ECONtribute
MARKETS & PUBLIC POLICY

ECONtribute
Discussion Paper No. 421

Market-Based Green Firms

Konrad Adler
Matthias Reiner
Oliver Rehbein
Jing Zeng

July 2026

www.econtribute.de

UNIVERSITÄT BONN
UNIVERSITÄT ZU KÖLN

Funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/2 – 390838866 – is gratefully acknowledged.

Market-Based Green Firms*

Konrad Adler
University of St.Gallen and SFI

Oliver Rehbein
WU Vienna and VGSF

Matthias Reiner
WU Vienna and VGSF

Jing Zeng
University of Bonn and CEPR

May 6, 2026

Abstract

We propose measuring firms' exposure to climate risk via the market. We build a theoretical foundation and construct empirical market-based greenness measures based on abnormal stock returns around UN climate conferences. Our measures cover around 36,000 international firms, tenfold the existing measures. Market-based greenness is associated with lower present and *future* carbon emissions, and provides explanatory power distinct from existing climate risk measures. Market-based green firms are more likely to file green patents, have lower stock price volatility, and are financially more robust. At the country level, market-based greenness correlates with lower emission intensity and larger shares of renewable energy.

JEL Classification: G14, G32, G38, Q54

Keywords: Climate change, greenness, green firms, climate risk

*We would like to thank Michela Altieri (discussant), Thomas Dangl (discussant), Kornelia Fabisik (discussant), Ping McLemore (discussant), Daniel Neukirchen (discussant), Nora Pankratz, Melissa Prado (discussant), Stefano Ramelli, Ryan Riordan, Zacharias Sautner, Ernst-Ludwig von Thadden (discussant), Alexander Wagner, Christian Wagner, Tingyu Yu, Josef Zechner, and the participants of the EEA Congress 2025, the IBEFA at the WEAI, the CRC retreat, the VGSF PHD Research seminar, the Vienna Banking workshop, the 15th Annual Financial Market Liquidity (AFML) Conference, the SFI research days, the IWH-FIN-FIRE workshop on challenges to financial stability, and the Bundesbank Research Seminar for helpful comments. Jing Zeng gratefully acknowledges support from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 (Project C03) and under Germany's Excellence Strategy – EXC 2126/2-390838866. Author emails: konrad.adler@unisg.ch, oliver.rehbein@wu.ac.at, matthias.reiner@wu.ac.at, jzeng@uni-bonn.de.

1 Introduction

Climate change poses one of the biggest challenges of our time, prompting policy responses to mitigate and adapt to its impact. In light of the significant heterogeneity in exposure to climate risk across different firms and regions, demand for "green" investment has increased significantly in recent years (Ilhan et al., 2019), while governments and central banks are looking to identify green firms for purposes of potential regulation.[1] Yet, existing measures of firms' greenness are often limited in time and scope, e.g., carbon emissions, or rely strongly on self-reported information, e.g., ESG scores. In this paper, we propose a simple but effective tool for assessing firms' greenness: the market.

We show in a rational expectations equilibrium (REE) model that a stock's abnormal return around significant climate policy events is increasing in its exposure to climate risk, i.e., its greenness. Building on this theoretical foundation, we estimate abnormal returns around UN climate conferences (COPs) empirically to construct a market-based greenness measure for stock-listed international firms.[2]

Our measure is based on the well-established idea that markets, through the price mechanism, can aggregate dispersed information—a concept widely applied in other contexts but novel in measuring climate risk.[3,4] One main advantage of our measure is the much broader coverage compared to other measures, as shown by Figure 1, particularly for firms outside Europe and the US. In an application, we show that this matters, for example for estimating the climate risk premium. Furthermore, our measure has three conceptual advantages: first, it should incorporate information about the future, unlike, e.g., carbon emissions. Second,

[1] We will use the terms "green" and "greenness" to refer to a firm's exposure to climate risk and omit quotes throughout the paper for better readability.

[2] While other climate-related events have been studied, UN COP conferences provide a relatively homogeneous and internationally relevant set of events. We are not the first to use COPs as climate-relevant events, of course. About a quarter of events identified by Barnett (2019) are COPs, for example.

[3] See, for example, Kogan et al. (2017); Ozdagli and Velikov (2020); Greenland et al. (2024)

[4] Market participants can infer a firm's exposure to climate risk from both hard information, e.g., disclosed carbon emissions, and soft information, e.g., business planning and strategy or corporate governance structure.

our measure should capture direct and indirect risks in a firm's value chain associated with transitioning to a green economy. Third, our measure is likely less prone to green-washing, to the extent that market participants can distinguish it from honest attempts to shift the firm's climate impact. Throughout the paper, we provide supporting evidence that these conceptual advantages are indeed present.

When we investigate the relationship of our measure with existing greenness measures and firm characteristics, we find intuitive, albeit weak, relationships with existing greenness measures, suggesting that our measure captures aspects of greenness that others are less likely to capture. Second, at the firm level, market-based greenness is associated with lower present and future carbon emissions, suggesting that our measure indeed contains information about the future. Importantly, abnormal returns from randomly chosen placebo events do not generate similar patterns. Green firms also have lower stock price volatility, are more likely to file a green patent, hold more cash, and are less levered. Finally, at the country level, market-based greenness is associated with lower emission intensity and a larger share of renewable energy. We then apply our measure to the climate risk premium debate. While we find no effects in samples comparable to those with CO_2 coverage, broadening to a global sample, however, reveals a greenium during periods of heightened climate attention.

– Figure 1 around here –

We first establish a theoretical foundation for our measure. We build a rational expectations equilibrium (REE) model, which features i) many assets, whose fundamentals are driven by a climate risk factor in addition to a market risk factor and idiosyncratic risks; and ii) informed investors who observe private signals about the realization of each risk factor. Our results show that, first, abnormal returns in equilibrium reflect firms' greenness. Second, the informativeness of abnormal returns for firms' greenness is increasing in the fundamental uncertainty in the climate risk factor, since higher fundamental uncertainty reduces market depth, increasing price responsiveness. These results are robust to endogenous information acquisition when investors optimally allocate limited attention to learn about each risk factor. Our model also highlights a trade-off regarding event selection due to the presence of firm-specific idiosyncratic risks: focusing on a few significant events increases the asymptotic precision of the measure, whereas including a larger number of events (albeit some less significant ones) increases the degrees of freedom and can thus improve the small-sample precision of the measure.

Motivated by this trade-off, our first greenness measure is based on the single most important event for international climate change regulation to date: the 2015 Paris Climate Agreement, where countries agreed to limit global warming to below 2°C. Concretely, we use CAPM cumulative abnormal returns in a two-day window around the announcement of the agreement.[5] To create our second, time-varying measure, we add abnormal returns around all other UN climate conferences. Not all climate conferences were as consequential as the Paris Conference and the outcomes diverged from expectations in different ways. For example, the 2009 climate conference in Copenhagen (COP15) was generally considered a failure and thus green firms' returns would be negative around such events. Consequently, we carefully investigate the success of each climate conference and reverse the signs of the cumulative abnormal returns around conferences that we deem to have had worse-than-expected climate change policy outcomes.

Our stock price and accounting data come from Compustat Global and allow for an extremely broad coverage of listed firms: our sample includes 36,000 public firms from over 90 different countries. Evaluating market reactions around UN climate change conferences enables international comparability, thus providing a broad picture of firms' climate risk exposure across the globe. We compute our greenness measure for 560,000 firm-year observations, which means our measure is available for ten times more observations than the

[5] While our model suggests CAPM abnormal returns as the best measure, we also use raw returns to address concerns that the market factor itself is to some extent green and Fama-French three factor adjusted returns to account for changes in other fundamentals.

major ESG-score providers (MSCI, Refinitiv) and earnings-call-based measures (Sautner et al., 2023a; Li et al., 2024). Overall, our measure, which is freely available online, significantly expands the potential scope of climate-risk related research across time and space (see Figure 1), especially before 2008 and outside the US and Europe.

Empirically, we find that industries more exposed to climate risk, such as the oil and gas industry, have lower abnormal returns compared to less exposed industries, as one might expect. This pattern also holds within industries; for example, in the transportation sector, rail-based logistics companies are greener than their truck-based counterparts. We also show that our measure is plausibly related to existing text-based measures on climate policy risk derived from quarterly earnings calls (Sautner et al., 2023a; Li et al., 2024). Depending on the provider, we find mixed relationships with E-scores, the environmental part of an ESG score. MSCI E-scores relate in the expected direction, whereas Refinitiv E-scores show no relationship. These results are in line with the literature documenting inconsistencies across ESG-score providers, especially highlighting problems with Refinitiv E-scores (Berg et al., 2021, 2022b). The mixed evidence is also consistent with the interpretation that E-scores might be a way to hide climate policy risk behind marketing cheap talk (Bingler et al., 2022). Despite these potential limitations, we control for these alternative measures of climate change risk in many of our subsequent results and show that, across a broad range of variables and analyses, our measure provides value that is distinct from, but often complementary to, these other measures.

As a next step, we correlate our measure with different firm-level outcomes. A key advantage of market-based greenness lies in markets' predictive capability regarding future climate-related outcomes. Consequently, a market-based measure should be able to predict firms' *future* climate risk. We show that greener firms have significantly lower carbon emissions, both currently and especially in future periods. Our Paris-based greenness measure performs best at predicting Scope 1 CO_2 emissions four years into the future: a one standard deviation higher market-based greenness is associated with 22% lower contemporaneous emissions and 36% fewer emissions four years later. We then show that this is not the case for randomly chosen placebo events in non-COP weeks, supporting the idea that abnormal returns around COP conferences capture distinct information about firms' (future) greenness. Turning to green patents, our analysis shows a positive and statistically significant correlation between market-based greenness and green patent filings over both short- and medium-term horizons. For example, a one standard deviation increase in the greenness measure leads to a 4.3 percentage point higher probability of filing at least one green patent within four years. In sum, these results highlight the forward-looking nature of our measure.

In addition to firm-level climate-related outcomes, we study the relationship between market-based greenness and financial variables. We find that market-based greenness is consistently associated with lower future stock return volatility. Specifically, a one percentage point increase in market-based greenness is associated with an approximately 2 percentage point reduction in implied volatility one year ahead. We also find that greener firms tend to have lower book leverage and higher cash ratios. These results suggest that firm-level greenness is associated with more conservative financial policies.

Because our measure covers international firms from a large set of countries, it enables us to aggregate from the firm to the country level. We show that at the country level, market-based greenness is negatively related to CO_2 emissions per capita and positively related to the share of renewable energy in the production mix. In particular, market-based greenness has predictive value for country-level *future* emissions and the mix of renewable energy. Country-level greenness also allows us to investigate the impact of physical risk, due to the availability of natural disaster data at the country level. Using up to 20-year leads in disaster losses, we fail to find a relationship between market-based greenness and losses from natural disasters. Thus, we find no evidence of market-based greenness being driven by physical risk.

Finally, we apply our market-based measure to the debate on climate risk premia. We first replicate the carbon premium documented by Bolton and Kacperczyk (2021) in their sample. In the US sample, we find no premium for green or brown firms using our measure, in line with Sautner et al. (2023b) and Zhang (2025). In the global sample, however, we document a premium for green firms during the peak of the climate change debate, consistent with the short-term demand increase as argued, e.g. in Pástor et al. (2021). Once again, our measure, by substantially expanding coverage, enables analysis across a much broader set of firms and geographies, especially where CO_2 data are scarce.

Contribution and related literature Our main contribution is to create a widely available, likely forward-looking measure of firms' exposure to climate risk based on the market. Firms' exposure to climate risk is traditionally measured by their CO_2 emissions, or by ESG scores provided by commercial rating agencies (Bolton and Kacperczyk, 2021; Pástor et al., 2022). Both approaches face important limitations. Carbon emissions data suffers from significant coverage and quality issues (Busch et al., 2022), is not forward looking (van Binsbergen and Brøgger, 2022), and fails to capture indirect risk exposures, for example from supply chains or competition. ESG ratings diverge across providers (Berg et al., 2022b) and are likely subject to manipulation (Berg et al., 2021) and green-washing (Gibson Brandon et al., 2022).[6] Sautner et al. (2023a) and Li et al. (2024) develop climate risk measures based on textual analysis of earnings call transcripts. Relative to these existing measures, market-based greenness is readily available for a large number of international firms over an extended period. Our measure is straightforward to compute, forward-looking, includes direct and indirect exposure links, and is arguably less susceptible to green-washing.

Our paper is related to a burgeoning literature that studies if and how asset prices reflect climate risks. Several studies have documented significant market responses to relevant climate news (Engle et al., 2020; Arteaga-Garavito et al., 2023) and climate policy developments (Krueger et al., 2020; Ramelli et al., 2021), including the Paris Agreement (Seltzer

[6] A growing literature documents various additional forms of green-washing (Bingler et al., 2022; Parise and Rubin, 2023; Gourier and Mathurin, 2024; Dumitrescu et al., 2022).

et al., 2022; Ramadorai and Zeni, 2024). Huij et al. (2023) estimate firm-level "carbon betas" by regressing returns on a carbon portfolio. Taking a different approach, we are not using any other greenness measure as input and construct a measure of firms' exposure to climate risk directly based on their stock market reactions to climate policy events.[7]

We also contribute to the corporate finance literature measuring the impact of climate risk on firm-level outcomes such as cash holdings (Heo, 2021), leverage (Ginglinger and Moreau, 2023), equity issuance (Kräussl et al., 2025), and patenting (von Schickfus, 2021). Moreover, our country-level analysis contributes to the literature studying the impact of climate risk on country-level outcomes, which is hitherto scarce due to limited international data on climate risk measurement.[8] Studies have demonstrated the aggregate negative economic effects of climate change (Burke et al., 2015; Kahn et al., 2021), and physical and transition risks of climate change (Botzen et al., 2019; Gu and Hale, 2023).

