Overall, green bonds serve as a critical financial instrument in accelerating global efforts to combat climate change and promote sustainable development.

The following figures illustrate the significance of the green bond market: as noted by Flammer (2020), total green bond issuance was under USD 1 billion in 2008, but skyrocketed to USD 143 billion by 2018. This impressive growth trajectory has continued; green bond issuance reached USD 870 billion in 2023, according to Climate Bonds Initiative (2023). This rapid expansion highlights the market's vital role in addressing the climate emergency and makes it a more than worthwhile area of study. A crucial aspect of green bonds is the principle of additionality, which requires that funded projects provide distinct environmental benefits beyond standard practices.

As for the related literature, a dominant theme in the financial economic analysis of green bonds is whether or not they are priced differently compared to conventional bonds due to the aforementioned environmental benefits: on the one hand, Flammer (2021) as well as Baker, Bergstresser, Serafeim, and Wurgler (2022) find that U.S. green bonds sell for a premium between zero and a handful of basis points over comparable ordinary bonds by the same issuer. On the other, Feldhütter, Halskov, and Krebbers (2024) find that investors are willing to accept a 1-2 basis points lower yield of sustainability-linked bonds due to the bond's Environmental, Social, and Governance (ESG) label. These authors interpret this as evidence for the environmental concerns among financial investors. The finance literature also has shown growing interest in this newly emerged asset class with a focus on the interplay between green bond markets and conventional financial markets. For instance, Karim, Lucey, Naeem, and Yarovaya (2024) examine extreme risk dependence between green bonds and broader financial markets. They highlight that green bonds can provide significant diversification benefits, along with safe-haven and hedging opportunities. Other recent studies contribute further insights: Ren, Xiao, Duan, and Urquhart (2024) investigate the dynamic correlation and inefficiency interplay between fossil energy markets and green markets, while Adekoya, Oliyide, Asl, and Jalalifar (2021) focus on market efficiency and volatility persistence differences between green and conventional bonds.[1]

This paper takes a traditional finance perspective to contribute to the broader literature on green bond pricing and evaluation: it examines the green bond market through the lens of the Efficient Market Hypothesis (EMH) proposed by Fama (1970). Thus, it is interested in the market's informational efficiency. According to the weak-form of the EMH, all publicly available information is already reflected in asset prices, which implies that future price movements are unpredictable based on past data. This principle is typically captured through the Random Walk model. Studying the informational efficiency of the green bond market is particularly relevant given its unique attributes, including the above-mentioned additionality criterion and environmental considerations of investors. These factors mean that investors in green bonds not only assess financial performance but also the issuer's environmental impact, which adds a layer of complexity to the

[1] Additional studies explore related areas, such as the interconnectedness of crude oil and green bond markets (Yousaf, Mensi, Vo, & Kang, 2024), volatility spillovers between green bond and new energy markets (Wu & Qin, 2024), the effects of green bond issuance on stock price crash risk (Zhang, Li, & Chen, 2024), and the impact of climate policy uncertainty on new energy market volatility (Raza, Khan, Benkraiem, & Guesmi, 2024).

information the market must process. Moreover, measuring environmental performance is inherently more challenging than evaluating financial performance, which could suggest that the green bond market may be less informationally efficient. However, it is also possible that green bonds have emerged as a distinct asset class which is primarily influenced by environmental factors rather than the complex fundamentals that are impacting conventional bonds. Additionally, despite its growth, the green bond market remains relatively niche, with participation largely limited to well-informed, specialized investors. This could, in fact, imply greater informational efficiency within the market.[2] Thus, this study explores whether green bonds operate within a more efficient market structure due to specialized investor activity or if their dual focus on financial and environmental metrics renders them less efficient overall.

The preceding discussion suggests that a quantitative, rather than qualitative, approach to measure informational efficiency is essential. Consequently, this paper adopts the measure for market inefficiency recently proposed by Duan, Li, Urquhart, and Ye (2021). The core idea of this approach is to quantify inefficiency by assessing how much observed price behavior diverges from the Random Walk model benchmark.[3] The distinctive contribution of Duan et al. (2021) lies in their novel application of fractional integration as a measure of market efficiency. In that framework, the order of integration d of a time series can take fractional values between 0 and 1; it is not restricted to integer values. This paper employs the Feasible Exact Local Whittle estimator to obtain precise estimates of d. Following Duan et al. (2021), market inefficiency is quantified as the absolute deviation of d from 1, defined by $D = |1 - d|$. To capture dynamic efficiency, or in other words, to measure how efficiency changes over time, a rolling window

[2]Relevant to this context is the finding by Sattarhoff and Gronwald (2022) that the European Union Emissions Trading Scheme exhibits higher informational efficiency than the U.S. stock market. The EU-ETS, which is primarily affected by EU Commission regulatory decisions, contrasts with the broader U.S. market, which is influenced by a wide range of fundamental factors.

[3]This methodology shares conceptual ground with prior measures, such as those by Kristoufek and Vosvrda (2013, 2014), which utilize Hurst exponents, and by Sattarhoff and Gronwald (2022), which employs a multifractal analysis.

approach is used in this analysis.

This research yields two main findings. First, fundamental factors that influence bond prices broadly are also influential in the green bond market, with the level of inefficiency in the green bond market closely resembling that of benchmark bond markets. Additionally, the green bond market appears more resilient to disruptive events, such as the COVID-19 outbreak in 2020 and the inflationary pressures of 2022/2023, compared to the benchmark markets. Second, drawing from the differences-of-opinion literature (Kandel & Person, 1995), the study suggests that new information leads not only to increased price volatility (Bollerslev, Li, & Xue, 2018) but also to larger deviations from the Random Walk model. To further explore this effect, data from the Philadelphia Fed Survey of Professional Forecasters is employed to measure the level of disagreement among market participants, which provides insight into how diverging expectations impact market efficiency and price dynamics.

These findings are novel in several key ways. First, they contribute to a broader evaluation of green bonds as an investment instrument. For instance, Flammer (2020) observes positive stock market responses to green bond issuance announcements, which suggests a favourable perception of green bonds in financial markets. Additionally, Flammer (2021) finds that issuing green bonds can increase ownership by long-term and environmentally focused investors and, thus, serves as a credible signal of a company's environmental commitment. This paper demonstrates that green bonds and conventional bonds are driven by very similar fundamental factors. One implication of this is that the price trends of both asset types have developed in parallel over the years, with inflation and monetary policy emerging as dominant influences, particularly evident since early 2022. Given that empirical tests of the weak-form EMH are fundamentally based on price behavior, the finding that both green and conventional bonds exhibit comparable inefficiency levels implies similar price dynamics. However, while inflation concerns and general market uncertainty - such as those seen during the COVID-19 pandemic - certainly affect green bond prices, the impact is relatively milder than on conventional bonds. This comprehensive analysis aligns with studies such as Flammer (2021) as they further advance the understanding of green bonds within the wider financial landscape.

Second, the strong relationship between arrival of news and market activity is well-documented (see, e.g., Mitchell and Mulherin (1994); Engle, Hansen, Karagozoglu, and Lunde (2021)). This increase in market activity often results in increased volatility (Bollerslev et al., 2018; Engle et al., 2021). The “differences-of-opinion” literature (Banerjee & Kremer, 2010; Kandel & Person, 1995) provides a framework for understanding this phenomenon: differing interpretations of new information among investors lead to increased market activity and volatility. The empirical findings of this paper not only support this view, they also demonstrate that increased disagreement among investors leads to greater deviations from a random walk which is commonly interpreted as reduced market efficiency. This paper also relates to research focused on disagreement among forecasters (e.g., Mankiw, Reis, and Wolfers (2003); Patton, J, and Timmermann (2010); Andrade and Bihan (2013)), which seeks to understand the roots of these differences in opinion. Such analyses are particularly relevant in contexts like monetary policy and the anchoring of inflation expectations. The paper reveals that investor disagreement tends to increase markedly during times of elevated uncertainty, which indicates that uncertainty has an additional economic impact by intensifying divergences in market expectations which, in turn, affects inflation anchoring.

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 which. Section 5 offers some concluding remarks.

2 Data and Method

The dataset utilized in this paper closely resembles the one used in Pham (2021). The analysis employs the S&P Dow Jones Green Bond Index as a proxy for green bond pricing, with additional series outlined in Table 1. The data is collected at a daily frequency, covering the period from October 2014 to February 2024.[4] Data for this study were obtained via the Bloomberg terminal. For forecast dispersion, the analysis uses the dispersion of the Consumer Price Index (CPI) and a 3-month Treasury bill sourced from the Federal Reserve Bank of Philadelphia.