Finally, our paper is part of the literature using stock market reactions to measure quantities that are otherwise difficult to measure. Stock returns have been used to infer patent value (Kogan et al., 2017), exposure to trade shocks (Amiti et al., 2020; Greenland et al., 2024), firms' exposure to monetary policy (Ozdagli and Velikov, 2020), or tax policy changes (Borochin et al., 2021). We extend this approach to measure firms' exposure to climate change risks.[9]

2 Model

In this section, we develop a noisy rational expectations equilibrium (REE) model of asset prices in order to illustrate when and to what extent realized returns provide information

[7]More generally, this literature has demonstrated that stock prices incorporate risks of drought (Hong et al., 2019), carbon emissions (Görgen et al., 2020; Ilhan et al., 2021; Bolton and Kacperczyk, 2021, 2023), pollution (Hsu et al., 2023), and investor attention to climate risk (Choi et al., 2020).

[8]Gavriilidis et al. (2023) find large effects of climate policy uncertainty for the US.

[9]In related work, Ramelli et al. (2021) find that the US elections in 2016 and 2020 caused diverging stock reactions for green and brown firms depending on investors' horizon.

about the "greenness" of a stock. Based on the results, we propose a greenness measure based on the abnormal returns of the stock around the most significant climate policy events.

Section 2.1 sets up a noisy REE model in which informed investors trade many assets, whose fundamentals are driven by a climate risk factor in addition to a market risk factor and idiosyncratic risks. Section 2.2 characterizes the equilibrium and shows that equilibrium abnormal returns of a stock reflect its exposure to the climate risk factor, particularly when fundamental uncertainty in the climate risk factor is high. Section 2.3 then defines a greenness measure based on the abnormal returns of the stock around the most significant climate policy events, i.e., during periods of high fundamental uncertainty about the climate risk factor, and discuss its properties. Section 2.4 shows that all results continue to hold in an extension with endogenous information, in which investors choose to allocate their limited attention to learn about the stocks' risk exposures.

2.1 Setup

There are three dates, $t = 0, 1, 2$. There is a market with a riskless asset and n risky assets, which are traded by risk-averse investors and risk-neutral liquidity traders. All assets are initially held by liquidity traders at $t = 0$, who face liquidity shocks at $t = 1$. At $t = 1$, investors choose their portfolios of risky and riskless assets. At $t = 2$, asset payoffs and utility are realized.

Assets. There is a riskless asset and n risky assets. The riskless asset is in infinite supply, and we normalize its net return to zero.

There are $n - 2$ stocks. Each stock $i \in \{1, \ldots, n-2\}$ has a random payoff f_i at $t = 2$ with loading b_i on a market risk factor z_m, loading g_i on a climate risk factor z_c, and faces stock-specific shock z_i:

$$f_i = \mu_i + b_i z_m + g_i z_c + z_i, \tag{1}$$

where μ_i are constants, and the risk factors $z_i \sim N(0, \sigma_s^2)$, $z_m \sim N(0, \sigma_m^2)$, and $z_c \sim N(0, \sigma_c^2)$ are mutually independent for all $i \in \{1, \ldots, n-2\}$. We henceforth interpret the loading g_i of firm i as its "greenness".

There are also two composite assets whose payoff has no stock-specific shock and only a loading of one on the market risk factor z_m and the climate risk factor z_c, respectively:

$$f_{n-1} = \mu_m + z_m, \tag{2}$$

$$f_n = \mu_c + z_c, \tag{3}$$

where μ_m and μ_c are constants. These composite assets can be interpreted as a stand-in for diversified portfolios of other assets; for example, asset m can be interpreted as the market portfolio, whereas asset c can be interpreted as a hedging portfolio for climate risk.

For notational ease, we will henceforth refer to risk factors z_m and z_c as z_{n-1} and z_n, respectively. Stacking the equations above, we can write $f = \mu + \Gamma z$, where f, μ, and z are $n \times 1$ vectors of asset payoffs, expected asset payoffs, and risk factors, respectively, and Γ is an $n \times n$ invertible matrix of loadings that map risk factors, z into the mean-zero payoff $(f - \mu)$.

Market participants. Model participants consist of a continuum of risk-averse investors and risk-neutral liquidity traders.

There is a continuum of investors indexed by $j \in [0, 1]$. Without loss of generality, we normalize each investor's initial wealth to zero. Each investor has mean-variance preferences over $t = 2$ wealth, with a risk-aversion coefficient ρ. Let E_j and V_j denote investor j's expectations and variances conditional on all information known at $t = 1$, which includes prices and signals. Thus investor j chooses how many shares of each asset i to hold, q_{ij}, to maximize $t = 1$ expected utility U_j of the return from trading the risky assets, π_j:

$$\max_{\{q_{ij}\}_{i+1}^{n}} U_j = \rho E_j[\pi_j] - \frac{\rho^2}{2} V_j[\pi_j], \tag{4}$$

$$s.t. \quad \pi_j = \sum_{i=1}^{n} q_{ij}(f_i - p_i). \tag{5}$$

Liquidity traders are endowed with all assets at $t = 0$. At $t = 1$, they face exogenous liquidity shocks and thus must sell the assets. As customary in the REE framework, the role of liquidity trading is to prevent the fully revealing prices.

Following Kacperczyk et al. (2016), we will work with risk factor payoffs and prices in order to solve the model in a tractable way.[10] We denote the liquidity trading demand for the risky assets by $(\Gamma')^{-1}\ell$, where Γ is the mapping between risk factors to asset payoffs described above, and ℓ is an $n \times 1$ vector of the liquidity traders' stochastic demand for each risk factor. We assume that the liquidity demand for each risk factor $\ell_i \sim N(\bar{\ell}_i, \sigma_\ell^2)$ is mutually independent. Additionally, we assume that the liquidity demand for aggregate risks are large relative to idiosyncratic risks: $\bar{\ell}_m \gg \bar{\ell}_i$ and $\bar{\ell}_c \gg \bar{\ell}_i$ for all $i \in \{1, \ldots, n-2\}$. This is what makes aggregate risks fundamentally different from idiosyncratic risks in the economy.

Prices. Equilibrium prices p_i at $t = 1$ are determined by market clearing:

$$\int_0^1 q_{ij} dj = \ell_i \ \forall i \in \{1, \ldots, n\}. \tag{6}$$

[10]See Appendix B.1 for detailed derivations.

Since all assets are initially held by risk-neutral liquidity traders, equilibrium prices at $t = 0$ are equal to the expected value of $t = 1$ prices:

$$\bar{p}_i = E\left[p_i\right] \ \forall i \in \{1, \ldots, n\}. \tag{7}$$

Information. The factor structure of the stocks and the composite assets given in (1)–(3) and the loadings b_i and g_i of each stock in (1) are common knowledge. The risk factors z are realized at $t = 2$.

Each investor j privately receives signals at $t = 1$ for each risk factor. That is, $\eta_{mj} = z_m + \nu_{mj}$, $\eta_{cj} = z_c + \nu_{cj}$, and $\eta_{ij} = z_i + \nu_{ij}$ for all $i \in \{1, \ldots, n-2\}$, where $\nu_{mj} \sim N(0, K_m^{-1})$, $\nu_{cj} \sim N(0, K_c^{-1})$, and $\nu_{ij} \sim N(0, K_s^{-1})$ for all $i \in \{1, \ldots, n-2\}$.[11]

2.2 Equilibrium and main results

Let us define abnormal return on stock i realized at $t = 1$, r_i, as the return on the stock $p_i - \bar{p}_i$, minus its CAPM expected return $b_i(p_m - \bar{p}_m)$. The following proposition summarizes the equilibrium and the main results of the model. We relegate the derivation and characterization of the equilibrium to the Appendix.

Proposition 1 *There exists a unique linear rational expectations equilibrium, in which the equilibrium abnormal return on stock i at $t = 1$ takes the form:*

$$r_i = g_i \gamma_c \hat{z}_c + \gamma_s \hat{z}_i, \tag{8}$$

where $\hat{z}_c$ and $\hat{z}_i$ are noisy unbiased signals of the risk factors z_c and z_i, respectively.

Moreover, the parameter γ_c is increasing in σ_c.

Proposition 1 shows that the abnormal returns in equilibrium reflect the stock's exposure

[11] In the Appendix, we endogenize the precision of the private signals by allowing investors to choose to allocate their limited attention to learn about each risk factor.

to the climate risk factor and its idiosyncratic risk factor. Two observations are worth commenting. First, due to the presence of liquidity traders, the abnormal returns incorporate information about the risk factors only with noise, where $\hat{z}_c$ and $\hat{z}_i$ are the unbiased signals generated by the market prices about the risk factors.

Second, the abnormal returns respond to the climate risk factor and the idiosyncratic risk factors up to parameters γ_c and γ_s, respectively. Importantly, the parameter γ_c is increasing in the fundamental uncertainty in the risk factor σ_c, since fundamental uncertainty deters risk-averse investors from engaging in market making. As a result, an increase in the fundamental uncertainty about the climate risk factor σ_c increases the responsiveness of the abnormal return on stock i in equilibrium to the climate risk factor $\hat{z}_c$.

2.3 From model to an empirical measure of greenness

The theoretical results help us formalize an empirical measure of firms' greenness based on abnormal returns on the stocks around significant climate policy events, such as the Paris Climate Agreement and other climate conferences. We interpret such events as periods during which the fundamental uncertainty in the climate risk factor, σ_c, is high. This interpretation is based on the assertion that the ultimate outcome of international climate conferences, and thus the consequences faced by firms from regulation is uncertain until the final agreement has been signed.

Proposition 1 shows that, given the realization of the climate risk factor, the magnitude of a stock's abnormal return is increasing in its greenness. Since the realization of the climate risk factor can be positive or negative, the following corollary shows that the sign-adjusted realized abnormal return of a stock, $\hat{r}_i$, can serve as a measure of its greenness g_i, where

$$\hat{r}_i = r_i \times sgn(\hat{z}_c). \tag{9}$$

Corollary 1 *Given the realization of a climate risk shock, $\hat{z}_c$, $E[\hat{r}_i \mid \hat{z}_c]$, is strictly increasing* *in its exposure to the climate risk factor, g_i.*

Since the abnormal return r_i is only a noisy measure because of the presence of stock-specific risk $\hat{z}_i$, we discuss next the informativeness of the market-based measure defined in (9) about stock i's greenness, g_i. (8) implies that a transformation of the realized abnormal return given the realization of a climate risk shock, $\hat{z}_c$, yields an unbiased signal $\eta_{ir} = g_i + \nu_{ir}$ about the greenness g_i of the stock i, where

$$\nu_{ir} = \frac{\gamma_s}{\gamma_c \hat{z}_c} \hat{z}_i. \tag{10}$$

From Proposition 1, we derive the following property of the greenness measure:

Corollary 2 *Given the realization of a climate risk shock, $\hat{z}_c$, the signal precision, $Var^{-1}(\nu_{ir})$, is increasing in the fundamental uncertainty in the climate risk factor, σ_c.*

Corollary 2 shows that the precision of the greenness measure is higher if one focuses on periods in which the fundamental uncertainty about the climate risk factor is higher, i.e., during significant climate policy events such as the UN climate change conferences.

Moreover, in finite samples, one would expect a trade-off between the precision of the greenness measure and the number of significant climate policy events considered. Focusing on a smaller number of most significant climate policy events increases the asymptotic precision of the measure (Corollary 2), but reduces the degrees of freedom and thus the small sample precision of the measure. This suggests that considerations should be given to the number of significant climate policy events to include when constructing the empirical measure of greenness.

2.4 Extension: Endogenous attention allocation

In the baseline model, we have assumed that investors' information about the assets is exogenous. In practice, however, investors may pay attention to learn about different risk factors depending on what is more relevant. In this extension, we show that our empirical measure of greenness is robust to incorporating endogenous attention allocation by investors. Moreover, this extension demonstrates that our empirical strategy of focusing on significant climate policy events is likely not adversely affected by the attention that accompanies international climate change conferences. That is, the precision of our greenness measure is higher when the fundamental uncertainty in the climate risk factor is higher because investors optimally choose to allocate more attention towards learning about the climate risk factor and away from learning about the idiosyncratic factor of each stock.

Specifically, we assume that, at $t = 0$, each investor chooses the precisions of signals that she will receive at $t = 1$. Allocating attention to a risk factor means that the investor receives a more precise signal about that risky outcome. That is, each investor j obtains n signals for each risk i, $\eta_{ij} = z_i + \nu_{ij}$, where $\nu_{ij} \sim N(0, K_{ij}^{-1})$ for all $i \in \{1, \dots, n\}$, where $K_{ij} \geq 0$ denotes the precision of investor j's signal about the risk factor z_i. Signal precision choices maximize $t = 0$ expected utility of the investor's final profit π_j, and is constrained by the following information capacity constraint, which states that the sum of the signal precisions must not exceed the information capacity:

$$\sum_{i=1}^{n} K_{ij} \leq K. \tag{11}$$

Before we solve the investors' attention allocation problem at $t = 0$, notice that, in a symmetric equilibrium, $K_{ij} = K_i$ for all j. The equilibrium in the asset market at $t = 1$ is thus given by Proposition 1. Moreover, the equilibrium has the following property:

Corollary 3 *The parameters γ_c and γ_s, which are defined in Proposition 1, are increasing in K_c and K_s, respectively.*

The following proposition characterizes the equilibrium attention allocation:

Proposition 2 *In equilibrium, the aggregate investor attention allocated to the climate risk factor K_c is increasing in σ_c, and the aggregate investor attention allocated to idiosyncratic risk factors K_i is decreasing in σ_c.*

This result demonstrates that, when fundamental uncertainty regarding the climate risk factor is high, investors optimally shift their attention away from idiosyncratic risk factors and towards learning about the climate risk factor. This result is in line with the existing literature on attention allocation (e.g. Maćkowiak and Wiederholt, 2009; Kacperczyk et al., 2016).

It then follows that the properties of our greenness measure given in Corollaries 1 and 2 continue to hold. That is, the abnormal return $\hat{r}_i$ of a stock around significant climate policy events serves as a measure of its greenness, g_i, even when taking into account the significant attention generated by these events. Moreover, the precision of this greenness measure is higher for more significant climate policy events (i.e., those with higher fundamental uncertainty σ_c) for two reasons. First, like in the baseline model, fundamental uncertainty increases the responsiveness of share price towards information about the green factor. Second, additionally in this extension, greater fundamental uncertainty also incentivizes investors to allocate more attention towards learning about the green factor.

3 Market-based greenness

This section describes the data and the construction of our market-based greenness measure.

3.1 Data

Return data We obtain stock price data from Compustat North America and Compustat Global and compute returns based on the daily closing price (*prccd*), the adjustment factor (issue)-cumulative by ex-date (*ajexdi*) and the daily total return factor (*trfd*).[12] We compute daily raw returns as follows:

$$R_t = \frac{P_t^{adj} - P_{t-1}^{adj}}{P_{t-1}^{adj}} \tag{12}$$

We use adjusted prices $P_t^{adj} = \frac{prccd_t \cdot trfd_t}{ajexdi_t}$. To calculate abnormal returns relative to the CAPM and the Fama-French three-factor-model (Fama and French, 1993), we download risk-free rates and market, value and size factors for various regions from Kenneth R. French's website.[13] Depending on the location of a company's headquarters, we use North American, European, Japanese, or Asia Pacific ex Japan regional factors to compute its abnormal stock return.

Carbon emissions and other climate-risk measures We retrieve carbon emission data for a subset of companies from Refinitiv, Eikon. Refinitiv adopts a stepwise approach, estimating emissions when the company does not disclose them. In that case, their proprietary model incorporates CO_2 data from past years, total energy consumed, or industry peers' data to estimate a firm's CO_2 equivalent emissions.

We use E-scores from two different providers: first, MSCI's environmental pillar score, a weighted average of all environmental themes (climate change, natural capital, pollution & waste, and environmental opportunities) ranging from 0 to 10, with a higher score indicating more environmentally friendly firms. Second, we retrieve Environmental Scores (E-Scores) from Refinitiv, Eikon. They range from 0 to 100 with higher scores indicating more climate friendly business models.[14]

Textual analysis measures are taken from Sautner et al. (2023a) and Li et al. (2024).

[12]We do not use CRSP data because we want to use the same data source for both North American and international firms. We use the R API provided by WRDS and perform similar steps as in Scheuch et al. (2023).

[13]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Developed

[14]We also control for RepRisk's Reputation Risk Rating (RRR) in some of our regressions. This measure is constructed from company-specific news articles. As Lindsey et al. (2024), we translate the rating into a scale from 1 to 10, such that a higher number indicates a lower risk.

These measures are positively correlated with carbon emissions and thus tend to be higher for brown firms which have a higher risk of facing regulatory challenges due to future climate policies. We trim all E-scores at the 1% level except for the text-based measures, which we trim at the 5% level, due to a large number of extreme values.

Additional firm-level data We obtain volatility data from Alfaro et al. (2024) provided on Nicholas Bloom's data website.[15] The authors compute firms' forward-365-day option-implied volatility based on OptionMetrics data.

We collect patent data from the US Patent and Trademark Office (UPSTO) and identify green patents following Leippold and Yu (2023). In particular, all patents with Cooperative Patent Classification (CPC) class Y02, a patent group for "technologies or applications for mitigation or adaptation against climate change", are considered green innovations. The subclasses include, among others, capture and storage technologies of greenhouse gases (Y02C) and technologies to lower emissions from transportation (Y02T). In the full sample, around 7% of patents are classified as green. We then match patents to firms using the updated cross-walk in Kogan et al. (2017).[16]

Country-level data For our analysis at the country level, we use data on countries' CO_2 emissions, CO_2 intensities, and macroeconomic control variables from the World Bank. The macroeconomic control variables are GDP growth, log(GDP), log(GDP per capita), log(GNI per capita), inflation, log(population), and the Worldwide Governance Indicators. We also use data from the OECD's "Green Growth" indicators..[17]

[15] https://www.policyuncertainty.com/firm_uncertainty.html

[16] Patent matches are centered on US firms (89%).

[17] https://stats.oecd.org/wbos/fileview2.aspx?IDFile=0eddc076-a4f9-4a2b-8e86-4190c8523b59

3.2 Construction of abnormal returns

Equation (13) is the starting point for the computation of our climate risk exposure measures:

$$AR_t = R_t - E(R_t) \tag{13}$$

For our main results we set $E(R_t)$ equal to the firm's CAPM expected stock returns. In each month we use one year of preceding daily return data to estimate a stock's market beta β_M. CAPM returns are then given by:

$$E(R_t) = r_{ft} + \beta_M(E(R_{mt}) - r_{ft}) \tag{14}$$

We compute $E(R_t)$ conditional on the event date market return and thus set $E(R_{mt}) = R_{mt}$. In additional robustness checks, we also use the stock's raw return by setting $E(R_t) = 0$. Alternatively, we set $E(R_t)$ equal to the firm's expected return according to the Fama-French three factor model (Fama and French, 1993):

$$E(R_t) = r_{ft} + \beta_M(E(R_{mt}) - r_{ft}) + \beta_{HML}HML_t + \beta_{SMB}SMB_t \tag{15}$$

Timing For all firms in our sample, we calculate the cumulative abnormal return (CAR) between t_1 and t_2:

$$CAR_{t_1,t_2} = \prod_{t=t_1}^{t_2}(1 + AR_t) - 1 \tag{16}$$

Since most climate conferences end on a Friday, our event days are typically the Monday after a conference. Depending on the time zone of the conference location, however, some markets may still be open when conference results start to become known on the last Friday of the conference. For our baseline results, we therefore compute the cumulative return from the trading day before the event ($t_1 = -1$), i.e., Friday, up to and including the event day itself ($t_2 = 0$), i.e., usually a Monday, and provide robustness checks using alternative event windows. Cumulative abnormal returns are winsorized at the 5% and 95% levels to account for outliers.

3.3 Paris-based and time-varying market-based greenness

Following our model, we consider two versions of our measure: Paris-based and time-varying. While the Paris-based approach calculates abnormal returns around a single event, the 2015 Paris Climate Conference, the time-varying version of market-based greenness incorporates abnormal returns around all UN climate change conferences from 1992 to 2022.

Paris-based market-based greenness The Paris-based version is constructed from abnormal returns following the 2015 UN climate change conference in Paris (COP 21).[18] The conclusion of the Paris Agreement was, by all accounts, a significant and unexpected change towards more climate change regulation. Accordingly, the Paris Agreement is a positive climate policy shock that positively impacts green firms and negatively impacts brown firms. Consistent with this interpretation, Ramadorai and Zeni (2024) show that firms substantially revised their expectations about future climate regulation and adjusted their planned emissions abatement following the Paris Agreement and Kruse et al. (2024) observe larger cumulative returns for companies with a larger share of green revenue following the agreement.

Time-varying market-based greenness For the time-varying version of our measure, we include abnormal returns around all UN climate conferences to construct a time-varying measure of firms' climate change risk. In total, we construct abnormal returns for 28 climate

[18]The Paris Agreement is currently signed by 195 parties aiming to curb manmade global warming to well below two degrees Celsius, and was adopted on December 12th, 2015. It entered into force on November 4, 2016, 30 days after at least 55 parties accounting in total for at least 55% of the total global greenhouse gas emissions, had ratified the agreement.

conferences (1992, 1995-2022). The UN climate conferences provide a unique setting in that around these conferences *global* changes in regulation become more or less likely. Put differently, they provide an international shock to climate policy risk.

The significance of these events is reflected in the substantial media attention they receive. Figure 2 compares two well-known climate news indices against the conference dates. First, the Media Climate Change Concerns (MCCC) index by Ardia et al. (2023), based on tone-, risk-, and uncertainty-weighted news articles in major US newspapers. Second, the index by Engle et al. (2020), who create an index based on Wall Street Journal articles. Both indices exhibit a peak during the COP15 in Copenhagen, which, as we will argue below, got a lot of press coverage due to its failure to make significant progress. Panel B of Figure 2, also indicates peaks during the COP0 in Rio de Janeiro, the landmark COP3 Kyoto, and a few more. In Panel A, the COP21 in Paris is the second-highest peak of news attention. Overall, the two climate news indices exhibit peaks during several UN climate conferences, indicating the increased media attention due to their global importance.

– Figure 2 around here –

Unlike the COP21 in Paris, however, some climate conferences have resulted in disappointing outcomes. We determine the direction of climate policy shocks by comparing the outcomes of the conferences to their expectations. When a conference is considered a "failure" in achieving its goals, it is considered a *negative* climate policy shock. After intensive reading of official reports and press coverage around these conferences, we manually identify five such "failed" climate policy conferences: 2000, 2005, 2009, 2012, and 2016. As an example, the 2009 climate conference in Copenhagen did not lead to a unanimous agreement, and led to widespread press coverage acknowledging a disappointing outcome of the talks. For example, the New York Times writes that "[...] Many delegates [...] left Copenhagen in a sour mood, disappointed that the pact lacked so many elements they considered crucial, including firm targets for mid- or long-term reductions of greenhouse gas emissions and a deadline for concluding a binding treaty next year."

For some conferences, the outcome with respect to prior expectations is difficult to parse. In this case, we still classify them as positive shocks to climate policy. This choice is partially motivated by our theoretical framework in Section 2.4, which suggests that this approach is conservative: if these conferences are uninformative, they will only add noise and bias our estimates toward zero, making it harder to detect significant effects. Second, even conferences with little information could create positive price effects for green firms if investors have non-pecuniary motives when purchasing green assets (Hartzmark and Sussman, 2019).

Our classification of conferences including relevant quotes from press coverage is summarized in Table 1. To obtain a firm's market-based greenness, we adjust the cumulative abnormal returns around each climate conference by whether the conference is a success or not (analogous to Equation (9) in the model):

$$\text{Market-based greenness}_{i,t} = CAR_{i,t} \cdot sgn(\hat{z}_c) \tag{17}$$

where $sgn(\hat{z}_c)$ is negative for the climate change conferences in 2000, 2005, 2009, 2012 and 2016 and positive otherwise.

– Table 1 around here –

3.4 Descriptive statistics

Unless specified otherwise, we winsorize variables at the 1% level, and the market-based and text-based greenness measures at the 5% level, to mitigate the influence of outliers. We provide summary statistics for the firm-level data in Table 2. In the full sample, market-based greenness varies between negative 4.4 and positive 4.4 percentage points when comparing the 10th to the 90th percentile. This range is similar whether we use the baseline (CAPM-adjusted) abnormal returns, the raw returns, or the Fama–French three-factor–adjusted returns. Our measure's coverage is substantial, with over 560,000 firm-year observations, about ten times larger than the next most populated variable category (the text-based greenness measures).

In contrast, the CO_2 emissions and patent data are much less populated. The average firm with non-missing CO_2 data emits 3,454 kilotons CO_2 (Scope 1) annually, but the median is far lower at roughly 125 kilotons, indicating a highly skewed distribution with a few large emitters. Total CO_2 emissions are similar, with an average of 4152 kilotons, and a median of 430 kilotons.

Conditional on filing any patent, the average firm in the sample has a 30.49% probability of filing at least one green patent. Across all firms with non-missing patent data, the mean number of green patents is about 3.22, with a median of zero, highlighting that green patenting is concentrated among a relatively small subset of firms.

Finally, the last set of statistics shows that the median firm in our sample has an implied volatility of 38%, a book leverage of about 20%, holds 10% of its assets in cash, and has about 900 employees.

– Table 2 around here –

4 Market-based greenness: Descriptive facts

In this section, we present descriptive evidence supporting the use of market reactions to assess firms' exposure to climate risk. We show that market responses align with expected sectoral differences, and that they correlate in the anticipated direction with established metrics. Finally, we demonstrate that market-based greenness provides additional explanatory power beyond other measures.

4.1 Sector-level variation

Intuitively, we would expect that oil companies are more exposed to climate risk than producers of renewable energies. To examine whether this holds, we plot average market-based greenness (CAPM-adjusted abnormal returns) by Global Industry Classification Standard sectors (GICS) and display the results in Figure 3.[19] The figure also indicates manually identified industries with an expected negative exposure to climate risk in brown and industries with a positive exposure to climate risk in green.