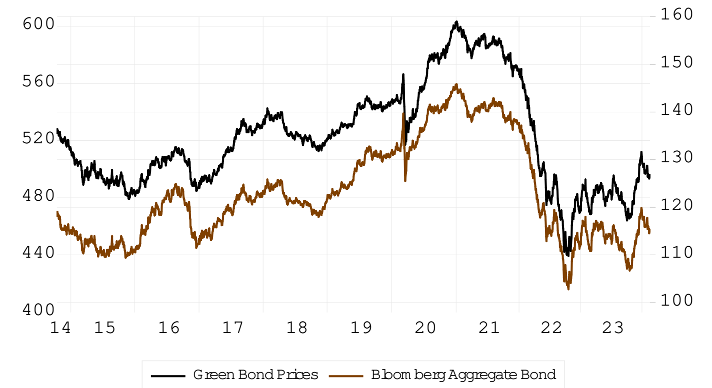
Table 1: Details of data

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

Figure 1 illustrates the key variables analysed in this paper: the green bond price index and the aggregate bond index, along with the MSCI World index as a broad stock market benchmark and the S&P Clean Energy index. Throughout the early part of the sample, up until the end of 2019, the green bond price index remains relatively stable, with occasional sharper fluctuations. However, the second half of the sample is marked by significant turbulence, including the onset of the COVID-19 pandemic, a notable decline in green bond prices in response to the inflation shock in early 2022, and increased volatility in 2023. The trend in the aggregate bond price series generally mirrors that of the green bond prices, albeit with slightly greater fluctuations. In contrast, the two stock price indices display markedly different trends over time. The MSCI World index shows a consistent upward trajectory throughout the sample period, with notable deviations occurring

[4] As previously noted, green bond issuance levels saw significant growth between 2008 and 2023. However, studies such as Flammer (2020) indicate that the surge began in earnest in 2013. What is more, Flammer (2021) highlights that corporate green bonds were virtually non-existent before that year. The observation period in Lam and Wurgler (2024) spans 2013 to 2022. Thus, it a common practice in the literature not to consider the very early stages of the green bond market.



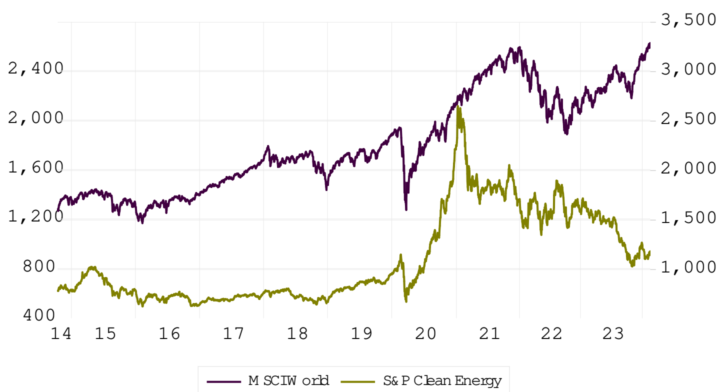


Figure 1: Selected time series used in this paper.

in 2020 and 2022. Meanwhile, the S&P Clean Energy index remains relatively flat until 2019, followed by a sharp increase starting in 2020. This is followed by a steep decline in early 2021 and a downward trend persisting through 2021-2023.

Having outlined the data, the focus now shifts to the methodological approach. Fractionally integrated processes, denoted as $I(d)$, have gained increasing prominence among empirical researchers in economics and finance due to their ability to capture the long-term dependencies present in economic and financial data (see Zaffaroni and Henry (2003) for further details).

This paper applies the methodology of Duan et al. (2021), which utilizes fractional integration within a framework specifically designed for such dependencies, including Shimotsu (2010)'s semiparametric Feasible Exact Local Whittle (FELW) estimator. Shimotsu (2010) introduce a modified two-step ELW estimator, adapted for economic data analysis to account for both an unspecified mean (requiring estimation) and polynomial time trends.[5] This approach aligns with the fully extended local Whittle estimator by Abadir, Distaso, and Giraitis (2007), which incorporates a fully extended discrete Fourier transform. The FELW estimator builds on the Type II process, while the fully extended local Whittle estimator is based on the Type I process.[6]

Duan et al. (2021) build on Hamilton (1994) to explain different forms of "memory" within a time series, aiming to identify any underlying fractional integration order - an essential metric for assessing market informational efficiency.[7] This approach incorporates fractional integration by modeling "long-memory" dynamics, effectively capturing the persistence characteristics within the system.