– Figure 3 around here –

The ranking in Panel A of Figure 3 is largely in line with what one would expect: The oil and gas industry shows the largest negative abnormal returns and other "brown" sectors such as marine shipping and energy services also display a large negative exposure to climate risk. On the other hand, the renewable energy sector and the electrical equipment sector display one of the largest positive abnormal returns. At the same time, the ranking of other sectors is less readily explainable: For example, beverages and IT services show high positive abnormal returns. This might be due to sector-specific idiosyncratic variation, or may indicate that the market thinks that some firms within these sectors will benefit from the green transition.

Sector averages based on the time-varying market-based greenness are displayed in Panel B of Figure 3. The relative ranking of green and brown firms remains, with the energy equipment and the oil and gas industry among the brownest, and the renewable energy sector among the greenest sectors. The ranking of sectors does not depend much on the method that we use for adjusting returns. Both raw returns (Figure A.1) and Fama-French three factor adjusted returns (Figure A.2) show a similar hierarchy of sectors. Results remain similar when we demean the returns by country, to remove the effect of expected regulatory

[19]For ease of viewing, we include only industries with at least 2000 firm-year observations.

follow-through (Figure A.3).[20]

Within sector variation Market-based greenness also uncovers intuitive patterns within industries. For example, within the "Ground Transportation" industry, firms with a low greenness score tend to be trucking companies, such as Universal Logistics and XPO, who specialize in truckload and less-than-truckload logistic services, or car rental companies such as AVIS and Hertz. On the other end of the greenness spectrum, we find mostly rail-based logistics companies such as CSX and Union Pacific. Since rail-based transportation is likely easier to electrify than truck-based logistics, this sorting likely reflects within-industry variation in regulatory risk that market-based greenness is capable of identifying.

Indirect risk exposure Our market-based greenness measure should also incorporate *indirect* transition risk from supply chains, as opposed to, for example, Scope 1 carbon emissions. To examine whether this is the case, we turn to anecdotal evidence because there are no large-scale measures capturing indirect risk available for a direct test.

The investment firm BlackRock, for example, is in the bottom greenness decile, with a negative Paris-based score of -5.2, despite also being in the bottom decile of CO_2 emitters, having essentially no direct emissions. We think that this correctly reflects high transition risk, because BlackRock is one of the world's biggest institutional investors in fossil fuels.[21] Conversely, less exposed financial firms have higher greenness scores. Northern Trust, for example, an investment firm that gained notoriety for being blacklisted by West Virginia for alleged "ESG boycotting" of fossil fuel companies, has a higher Paris-based greenness score of -0.68.

[20]A potential concern is that sectoral composition differs starkly across countries and countries also might differ in their strength of implementation of the Paris Climate Accords. Since markets are likely to price the expected country-level reaction, we might be picking up a country-level effect that skews the results. In fact one of the advantages of a market-based measure is that it captures this "part" of climate risk exposure, namely the likelihood of countries actually following through on their promises.

[21]BlackRock is also the subject of an OECD complaint over the deforestation of the Amazon Rainforest.https://www.theguardian.com/environment/2024/nov/20/blackrock-climate-human-rights?

On the other end of the CO_2 emission ranking, several utility companies with high emissions also have high market-based greenness scores, although this is less frequent. Xcel Energy and Idaho Power, for example, are green by Paris-based greenness (2.5, 1.8), despite being significant emitters of CO_2. Both firms have publicly committed to full decarbonization by 2050 and 2045, respectively.[22]

4.2 Relationship with other climate-risk measures

E-scores First, we start by looking at the relationship between market-based greenness and the environmental part of the ESG score of different data providers. E-scores are widely used by investors and researchers (Pástor et al., 2022; Avramov et al., 2022). At the same time, they have received attention for significant measurement issues that call into question their reliability (Berg et al., 2021, 2022a).

– Figure 4 around here –

Figure 4 shows the relationship of market-based greenness with two widely used E-Scores: MSCI E-Scores and Refinitiv E-Scores. The figure demonstrates an intuitive positive relationship with MSCI E-Scores, but no relationship with Refinitiv E-Scores, which have been subject to significant criticism (Berg et al., 2021, 2022b).[23] Similarly, we find that the relationship between E-scores and CO_2 emissions is only intuitive for market-based greenness and the MSCI E-Scores (Figure A.5).[24]

[22] Xcel Energy Press Release, IDACORP Press release. While the targets were announced only after the 2015 Paris conference, the two companies showed significant green signals before the announcement, such as the early closure of certain power plants or long-term contracts for renewable energy, making it plausible that well-informed investors positively evaluated the green transition paths of these firms even before the 2015 Paris conference.

[23] We also show the relationship with RepRisk scores in Figure A.4. RepRisk scores represent the inverted reputation risk to firms from all sources.

[24] For MSCI E-Scores, higher E-Scores are associated with lower emissions. For Refinitiv E-scores, higher E-scores are associated with higher emissions.

Measures based on earnings calls Sautner et al. (2023a) and Li et al. (2024) identify climate-change related words in earnings call transcripts and score firms' climate change risk based on their prevalence. While the approach is innovative and valuable, and quarterly earnings calls likely reflect investor concerns, it is unclear whether text can effectively capture the market's opinion about firm risk. First, climate change might be a relevant concern for *both* green and brown firms. It is, for example, not clear whether investors bring up climate change concerns more for solar energy or oil producers. Second, the managers' answers are subject to cheap talk. Managers might be talking extensively about their climate transition plans, but there is no immediate way to evaluate the credibility of these claims. We suggest that market reactions complement these text-based measures because market prices may reflect the credibility of firms' claims.

– Figure 5 around here –

We plot market-based greenness against the text-based measures of climate change exposure by Sautner et al. (2023a) and Li et al. (2024) in Figure 5. We find a negative relationship with both text-based measures when using our Paris-based measure (left-hand side panels). The time-varying measure (right-hand side panels) shows similar but weaker negative relationships. Overall, higher climate change exposure in Sautner et al. (2023a) and higher transition risk in Li et al. (2024) is associated with browner firms according to our measure. At the same time, the binned scatter plots also reveal significant heterogeneity, suggesting that text-based and market-based measures might capture slightly different aspects of firms' climate change risk, thus potentially complementing each other.

In Table A.2, we examine the relationship between our measure and the E-Score as well as the measures based on earnings-call transcripts more formally. In line with Figure 4, we find a statistically significant correlation between E-scores and our greenness measure only for MSCI E-Scores. Columns 3 and 4 of Table A.2 indicate a significant negative correlation of our measure with the text-based measures by Sautner et al. (2023a) and Li et al. (2024) only for our Paris-based measure (Panel A). While we find statistically significant correlations of our measure with some existing measures of firms' greenness, the R^2 is low across all columns in Table A.2, indicating that market-based greenness captures cross-sectional variation in climate risk exposure that differs from existing measures.

5 Market-based greenness at the firm-level: Green outcomes

In this section, we correlate our measure with firm-level CO_2 emissions and green patent issuance. We show that the information in our measure has explanatory power for current and future CO_2 emissions at the firm level, which is distinct from, but complementary to, the previously discussed measures.

5.1 Future CO_2 emissions

One of the main advantages of a market-based measure is that it is conceptually *forward looking*. Market participants can evaluate the likelihood of changes in future emissions as opposed to merely evaluating current emissions. In an important sense, this is what regulators and policymakers should care about *more*, when evaluating a firm's climate change risk. Any given firm can emit a lot today if it can credibly commit to reducing emissions by a larger share tomorrow. Using data on future CO_2 emissions, we can partially test this conjecture by regressing firms' current and future carbon emissions on our measure:

$$log(CO_2)_{i,t+n} = \beta_1 \cdot \text{Market-based greenness}_{i,t} + \epsilon_{it} \ ,$$

where i is a firm in year $t + n$ and n is a value from 0 to 6. That is, we investigate the relationship between market-based greenness and current $(t+0)$ and future carbon emissions up until six years into the future ($t + 6$). The results are displayed in Table 3. The number of observations in these regressions is limited by the availability of carbon emissions data, highlighting the need for more comprehensive measures of firms' greenness.

Baseline results Panel A of Table 3 shows the relationship between carbon emissions and the Paris-based measure. Column 1 demonstrates that green firms, i.e., firms with higher abnormal returns around the announcement of the Paris Agreement, have significantly lower carbon emissions. An increase in announcement returns by one percentage point is associated with about 10% lower carbon emissions. More importantly, *future* carbon emissions are also closely associated with our measure of a firm's greenness. The strongest correlation occurs with carbon emissions four years into the future. For the Paris-based measure, an increase in returns by one percentage point is associated with a decrease in 2019 carbon emissions by about 15% (Column 5). The four-year horizon regression also displays the highest R^2 of all specifications, indicating that our measure not only correlates well with current, but especially future emissions, which is in line with our predictions.

– Table 3 around here –

Panel B of Table 3 employs the time-varying market-based greenness. Similarly to the Paris-based results, higher market-based greenness is associated with lower contemporaneous carbon emissions (Column 1). The strength of this effect is increasing the further into the future we predict CO_2 emissions. It is strongest four and five years into the future, where an increase in the measure of greenness by one percentage point is associated with 7% lower CO_2 emissions. All of these results hold when using a harmonized sample (Table A.3), when varying the method of calculating expected returns, and when using total CO_2 emissions instead of Scope 1 emissions (Table A.4).

– Table 4 around here –

Horse race results An important question is whether our measure has predictive power for CO_2 emissions beyond existing measures and other factors likely impacting firms' future emissions, such as their size and sector. To test this, we extend the previous regression and add E-scores, the text-based measures, firm size (log(market cap)), and sector and country fixed effects as control variables. Panel A of Table 4 shows the results using the Paris-based measure of market-based greenness. In all specifications, our greenness measure is highly statistically significant and has the expected negative sign. Here, the relationship is particularly strong in the years closer to the respective climate conference, although due to the inclusion of all measures, the sample becomes very small.

When we harmonize the sample in Table A.5, we generally find that market-based greenness predicts CO_2 emissions in a similar fashion across different horizons. Results also remain similar when using the MSCI Climate Change Theme Score instead of the E-Score and the regulatory risk measure by Sautner et al. (2023a) in Table A.6.

5.2 Placebo events

To further verify that our measure does not simply capture random market variation, we create market-based greenness measures from placebo events and test if they show similar correlations with future CO_2 emissions. To construct our placebo events, we first identify the calendar weeks in which the analyzed climate conferences occur. We then randomly sample 20 placebo weeks from the remaining calendar weeks, i.e., we draw 20 values without replacement from the set $\{w \in \{1, 2, \ldots, 52\} \mid w \text{ is not a COP week}\}$. For each selected placebo week, we calculate a corresponding measure for each year, covering the period from the Friday of the week to the following Monday, as we do for our real market-based greenness measure.

Figure 6 shows the estimated correlations between returns around placebo events and firms' future CO_2 emissions across six time horizons (t+1 to t+6), with the baseline estimate shown in red and placebo events in blue. The placebo estimates are mostly either statistically insignificant at several horizons or positive and statistically significant, supporting the idea that returns around UN climate conferences are uniquely informative about firms' greenness.

– Figure 6 around here –

5.3 Patents

Next, we test whether our measure is correlated with future climate-related innovation, as reflected in green patenting activity. Because investors are likely to price planned investments in green innovation, our measure should identify those firms that are more likely to focus on clean technologies, sustainable processes, and green product development. Put differently, firms green patenting activity is one way through which firms are exposed to climate risk, and thus we would expect a positive correlation between both.

Because most firms do not file any or file just one patent in a given year but some large firms file a lot of patents, we focus on the extensive margin and create variables indicating when a firm files any green or any non-green patent. In our sample, there are 44,758 firm-years with at least one patent filed. Conditional on filing any type of patent, 97% of filings include at least one non-green patent, and 28% include at least one green patent.[25]

– Table 5 around here –

We then regress the variable indicating filing at least one green patent on our measure of market-based greenness. The estimates in Panel A of Table 5, where we restrict the sample to our Paris-based measure, indicate a positive correlation between our measure and the likelihood that firms file at least one green patent. The correlation is also statistically significant at the two, four, and six-year horizons, similar to the results using CO_2 as the dependent variable. The four-year horizon coefficient implies that a one standard deviation

[25]The fractions do not add up to one because firms file green and non-green patents at the same time.

higher market-based greenness is associated with a 4% higher probability of filing a green patent. With respect to our time-varying measure, we find that almost all the correlations are positive but not statistically significant. However, in Table A.9 we restrict our full sample to firms with non-missing data at all horizons and find statistically significant positive correlations at five out of seven horizons.

6 Market-based greenness at the firm-level: Financial and real outcomes

Having established market-based greenness as a reasonable proxy for firms' climate risk exposure, in this section, we ask how these green firms perform financially and whether their investment behavior differs from that of other firms. We do so by descriptively relating market-based greenness with firm-level share-price volatility and other financial and real outcomes.

6.1 Share-price volatility

What is the relationship between market-based greenness and the future volatility of firms' stock returns? Due to the forward-looking nature of our measure, we suspect that browner firms should be riskier, given that increased future climate risk could render parts of their business model unprofitable.

We obtain volatility data from Alfaro et al. (2024) and use the forward-365-day option-implied volatility based on OptionMetrics data provided by the authors. We regress contemporaneous, one-year, two-year, three-year and four-year leading implied volatility on market-based greenness[26]. Panel A in Table 6 shows the results. We observe significant

[26] We restrict the forecasting horizon to four years, as volatility data are available only up to 2019 and our Paris-based market-based greenness measure is from 2015.

negative correlations between our measure and volatility across all specifications, both contemporaneous (Column 1) and future (Columns 2-5), consistent with our prior. On average, a one percentage point increase in our Paris-based market-based greenness measures is associated with a 1.2% decrease in option-implied return volatility in 2017 (Column 3). Panel B of Table 6 reports results using our time-varying measure. As Column 1 shows, there is a significant and negative correlation between our greenness measure and firms' return volatility.[27] Results are more significant for the time-varying measure when using a harmonized sample, which we report in Panel B in Table A.7.

– Table 6 around here –

Analogous to before, we ask if our measure provides additional explanatory power for firms' return volatility relative to existing measures. In Table A.8, we present results when controlling for textual-analysis based measures (Sautner et al., 2023a; Li et al., 2024), RepRisk scores, as well as Refinitiv and MSCI E-Scores.[28] Similar to the results in Table 6, Table A.8 shows a negative association between market-based greenness and firms' implied volatility. This holds true for all specifications in Panel A (Paris-based measure) and for two specifications (columns 4 and 5) in Panel B (time-varying measure). While higher Refinitiv E-Scores seem to be significantly associated with lower return volatility too, results are mixed for the text-based measures.

6.2 Other firm-level outcomes

In this section, we examine whether and how market-based greenness correlates with other firm-level outcomes.

[27] These results are consistent with Ilhan et al. (2021) who find that carbon-intensive firms display significant tail risk, based on option data. Results also align with Pástor and Veronesi (2013), who, in a model of government policy choice, show that policy uncertainty can lead to increased price risk.

[28] In order to increase our sample size, we do not include carbon emissions as control variable, though results remain largely unchanged.

Table 7 presents these correlations. For book leverage, both the Paris-based (Panel A) and time-varying (Panel B) measures show a negative association, implying that greener firms have lower leverage. This correlation is in line with Kräussl et al. (2025), who find that higher E-scores lead to lower debt but higher equity issuance. For liquidity (measured by the cash to asset ratio), the time-varying measure shows a significant positive association, suggesting that greener firms tend to hold more cash. In contrast, the Paris-based measure does not show a statistically significant relationship with cash holdings. These correlations suggest that greener firms may adopt more conservative financial policies, reflected in higher cash holdings and lower leverage, in line with the findings in Heo (2021) and Ginglinger and Moreau (2023), who find that these variables tend to be correlated with climate risk.

Turning to real outcomes, Table 7 shows that investment is statistically significantly negatively correlated with both versions of our greenness measure. Within a given industry cell, firms spending less on capital expenditures are perceived as greener by the market. Turning to R&D expenditures, we find no statistically significant correlation. This is not surprising, as we cannot distinguish between green and non-green R&D, for example, and is consistent with the findings in Kräussl et al. (2025). For employment, we find a weakly significant negative correlation using our time-varying measure but no correlation using the Paris-based measure. In sum, greener firms appear to have lower leverage, hold more cash, and spend less on physical capital.

7 Market-based greenness at the country-level

In this section, we take advantage of the larger available sample of our measure compared to existing measures (see Figure 1) to investigate correlations of market-based greenness at the country-level.

Although policymakers need to evaluate countries' progress in transitioning to a green economy, this is difficult to measure because it depends on the credibility of enacting or continuing certain policies in the future (similar to the challenges at the firm-level, see above). Aggregating our measure to the country level provides a potential solution: firms' stock price changes in reaction to UN climate change conferences likely incorporate the probability of regulatory implementation of international climate agreements. If, for example, investors expect a country not to implement a climate change agreement, firms that are potentially subject to regulation in this country will not see a change in their stock price.[29] Capturing this exposure to regulatory implementation is a crucial *feature* of market-based greenness, which other measures are less likely to incorporate.

To investigate these relationships, we aggregate our measure to the country level.[30] In total, market-based greenness can be calculated for 91 different countries. We then regress different lags of country-level market-based greenness on countries' emissions, their shift to green energy, and their GDP. All regressions include the following macro-control variables (except when they are the dependent variable): GDP growth, log(GDP), log(GDP per capita), log(GNI per capita), inflation, log(population) and Worldwide Governance Indicators (WGI)[31] and country fixed effects.

CO_2 per capita We first look at the association of market-based greenness with future changes in countries' CO_2 emissions. Figure 7, Panel A, shows that our measure correlates negatively with future country-level per capita CO_2 emissions. While there is almost no relationship between market-based greenness at the country level and concurrent CO_2 emissions, this relationship is statistically significant when market-based greenness is lagged by various periods. The correlation becomes stronger over time, indicating that market-based greenness is particularly strongly associated with *future* emissions. We find a very similar

[29] At least insofar as impacts from regulation within the headquarters country are concerned. Effects might still occur via supply chains or other interactions.

[30] In each year, we take the simple average of all firms with headquarters in the country.

[31] Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law, Control of Corruption. Indicators are provided by the World Bank.

pattern, when we scale emissions by GDP, instead of by population in Panel B: market-based greenness is strongly related to the future energy efficiency in terms of CO_2 per unit of output. This result is unique to our measure, because the existing text-based measures are limited to the US (Li et al., 2024), or do not correlate with future CO_2 emissions at the country level (Panel A of Figure A.6).[32] Further, the predictive power of lagged emissions declines with the forecasting horizon (Panel B of Figure A.6), while the predictive power of market-based greenness improves. Consequently, even when controlling for lags of CO_2 emissions per capita, our market-based greenness measure has a significant negative correlation with future CO_2 emissions six and more years into the future (Figure A.7).

– Figure 7 around here –

Renewable energy A key aspect that countries regulate to reduce emissions is the energy mix, particularly the composition of electricity generation. If market-based greenness on the country level is related to regulatory intensity, we would expect it to correlate positively with the share of renewables that each country adopts. To test this, we merge our country-level data with the OECD's "Green Growth" indicators, which report the share of renewable energy in each country. We find support for a positive relationship between the share of renewables and market-based greenness in Panel C of Figure 7. Market-based greenness shows no correlation with the share of renewable energy today, but a significant positive correlation with the *future* share of renewable energy each country uses.[33] This relationship remains significant, when controlling for log(CO_2 per capita) in the same period (Panel B) at long horizons.

Physical risk Since markets might extrapolate far into the future, it is possible that market-based greenness is capturing long-term physical risk in addition to (or instead of)

[32] Sautner et al. (2023a) only cover about 30% of our sample of countries, when used in our country-level regressions.

[33] This relationship is not detectable in text-based measures (Figure A.8).

regulatory risk. In other words, since climate agreements might impact long-term physical risk, markets might adjust their prices not only in anticipation of regulation but also in anticipation of changes in physical risk. While this is difficult to test at the firm-level, we can test if our country-level measure of market-based greenness is associated with a higher disaster frequency or intensity. Consequently, we merge our data with natural disaster data from the International Disaster Database (EMDAT) and investigate if market-based greenness is associated with the country-level annual total disaster damages. Given that changes to physical risk are likely to accumulate only over long time horizons, we use up to 20 year lags of market-based greenness in these regressions. Nevertheless, we find little to no relationship between market-based greenness and losses from disasters (Figure A.9). This does, however, not rule out the possibility that physical risk will change in the future but has not significantly changed over our sample period.

Economic performance of green countries The economic costs and benefits of the transition away from fossil fuels are the subject of a heated debate. Using our country-level market-based greenness measure, we can investigate whether countries with a larger share of green firms perform better or worse in terms of their economic output. Consequently, we run a cross-country regression relating our country-level measure of greenness with various (future) output measures and display the resulting coefficients in Figure 8.

– Figure 8 around here –

In Panel A, we use a country's GDP per capita as the dependent variable. The result suggests that there might be a 1.4 % decrease in GDP per capita per standard deviation increase in market-based greenness, a rather small short-term cost associated with a green economy. However, this negative effect is not statistically significant and immediately disappears in the next year. Using GDP growth as the dependent variable (Panel B) also suggests no statistically significant changes at any future horizon, neither positive nor negative. Overall, we do not find consistent evidence for a country-level benefit (or cost) of having a larger share of green firms.

8 Application: Brownium or Greenium?

In this section, we apply our measure to the controversial question of whether stocks of brown or green firms earn premiums and add to the debate by leveraging the broad coverage of the market-based measures. Using carbon emissions data, Bolton and Kacperczyk (2021) show that brown firms are traded at a premium in the US, and Bolton and Kacperczyk (2023) establish this relationship globally. Yet, Aswani et al. (2024) present evidence that this relationship is based on estimated carbon emissions and find no carbon premium when using emission intensities. Additionally, Engle et al. (2020), Choi et al. (2020), and Pástor et al. (2022) provide evidence that this "browninum" can reverse, resulting in a premium for green firms depending on time and place. Sautner et al. (2023b) find higher risk premiums for firms with a larger exposure to climate-related opportunities, and mostly no effects for those exposed to regulatory risk. In a review and replication exercise, Eskildsen et al. (2025) find limited evidence of a premium for brown or green firms.

We begin by replicating Bolton and Kacperczyk (2021) to the best of our ability.[34] Within their sample period of 2005-2017, we lack some information on CO_2 emissions available to them, resulting in a smaller sample. Nevertheless, we are able to replicate their finding of a carbon premium for this sample period in Column 1 of Table 8. When extending to our full sample period, the effect remains positive but is no longer statistically significant (Column 2).

– Table 8 around here –

We then use our measure of market-based greenness instead of CO_2 emissions as an

[34] We compute stock returns using Compustat data and we exclude climate conference months throughout.

indicator of climate risk. Despite the negative correlation between CO_2 emissions and our market-based greenness measure (see Section 5.1), we do not find evidence of a significant premium for brown firms using our market-based measure. This holds in the Bolton and Kacperczyk (2021) time period (Column 3) and our full sample period (Column 4). Using our market-based measure increases the number of observations by an order of magnitude in our sample and roughly doubles it relative to Bolton and Kacperczyk (2021).[35] The absence of a brown premium may reflect limitations of carbon emissions as a proxy for regulatory risk. Emissions correlate with firm sales (Zhang, 2025), and brown premia are difficult to detect in emissions data more generally (Aswani et al., 2024).

We then extend our analysis to a global sample, which is easily achieved due to the broad coverage of the market-based measure. The results in Column 5 show higher returns to green firms. This is consistent with findings by Sautner et al. (2023b), Choi et al. (2020) and Pástor et al. (2022), who attribute this phenomenon to changing investor preferences that increased demand for green assets. Increasing visibility of climate-related events and heightened public attention to climate change also contributed to rising demand for green assets from around 2015 to 2020.[36] We show in Column 6 that the returns to our market-based greenness measure from 2015 to 2020 are indeed about twice as large as in the full sample, while we find no significant correlation for the pre-2015 period (Column 7). Overall, this pattern suggests that outside the US, green assets earned higher returns from 2015 to 2020, but were neither at a premium nor a discount in other periods.

[35]In Bolton and Kacperczyk (2021), there are roughly 184,000 observations. The difference to Column 1 in our case is due to the lack of availability of CO_2 data at our institutions.

[36]The Paris Agreement in 2015 marks the beginning of this heightened interest and the decline in public attention during the pandemic arguably marks its end.

9 Conclusion

This paper proposes a market-based measure of firms' greenness by using equity market reactions around UN climate conferences. We first show theoretically that equity price movements around these events are proportional to firms' underlying greenness.

We then construct our measure for about 36,000 international firms from 1992 to 2022. This new measure covers eight times as many firms and spans a significantly longer time horizon than existing greenness measures, extending the possible scope for research across time and countries. An additional advantage of our measure is that it includes firms' indirect exposure to climate-related regulatory risk, even when they are not directly emitting CO_2. We show that our measure has predictive power for both current and future carbon emissions and green patenting activity, indicating that our measure incorporates information about the future.

Our measure generally correlates with existing greenness metrics in the expected direction, yet our evidence also suggests that it contains important variation distinct from existing measures. We show that correlations of our measure with different firm characteristics align with economic intuition and existing research, and that our measure contains meaningful variation within sectors and across countries. It can also be easily applied to important climate finance discussions, such as estimating climate risk premia. In sum, our measure is a valuable addition to the toolbox of investors, regulators, and policymakers committed to accurately assessing firms' greenness.

References

Admati, A. R. (1985). A noisy rational expectations equilibrium for multi-asset securities markets. *Econometrica*, 53(3):629.

Alfaro, I., Bloom, N., and Lin, X. (2024). The finance uncertainty multiplier. *Journal of Political Economy*, 132(2):577–615.

Amiti, M., Kong, S. H., and Weinstein, D. (2020). The effect of the U.S.-China trade war on u.s. investment.

Ardia, D., Bluteau, K., Boudt, K., and Inghelbrecht, K. (2023). Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632.

Arteaga-Garavito, M. J., Colacito, R., Croce, M. M. M., and Yang, B. (2023). International climate news. *Available at SSRN 4713016*.

Aswani, J., Raghunandan, A., and Rajgopal, S. (2024). Are carbon emissions associated with stock returns? *Review of Finance*, 28(1):75–106.

Avramov, D., Cheng, S., Lioui, A., and Tarelli, A. (2022). Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*, 145(2):642–664.

Barnett, M. D. (2019). *A run on oil: climate policy, stranded assets, and asset prices.* Dissertation, THE UNIVERSITY OF CHICAGO, Chicago.

Berg, F., Fabisik, K., and Sautner, Z. (2021). Is history repeating itself? The (un)predictable past of ESG ratings. *SSRN Electronic Journal*, pages 1–59.

Berg, F., Koelbel, J. F., Pavlova, A., and Rigobon, R. (2022a). ESG confusion and stock returns: Tackling the problem of noise. Technical report, National Bureau of Economic Research.