The empirical analysis is initiated by estimating d, the 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). Taking into account that overly high or low bandwidths can result in a reduced or increased number of valid observations utilised in the estimation of d using the FELW methods (Shimotsu, 2010), causing unstable outcomes, a moderate bandwidth of 0.6 is chosen to generate the

[5] Traditional estimators for d, such as Rescaled Range (R/S), may suffer from biases and inconsistencies, while Detrended Fluctuation Analysis (DFA) estimators tend to underestimate d when the data's memory structure is unknown. Though the Exact Local Whittle (ELW) estimator improves on some limitations, it can still be unstable, particularly with non-stationary series. The FELW estimator addresses these issues, offering a more robust approach to handle unknown trends and stationarity concerns.

[6] Further details on Type I and Type II processes can be found in Shimotsu and Phillips (2006).

[7] Subsequently, they apply the Fractionally Cointegrated Vector Autoregressive (FCVAR) model, as introduced by Johansen (2008) and Johansen and Nielsen (2012), which addresses both short-term error corrections and long-term relationships among variables. For further details, see Section 3.1 of Duan et al. (2021).

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.

time series for d. Subsequently, 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 for 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

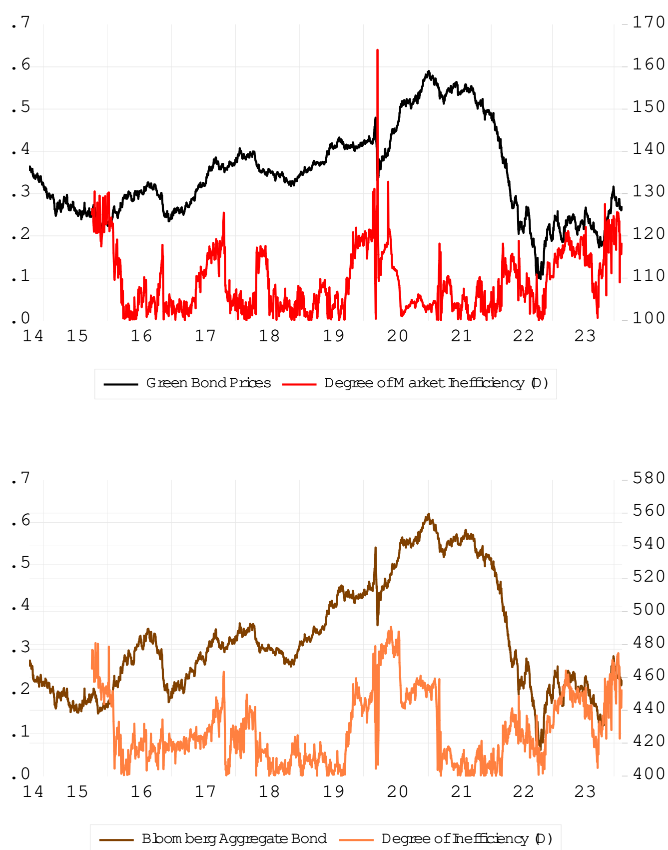


Figure 2: Inefficiency of green bond as well as aggregate bond markets.

The upper panel of Figure 2 shows the green bond price index along with the estimate of the degree of inefficiency, D, for the green bond market. The degree of inefficiency generally fluctuates between 0 and 0.2, and exceeds 0.1

only in some periods. Often, the degree inefficiency remains close to 0, which corresponds to the random walk benchmark. This indicates near-full market efficiency. Notable increases in inefficiency in the first half of the sample period correspond to sharp movements in the green bond price index, particularly at the end of 2016, mid-2017, and mid-2018. During the onset of the COVID-19 pandemic in early 2020, green bond prices showed pronounced volatility, causing inefficiency to spike to around 0.2. Another increase in inefficiency occurred in 2022, following the Russian invasion of Ukraine, when green bond prices fell sharply. In 2023, inefficiency remained elevated amid high inflation rates and corresponding shifts in monetary policy. This underscores the market's sensitivity to challenging economic conditions.

The lower panel of Figure 2 displays Bloomberg's Aggregate Bond Price Index, a key benchmark representing global bond market performance. As noted earlier, the aggregate bond price trend is broadly similar to that of green bonds, although its fluctuations tend to be slightly more pronounced. The inefficiency levels of the aggregate bond market generally mirror those of the green bond market, with a few notable distinctions: in the first half of the sample period, inefficiency levels are somewhat higher than in the green bond market, particularly in 2016 and 2017. Additionally, the period of elevated inefficiency observed in 2019 and 2020 is prolonged relative to green bonds. A similar pattern re-emerges in 2023 for both markets. In summary, shifts in green bond prices largely reflect broader challenges impacting the aggregate bond market, though the green bond market's inefficiency remains marginally lower. One possible reason for this difference is that the aggregate bond market processes a broader scope of information, not all of which is directly relevant to green bond pricing.