Berg, F., Koelbel, J. F., and Rigobon, R. (2022b). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, 26(6):1315–1344.

Bingler, J. A., Kraus, M., Leippold, M., and Webersinke, N. (2022). Cheap talk and cherry-picking: What climatebert has to say on corporate climate risk disclosures. *Finance Research Letters*, 47:102776.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549.

Bolton, P. and Kacperczyk, M. (2023). Global pricing of carbon-transition risk. *The Journal of Finance*, 78(6):3677–3754.

Borochin, P., Celik, M. A., Tian, X., and Whited, T. M. (2021). Identifying the heterogeneous impact of highly anticipated events: Evidence from the tax cuts and jobs act.

Botzen, W. W., Deschenes, O., and Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.

Busch, T., Johnson, M., and Pioch, T. (2022). Corporate carbon performance data: Quo vadis? *Journal of Industrial Ecology*, 26(1):350–363.

Choi, D., Gao, Z., and Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3):1112–1145.

Dumitrescu, A., Gil-Bazo, J., and Zhou, F. (2022). Defining greenwashing. *Available at SSRN 4098411*.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., and Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3):1184–1216.

Eskildsen, M., Ibert, M., Jensen, T. I., and Pedersen, L. H. (2025). Realized returns to green investing: A global replication. Working Paper, Available at SSRN: https://ssrn.com/abstract=6527562.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Gavriilidis, K., Känzig, D. R., and Stock, J. (2023). The macroeconomic effects of climate policy uncertainty. *Unpublished working paper*.

Gibson Brandon, R., Glossner, S., Krueger, P., Matos, P., and Steffen, T. (2022). Do responsible investors invest responsibly? *Review of Finance*, 26(6):1389–1432.

Ginglinger, E. and Moreau, Q. (2023). Climate risk and capital structure. *Management Science*, 69(12):7492–7516.

Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., and Wilkens, M. (2020). Carbon risk. *Available at SSRN 2930897*.

Gourier, E. and Mathurin, H. (2024). A greenwashing index. *Available at SSRN 4715053*.

Greenland, A., Ion, M., Lopresti, J., and Schott, P. K. (2024). Using equity market reactions to infer exposure to trade liberalization. *Journal of International Economics*, 152:104000.

Gu, G. W. and Hale, G. (2023). Climate risks and FDI. *Journal of International Economics*, 146:103731.

Hartzmark, S. M. and Sussman, A. B. (2019). Do investors value sustainability? a natural experiment examining ranking and fund flows. *The Journal of Finance*, 74(6):2789–2837.

Heo, Y. (2021). Climate change exposure and firm cash holdings. *Available at SSRN 3795298*.

Hong, H., Li, F. W., and Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics*, 208(1):265–281.

Hsu, P.-H., Li, K., and Tsou, C.-Y. (2023). The pollution premium. *The Journal of Finance*, 78(3):1343–1392.

Huij, J., Laurs, D., Stork, P. A., and Zwinkels, R. C. (2023). Carbon beta: A market-based measure of climate transition risk exposure. *Available at SSRN 3957900*.

Ilhan, E., Krueger, P., Sautner, Z., and Starks, L. T. (2019). Institutional investors' views and preferences on climate risk disclosure. Technical report, Swiss Finance Institute Swiss, Switzerland.

Ilhan, E., Sautner, Z., and Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*, 34(3):1540–1571.

Kacperczyk, M., van Nieuwerburgh, S., and Veldkamp, L. (2016). A rational theory of mutual funds' attention allocation. *Econometrica*, 84(2):571–626.

Kahn, M. E., Mohaddes, K., Ng, R. N., Pesaran, M. H., Raissi, M., and Yang, J.-C. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics*, 104:105624.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2):665–712.

Kräussl, R., Rauh, J., and Stefanova, D. (2025). Is ESG a sideshow? ESG perceptions, investment, and firms' financing decisions. Technical report, National Bureau of Economic Research.

Krueger, P., Sautner, Z., and Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111.

Kruse, T., Mohnen, M., and Sato, M. (2024). Do financial markets respond to green opportunities? *Journal of the Association of Environmental and Resource Economists*, 11(3):549–576.

Leippold, M. and Yu, T. (2023). The green innovation premium: Evidence from us patents and the stock market. *Swiss Finance Institute Research Paper Series 23-21*.

Li, Q., Shan, H., Tang, Y., and Yao, V. (2024). Corporate climate risk: Measurements and responses. *The Review of Financial Studies*, 37(6):1778–1830.

Lindsey, L. A., Pruitt, S., and Schiller, C. (2024). The cost of ESG investing. *Available at SSRN 3975077*.

Maćkowiak, B. and Wiederholt, M. (2009). Optimal sticky prices under rational inattention. *American Economic Review*, 99(3):769–803.

Ozdagli, A. and Velikov, M. (2020). Show me the money: The monetary policy risk premium. *Journal of Financial Economics*, 135(2):320–339.

Parise, G. and Rubin, M. (2023). Green window dressing. In *Proceedings of the EUROFIDAI-ESSEC Paris December Finance Meeting*.

Pástor, Ľ., Stambaugh, R. F., and Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2):550–571.

Pástor, Ľ., Stambaugh, R. F., and Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424.

Pástor, L. and Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3):520–545.

Ramadorai, T. and Zeni, F. (2024). Climate regulation and emissions abatement: Theory and evidence from firms' disclosures. *Management Science*, 70(12):8366–8385.

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., and Ziegler, A. (2021). Investor rewards to climate responsibility: Stock-price responses to the opposite shocks of the 2016 and 2020 US elections. *The Review of Corporate Finance Studies*, 10(4):748–787.

Sautner, Z., Van Lent, L., Vilkov, G., and Zhang, R. (2023a). Firm-level climate change exposure. *The Journal of Finance*, 78(3):1449–1498.

Sautner, Z., Van Lent, L., Vilkov, G., and Zhang, R. (2023b). Pricing climate change exposure. *Management Science*, 69(12):7540–7561.

Scheuch, C., Voigt, S., and Weiss, P. (2023). *Tidy Finance with R*. Chapman and Hall/CRC, Boca Raton.

Seltzer, L. H., Starks, L., and Zhu, Q. (2022). Climate regulatory risk and corporate bonds. Technical report, National Bureau of Economic Research.

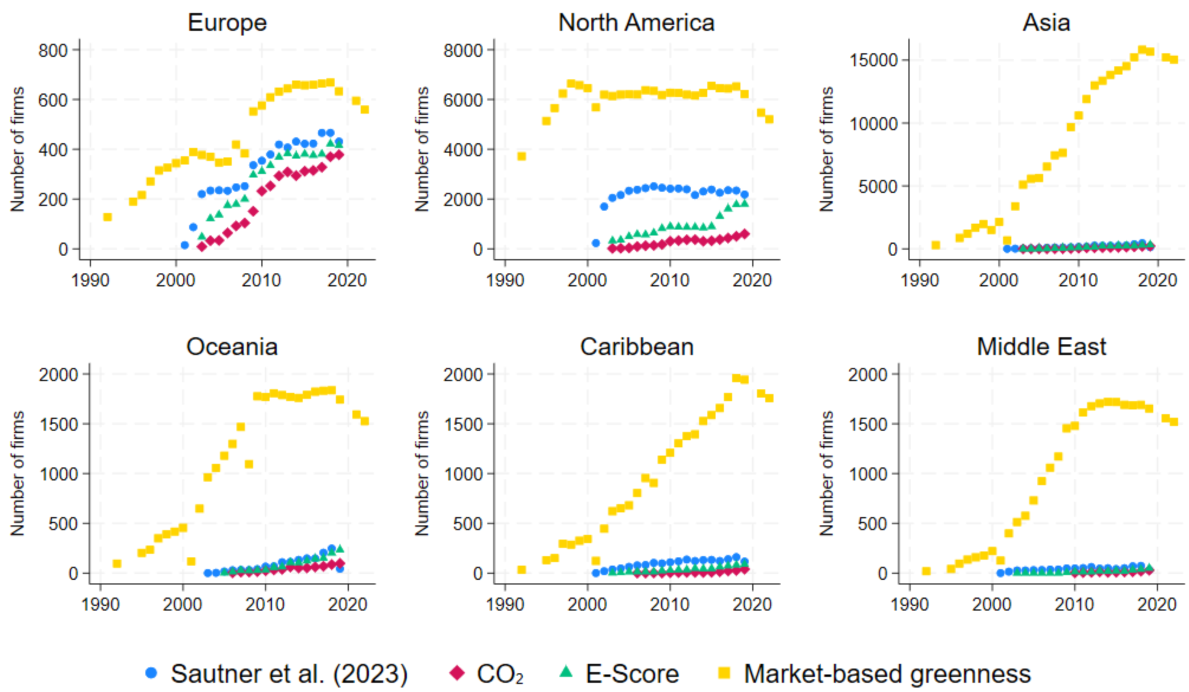
van Binsbergen, J. H. and Brøgger, A. (2022). The future of emissions. *Available at SSRN 4241164*.

von Schickfus, M.-T. (2021). Institutional investors, climate policy risk, and directed innovation. *ifo Working Paper*.

Zhang, S. (2025). Carbon returns across the globe. *The Journal of Finance*, 80(1):615–645.

Figures & Tables

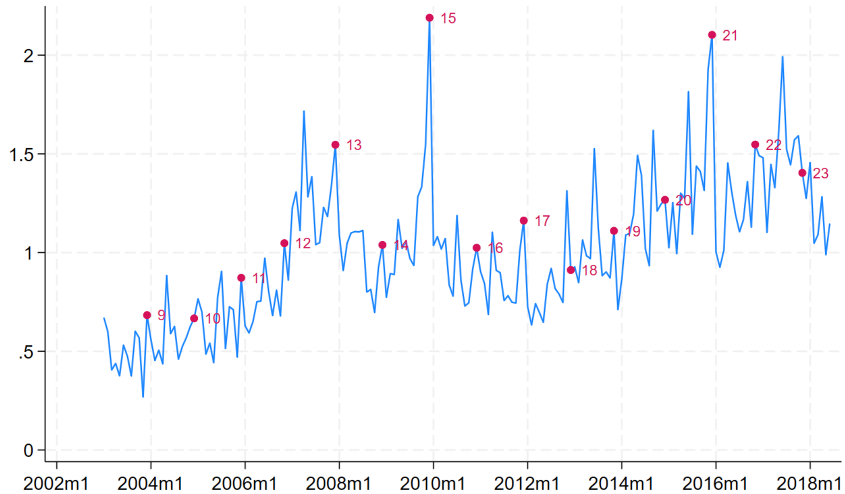
Figure 1: Data availability



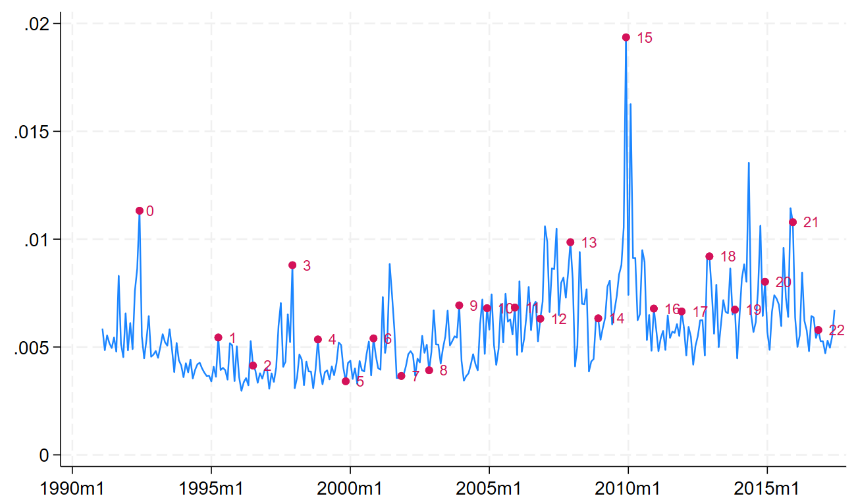
This figure shows the data availability of our measure and other common firm-level greenness measures. The blue dots indicate non-missing observations of the text-based measure from Sautner et al. (2023a). Red squares represent the non-missing CO_2 emission data sourced from Refinitiv. Green triangles show the availability of Refinitiv E-scores data. Yellow squares correspond to the number of non-missing greenness measures.

Figure 2: Climate change conferences (COPs) and climate news coverage

Panel A: News Data based on Ardia et al. (2023)



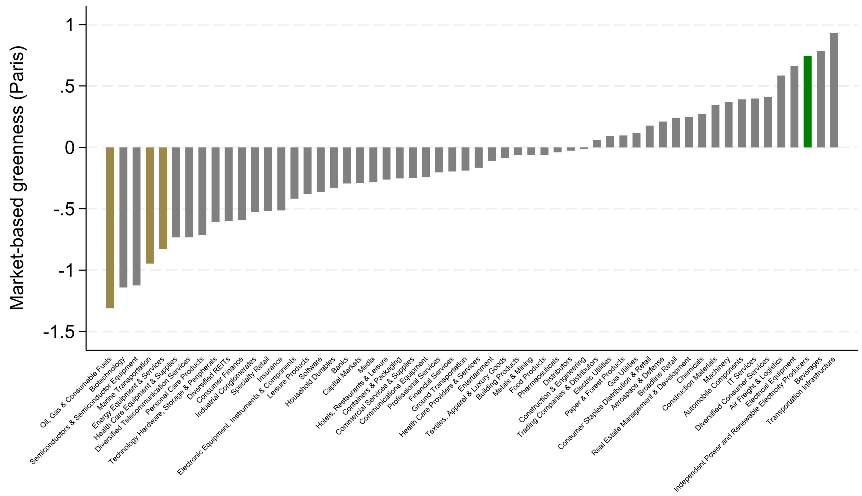
Panel B: News Data based on Engle et al. (2020)



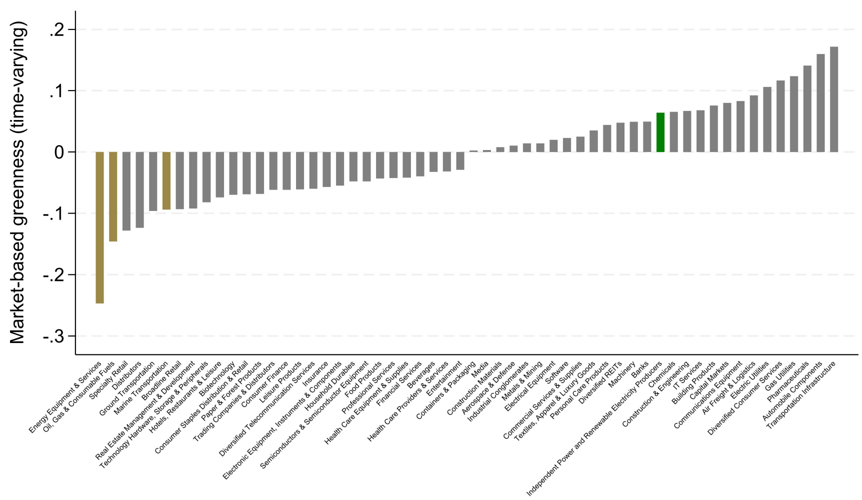
This figure shows the occurrence of COP conferences during the climate news cycle used in Ardia et al. (2023) and Engle et al. (2020). Numbers indicate the respective COP conference number. For example, COP 15 indicates the 2009 Conference of the Parties in Copenhagen, which was widely viewed as a failure to implement more climate policies, and COP 21 indicates the 2015 Conference of the Parties in Paris, where the Paris Climate Agreement was signed.

Figure 3: Market-based greenness by sector

Panel A: Paris-based measure

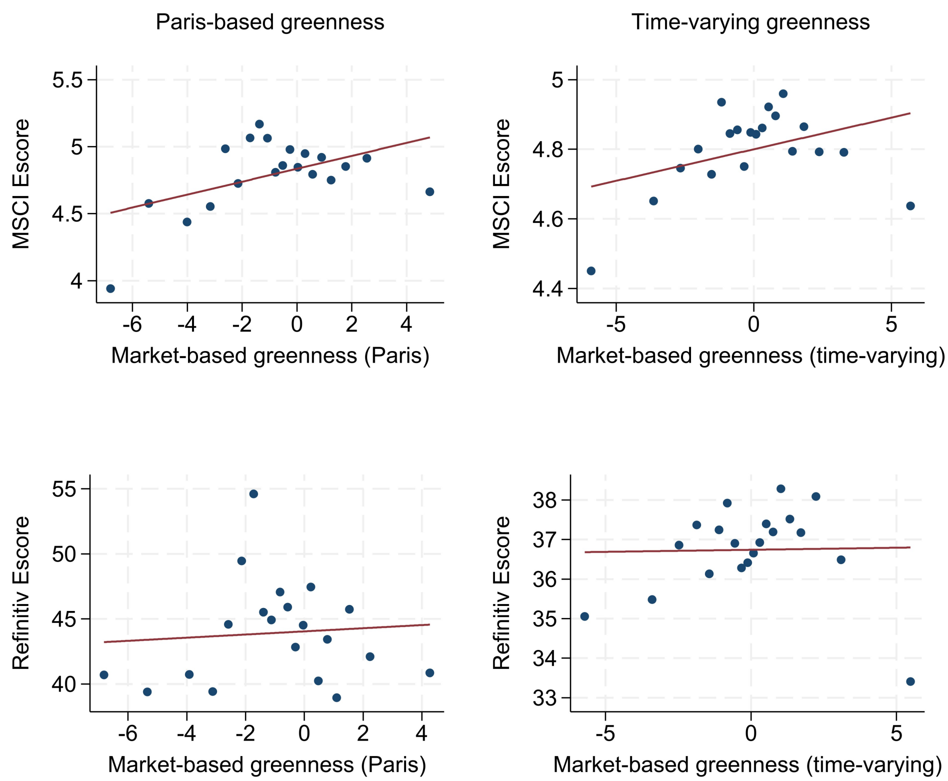


Panel B: Time-varying measure



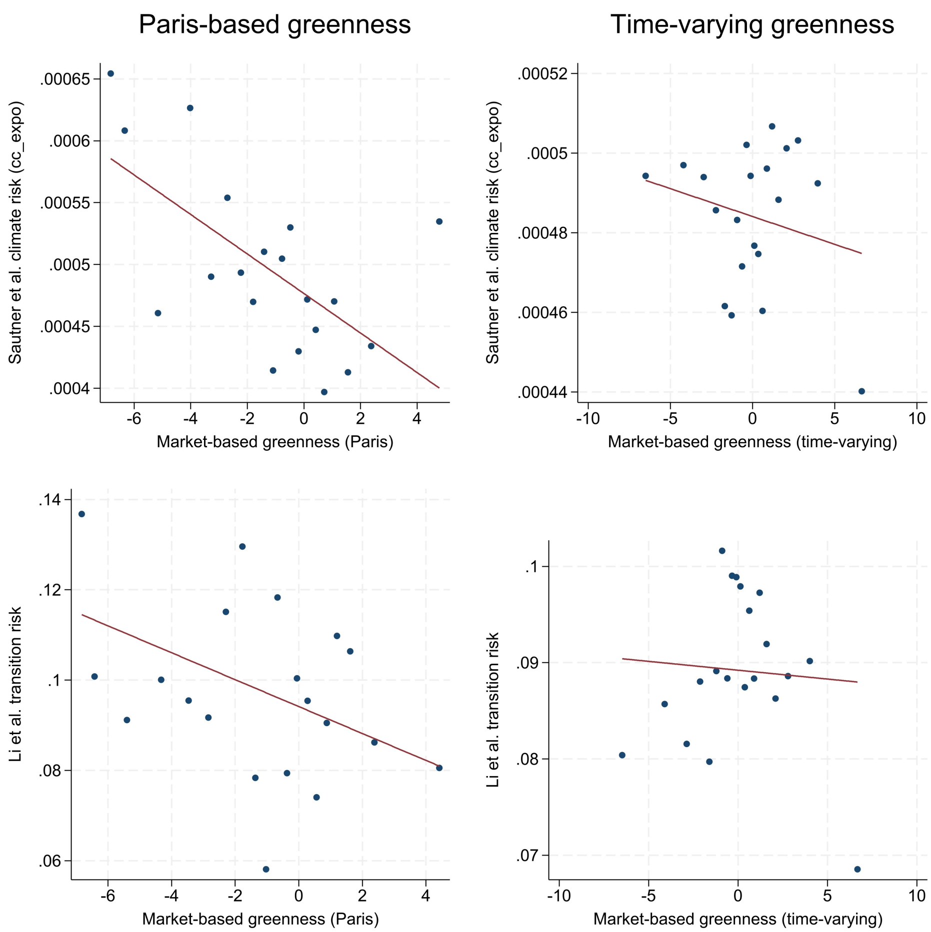
This figure shows firm-level market-based greenness (climate risk exposure) based on cumulative CAPM abnormal returns for different sectors. Abnormal Returns are displayed in %. Panel A shows returns between the end of the 2015 UN Climate Conference in Paris, COP 21, and the next trading day. Panel B shows the aggregated results of the time-varying measure. Sectors are classified according to the Global Industry Classification Standard (GICS). Only sectors with at least 2000 firm-year observations are displayed. Manually identified sectors with high market-based greenness are displayed in green. Manually identified sectors with low market-based greenness are displayed in brown.

Figure 4: Market-based greenness and E-scores



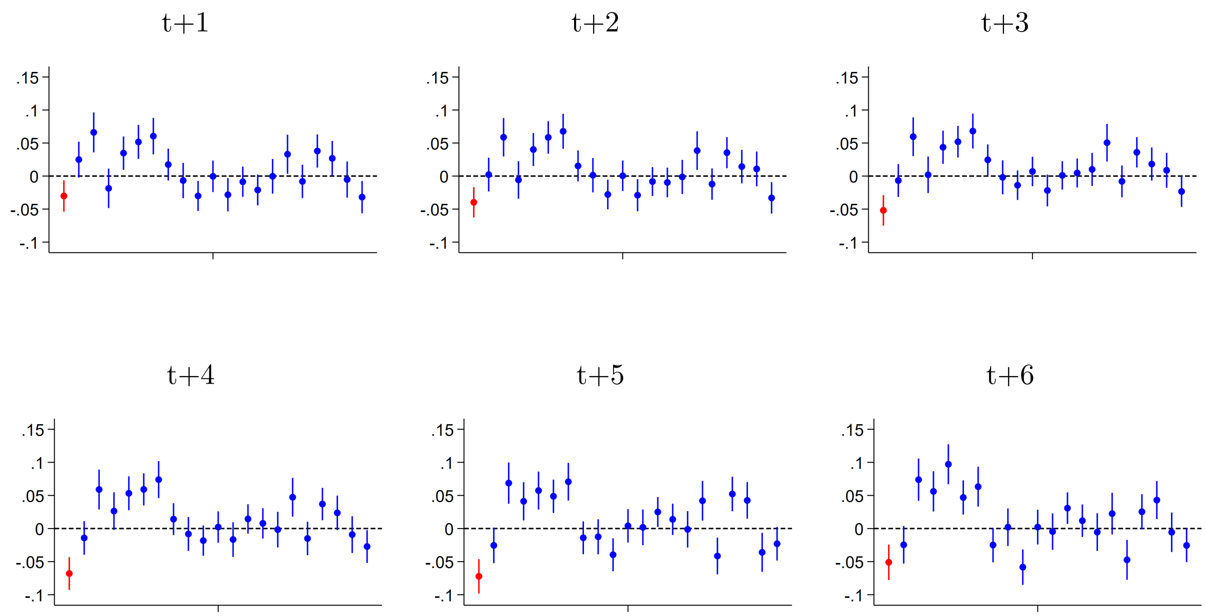
This figure provides binscatter plots of firm-level market-based greenness (%; x-axis) and different E-scores (y-axis). In the first column the market-based greenness is constructed based on returns between the end of the 2015 UN Climate Conference in Paris, COP 21, and the next trading day (Paris-based measure). In the second column market-based greenness is time-varying. The first row depicts MSCI E-scores on the y-axis. The second row depicts Refinitv E-scores on the y-axis. Fitted linear regression lines are depicted in red.

Figure 5: Firm level: Market-based greenness and text-based climate risk measures



This figure provides binscatter plots of firm-level market-based greenness (%; x-axis) and text-based climate risk measures (y-axis). In the first column, market-based greenness is constructed based on returns between the end of the 2015 UN Climate Conference in Paris, COP 21, and the next trading day (Paris-based measure). In the second column market-based greenness is time-varying. The first row uses text-based climate risk exposure from Sautner et al. (2023a). The second row uses a text-based transition risk measure from Li et al. (2024).

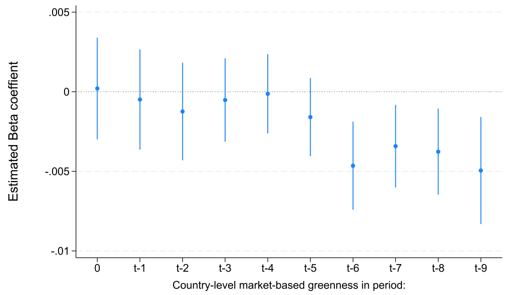
Figure 6: CO_2 regressions with placebo events



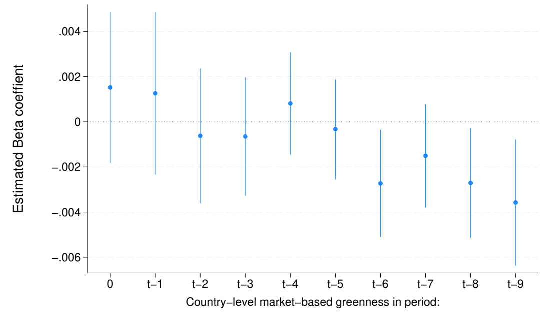
This figure shows coefficients of future CO_2 emissions predicted by the baseline greenness measure in red, and 20 placebo greenness measures in blue. The placebo measures are based on returns on randomly selected weekends. All regressions include sector and country fixed effects. Standard errors are clustered at the firm level.