A comparison of inefficiency levels between the green bond market and two major stock indices — the MSCI World (a broad stock market index) and the S&P Clean Energy index — reveals additional valuable insights; see Figure 3. The inefficiency in these stock markets generally aligns, hovering around 0.1, with noticeable deviations during predictable periods of market stress. One key observation is that during turbulent periods in 2020 and again in 2022/2023, stock market inefficiency remains lower than that

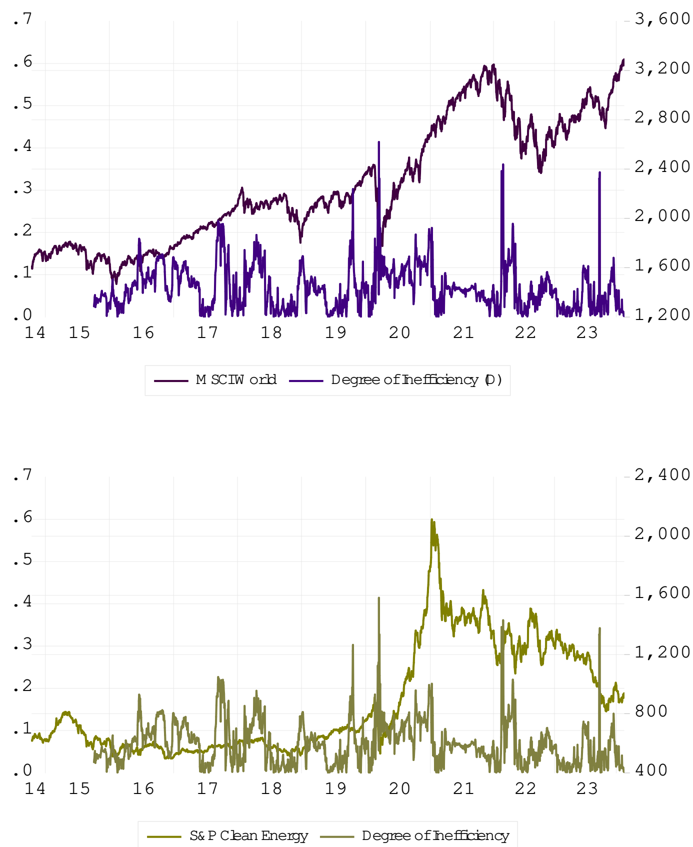


Figure 3: Inefficiency of MSCI World as well as S&P Clean Energy

observed in both the aggregate bond and green bond markets. This discrepancy likely reflects the fact that the inflation shock and subsequent monetary policy responses have a much greater impact on bond markets than on stocks. Processing this increased level of economic information creates added challenges for bond markets, resulting in higher degrees of inefficiency.

Figure 4 presents the results for broader green stock markets: NASDAQ OMX Green Economy (Clean Energy), along with various submarkets. Each index displays unique patterns, with some, like the NASDAQ OMX Wind Energy index, more closely mirroring broad market trends, while others,

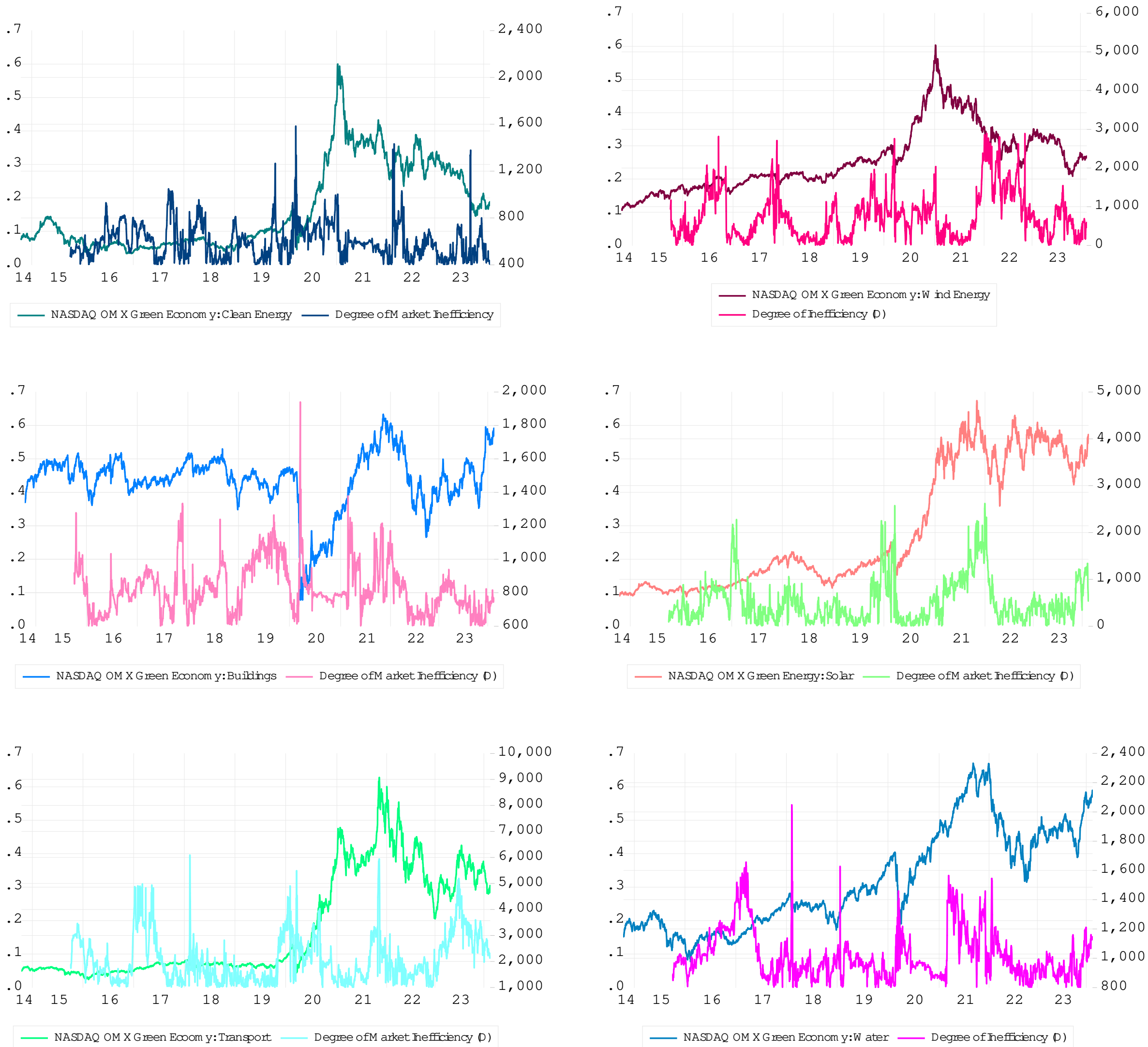


Figure 4: Inefficiency of other benchmark markets

such as NASDAQ OMX Buildings, show distinct behavior. The inefficiency level for the broader green market fluctuates between 0 and 0.1, occasionally exceeding 0.1. Similar to other stock markets, this index is less affected by monetary policy responses to COVID-19 and the inflation shock. The degree of inefficiency varies across submarkets: it remains below the broad market level for solar and transport-focused indices but is higher for those focused on buildings. The inefficiency of the green bond market is generally similar to these markets, often dropping to near zero - the Random Walk benchmark of an efficient market. While not all green energy indices achieve such low inefficiency levels, solar and transport-focused markets occasionally approach this efficient benchmark.

Following the analysis of green stock market results, the focus now shifts to additional benchmark bond markets. Figure 5 shows the results for the corporate bond market as well as the treasury bond market. The price trends in these two markets are generally similar; however, a notable distinction exists: the corporate bond price index has returned to levels comparable to those of 2017 following the decline in 2022, while treasury bond prices have experienced a more significant drop, falling well below the levels observed in the first half of the sample. In the first half of the sample, the degree of inefficiency for both bond markets generally fluctuates around 0.1, though the corporate bond market exhibits greater volatility. A significant difference arises during the 2019-2020 period, where the inefficiency in the treasury bond market is not only considerably higher but also remains elevated for an extended duration. Moreover, both markets show an increase in inefficiency throughout 2023. These last findings will be discussed in more detail in the next section.

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

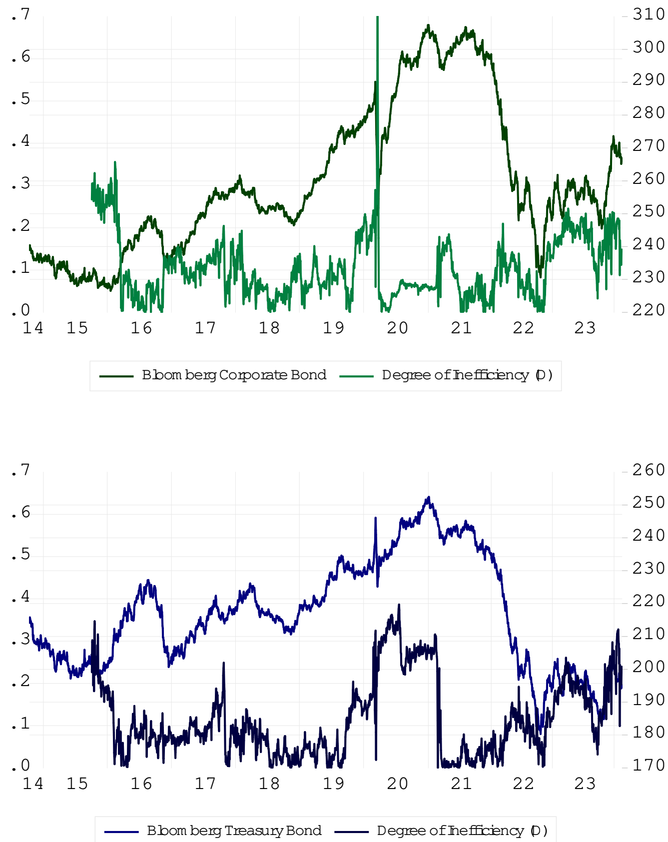


Figure 5: Inefficiency of corporate as well as treasury bond markets

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 refer to the so-called "differences-of-opinion" literature according to which 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 consequence 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

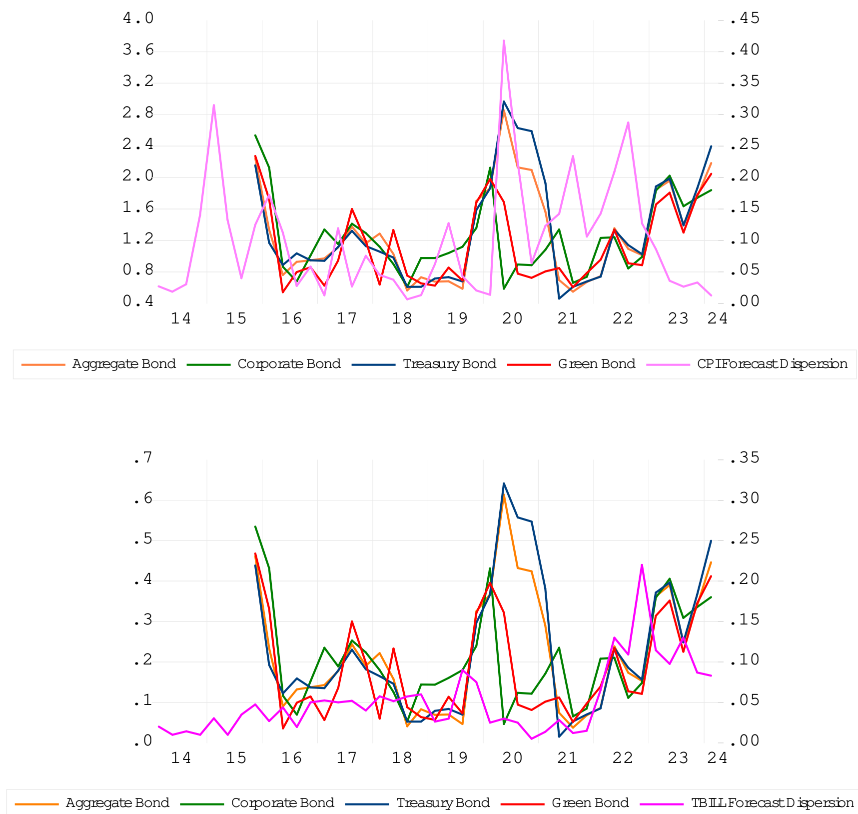


Figure 6: Bond market inefficiency and forecast dispersion

degrees of inefficiency of the green bond market, the three benchmark bond markets, along with the dispersion of CPI (left panel) as well as 3-months treasury bill (right panel) forecasts obtained from the Survey of Professional Forecasters, Federal Reserve Bank of Philadelphia.[8] These dispersion measures are used here to measure "differences-of-opinion": they capture the extent to which market participants disagree in terms of their evaluation

[8]Data source: Cross-Sectional Forecast Dispersion: Survey of Professional Forecasters, Federal Reserve Bank of Philadelphia. Forecast 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.

of the future development of these crucial economic variables. It is evident that CPI forecast dispersion sharply increase in 2020; this coincides with the increase in the degree of inefficiency of both the aggregate and the treasury bond market. The markets for corporate bonds and green bonds, respectively, do not undergo such a sharp increase in the degree of inefficiency. Additionally, the forecast dispersion for treasury bills shows a notable upward trend in 2022, remaining elevated through the end of the sample period. Throughout the 2022-2023 period, the degree of inefficiency across all bond markets also rises. In summary, during challenging market conditions, such as the COVID outbreak in 2020 and the inflation shock period 2022-2023, there is an increase not only in the dispersion of forecasts but also in the extent to which observed bond market prices deviate from the Random Walk benchmark. This deviation is typically interpreted as an increase in market inefficiency. This paper posits that during such challenging periods, processing new information which arrives in a market becomes more complex, resulting in not only increased price volatility but also greater departures from the Random Walk model. Ultimately, both are simply time series properties.

5 Conclusions

This paper examines a critical segment of climate finance markets: the green bond market, with a specific emphasis on its informational inefficiency. The primary finding indicates that the key factors driving green bond prices are largely the same general influences affecting aggregate bond markets. This conclusion is supported by observed similarities in price movements and the evolution of inefficiency of these markets over time. Notably, the degree of inefficiency in the green bond market is found to be slightly lower than that of the aggregate bond market. A significant role in this analysis plays the response of monetary policy to substantial exogenous shocks, such as the COVID outbreak in 2020 and the inflation shock experienced in 2022 and 2023. While all bond markets have been impacted by these events, green bond markets have been affected to a lesser extent, whereas treasury bond markets have experienced more pronounced effects. Furthermore, this paper demonstrates that during these extreme periods, not only does the degree of inefficiency increases, but so does the level of disagreement among professional forecasters regarding their predictions for key economic variables, including inflation and short-term interest rates.

This research presents two key insights: one that is particularly relevant for policymakers and investors, and another that contributes to a significant academic debate. First, while treasury bond prices reflect critical factors associated with treasury bond ownership, corporate bond prices similarly align with the fundamental considerations of holding corporate bonds. Both treasury and corporate bonds are vital financing instruments for governments and corporations, respectively. In contrast, green bonds are designed specifically to finance initiatives aimed at addressing climate change, underscoring the significance of this market in light of the pressing climate crisis. The findings in this paper are encouraging. Green bond prices generally track broader bond risk trends without showing significant deviations from fundamental values; they are influenced by factors such as monetary policy and inflation expectations. Moreover, despite being a relatively new and niche market, the informational inefficiency of the green bond market appears to be comparable to that of more established and mature markets.

This is good and bad news at the same time: while the green bond market exhibits a level of efficiency comparable to conventional bond markets, it is not shielded from the broader risks that impact traditional bonds. Consequently, if the appeal of bonds as an investment diminishes, green bonds are likely to experience similar challenges. This insight carries significant policy implications: the demand for climate investment funding is substantial and continues to grow. If the overall bond investment landscape turns unfavorable, policymakers must carefully consider this dynamic when determining how to direct funds toward climate initiatives.

The academic contribution this paper makes is related to the conventional understanding that asset prices in an efficient market can be modeled using the Random Walk model. According to the weak-form efficient market hypothesis, all past publicly available information is reflected in financial asset prices, rendering these prices unpredictable based solely on historical data; just as a Random Walk. This model is characterized by specific data properties, and deviations from the Random Walk benchmark are typically interpreted within the Efficient Market Hypothesis (EMH) literature as indicative of a less efficient or even inefficient market. Research examining the impact of new information on markets has established that the arrival of information can trigger increased market activity and volatility, the latter of which is simply another distinct data property. However, this paper posits that volatility is not the only aspect influenced by the arrival of information; how close a time series is to the Random Walk benchmark is also affected.

In conclusion, the efficient market hypothesis remains highly relevant because it asserts that asset prices reflect all available information, facilitating the optimal allocation of capital to investment projects. Although perfect efficiency in any market is unrealistic, the green bond market demonstrates a relatively high level of efficiency compared to other markets. This indicates that funds are allocated with a degree of efficiency comparable to that of traditional markets. While inefficient allocations of funds to investment projects are generally undesirable, the significance of climate finance in addressing climate change makes this issue particularly critical.

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