Figure 7: Market-based greenness, *country*-level emissions and renewable energy

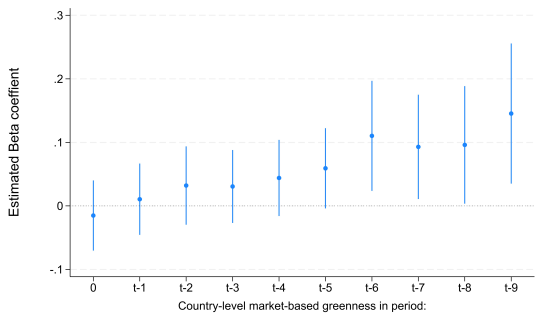
Panel A: log(CO_2 per capita)



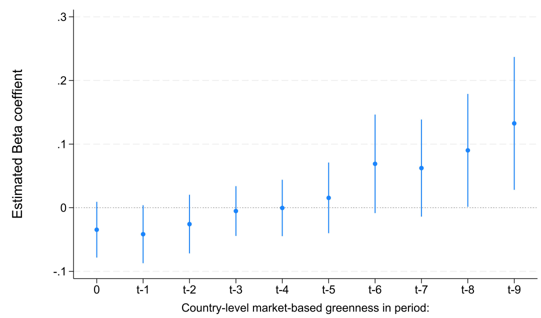
Panel B: CO_2 emission intensity log(CO_2/GDP)



Panel C: Share of renewable energy



Panel D: Share of renewable energy: Controlling for log(CO_2 per capita)



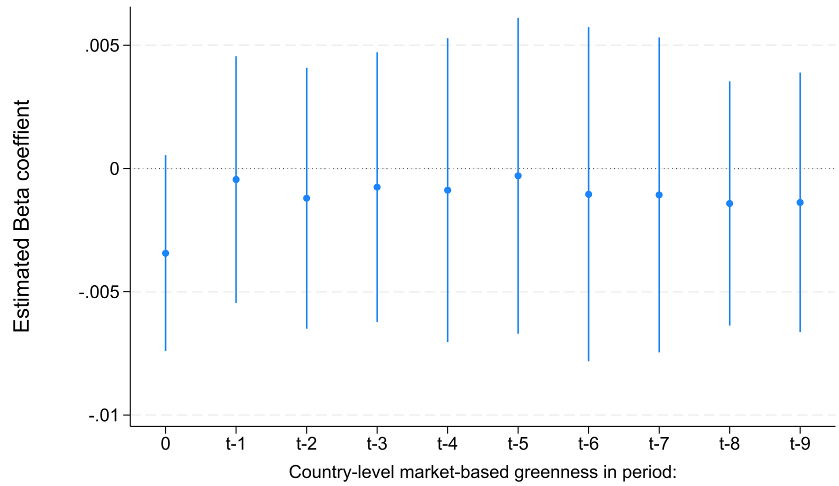
This figure plots beta coefficients of the following regression:

$$Y_{i,t} = \beta \text{ market-based greenness}_{i,t-k} + \gamma \text{ macro\_controls}_{i,t} + \alpha_i + \epsilon_{i,t}$$

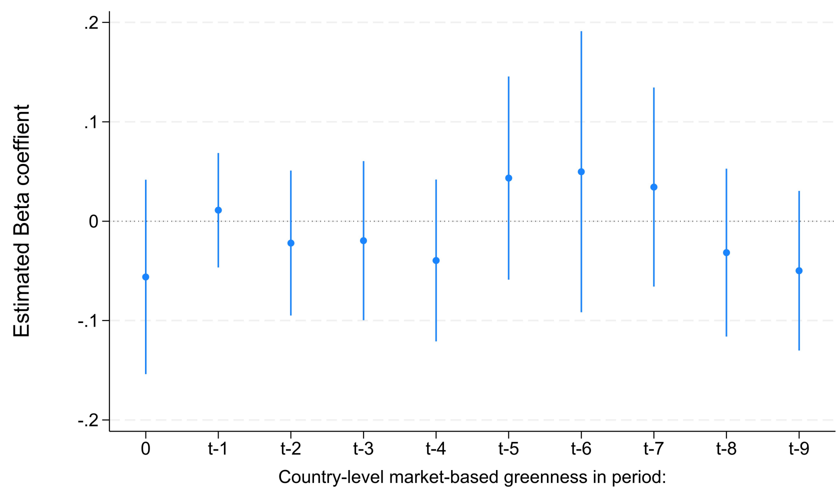
With countries i at year t, with lag k. Beta coefficients of the resulting regression and 90% confidence intervals are displayed on the y-axis. Different instances of $t-k$ are displayed on the x-axis. In Panel A, $Y_{i,t}$ is characterized as log(CO_2 per capita). In Panel B, $Y_{i,t}$ is characterized as log(CO_2/GDP), often referred to as emission intensity. In Panel C $Y_{i,t}$ is characterized as the share of renewable energy in the countries production mix. In Panel D, we additionally control for CO_2 per capita$_{i,t-k}$. Data on emissions is from the World Bank. Data on renewable energy is from the Green Growth Indicators provided by the OECD.

Figure 8: Relationship between market-based greenness and GDP per capita

Panel A: log(GDP per capita)



Panel B: log(GDP growth)



This figure plots beta coefficients of the following regression:

$$log(\text{growth indicator})_{i,t} = \beta \text{ market-based greenness}_{i,t-k} + \gamma \text{ macro\_controls}_{i,t} + \alpha_i + \alpha_t + \epsilon_{i,t}$$

With countries i at year t, with lag k. The respective growth indicator is shown in the panel headline: log(GDP per capita) and log(GDP growth). Beta coefficients of the resulting regression and 90% confidence intervals are displayed on the y-axis. Different instances of $t-k$ are displayed on the x-axis. Data on GDP per capita and GDP growth are from the World Bank.

Table 1: UN climate change conferences: Successes and failures

This table indicates our judgment of successful UN climate change conferences by a + and unsuccessful conferences by a −. These signs indicate the way we flip signs to create our measure of market-based greenness (see Section 3.3 and Equation (17)). The quotes are illustrative of the public's reception and are taken from press coverage or the official final press statements of the respective conferences.

Name	Location	End date	Sign	Press Quote
COP0	Rio de Janeiro, Brazil	Jun 14, 1992	+	"new-found prominence of the environment as an international issue" –NYT, Jun 14, 1992.
COP1	Berlin, Germany	Apr 7, 1995	+	"Defying the pessimistic predictions of some environmentalists, delegates at a United Nations conference agreed today to open negotiations to fix new limits on heat-trapping gases that threaten to change the global climate." –NYT, Apr 8, 1995.
COP2	Geneva, Switzerland	Jul 19, 1996	+	"The shift was welcomed by environmentalists as a significant step" –NYT, Jul 19,1996.
COP3	Kyoto, Japan	Dec 10, 1997	+	"After 10 days of tough negotiations, ministers and other high-level officials from 160 countries reached agreement this morning on a legally binding Protocol under which industrialized countries will reduce their collective emissions of greenhouse gases by 5.2%." –NYT, Dec 12, 1997.
COP4	Buenos Aires, Argentina	Nov 13, 1998	+	"proponents of the Kyoto Protocol, [...] declared victory in the two-week round of talks." –NYT, Nov 15, 1998.
COP5	Bonn, Germany	Nov 5, 1999	+	"Environmental ministers pledged on Thursday to lower emissions of greenhouse gases to combat global warming." –NYT, Nov 6, 1999.
COP6	The Hague, Netherlands	Nov 24, 2000	−	"It is extremely disappointing that political leaders were unable to work it out here and finalize guidelines for reducing greenhouse gas emissions, especially when the public had such high expectations," –UN Press release, Nov 25, 2000.
COP7	Marrakech, Morocco	Nov 10, 2001	+	"Global Warming Impasse Is Broken" –NYT headline, Nov 11, 2001.

Continued on next page

Name	Location	End date	Sign	Press Quote
COP8	New Delhi, India	Nov 1, 2002	+	"The New Delhi conference has achieved its main goals of further strengthening international collaboration on climate change while meeting the requirements of sustainable development" –UN Press release, Nov 1, 2002
COP9	Milan, Italy	Dec 12, 2003	+	"Parties adopted numerous decisions and conclusions on various issues" –IISD summary report.
COP10	Buenos Aires, Argentina	Dec 17, 2004	+	"During the meeting, Parties addressed and adopted numerous decisions and conclusions on various issues" –IISD summary report.
COP11	Montreal, Canada	Dec 9, 2005	−	"The United States and China, the world's current and projected leaders in greenhouse gas emissions, still refused to agree to mandatory steps to curtail the emissions" –NYT, Dec 10, 2005.
COP12	Nairobi, Kenya	Nov 17, 2006	+	"Big Conference on Warming Ends, Achieving Modest Results" –NYT headline, Nov 18, 2006.
COP13	Bali, Indonesia	Dec 14, 2007	+	"The world's faltering effort to cut greenhouse gas emissions got a new lease on life on Saturday" –NYT, Dec. 16, 2007.
COP14	Poznań, Poland	Dec 12, 2008	+	"While the Poznań negotiations did result in some progress, there were no significant breakthroughs, and negotiators face a hectic 12 months of talks leading up to the critical deadline of December 2009 in Copenhagen, Denmark." –IISD summary report.
COP15	Copenhagen, Denmark	Dec 18, 2009	−	"Low targets, goals dropped: Copenhagen ends in failure" –The Guardian, Dec 18, 2009; "Most delegates, however, left Copenhagen disappointed at what they saw as a "weak agreement," and questioning its practical implications given that the Copenhagen Accord had not been formally adopted as the outcome of the negotiations." –IISD summary report.
COP16	Cancún, Mexico	Dec 10, 2010	+	"Climate Talks End With Modest Deal on Emissions" –NYT headline, Dec 11, 2010.
COP17	Durban, South Africa	Dec 9, 2011	+	"Global climate change treaty in sight after Durban breakthrough" –The Guardian Headline, Dec 11, 2011.

Continued on next page

Name	Location	End date	Sign	Press Quote
COP18	Doha, Qatar	Dec 7, 2012	−	"extend the increasingly ineffective Kyoto Protocol a few years and to commit to more ambitious — but unspecified — actions" –NYT, Dec 8, 2012.
COP19	Warsaw, Poland	Nov 22, 2013	+	" pair of last-minute deals keeping alive the hope that a global effort can ward off a ruinous rise in temperatures." –NYT, Nov 23, 2013
COP20	Lima, Peru	Dec 12, 2014	+	"the first deal committing every country in the world to reducing [...] fossil fuel emissions [...]" –NYT, Dec 14, 2014
COP21	Paris, France	Dec 11, 2015	+	"Paris climate change agreement: the world's greatest diplomatic success" –The Guardian Headline, Dec 13, 2015; "A Climate Deal, 6 Fateful Years in the Making" –NYT headline, Dec 13, 2015.
COP22	Marrakech, Morocco	Nov 18, 2016	−	Donald Trump was elected president on Nov 8. "the election of Donald J. Trump — and his threat to withdraw the United States from the accord — shellshocked negotiators" –NYT, Nov 18, 2016.
COP23	Bonn, Germany	Nov 17, 2017	+	"negotiators said they had made headway on creating a formal process under the 2015 Paris agreement" –NYT, Nov 18, 2017.
COP24	Katowice, Poland	Dec 14, 2018	+	"Climate Negotiators Reach an Overtime Deal to Keep Paris Pact Alive" –NYT headline, Dec 15., 2018.
COP25	Madrid, Spain	Dec 13, 2019	+	"Climate talks in Madrid have ended with a partial agreement" –The Guardian, Dec 14, 2019.
COP26	Glasgow, UK	Nov 12, 2021	+	"Negotiators Strike a Climate Deal, but World Remains Far From Limiting Warming" –NYT headline, Nov 13, 2021.
COP27	Sharm El Sheikh, Egypt	Nov 18, 2022	+	"After 30 years of deadlock, a new U.N. climate agreement aims to pay developing countries for loss and damage caused by global warming." –NYT, Nov 19, 2022.

Table 2: Summary statistics

Summary statistics of the main firm-level dataset including data from 1992-2022. CO_2 emissions are reported in metric kilo tons. We report summary statistics based on regression samples with our time-varying greenness measure and the contemporaneous dependent variable, when applicable. Variables are defined in Table A.1.

	Mean	P10	P50	P90	SD	N
Full sample						
Market-based greenness (%)	−0.01	−4.35	−0.01	4.37	3.27	566787
Market-based greenness, raw	−0.24	−4.78	0.00	4.20	3.36	566787
Market-based greenness, FF3	0.02	−4.28	−0.01	4.40	3.26	566787
MSCI E-score	4.80	2.10	4.70	7.54	2.09	31745
RepRisk	7.13	5.00	7.00	9.33	1.77	84671
Refinitiv E-Score	36.74	0.00	33.01	79.59	29.44	26084
cc expo · 100 (Sautner et al., 2023a)	0.05	0.00	0.02	0.13	0.07	56733
Transition risk (Li et al., 2024)	0.08	0.00	0.00	0.29	0.19	42997
CO_2 sample						
Market-based greenness	−0.10	−2.84	−0.04	2.48	1.98	12506
Scope 1 CO_2 emissions (kt)	3454.10	3.95	125.44	9620.20	10032.80	12506
Total CO_2 emissions (kt)	4152.43	34.01	430.00	11307.00	10976.25	12346
Patent sample						
Market-based greenness	−0.08	−4.18	−0.13	4.00	3.19	23110
Any green patent	30.49	0.00	0.00	100.00	46.04	23110
Firm characteristics sample						
Market-based greenness	−0.01	−4.56	−0.01	4.64	3.38	412380
Implied volatility (%)	42.32	24.18	38.23	67.01	18.19	5900
Book leverage	0.24	0.00	0.19	0.52	0.25	412380
Cash to assets	0.17	0.01	0.10	0.43	0.19	381750
Investment	0.05	0.00	0.03	0.13	0.07	359435
R&D	0.23	0.00	0.02	0.18	1.45	142612
Employees (in thousands)	7.81	0.04	0.90	15.23	33.63	231534

Table 3: Relationship of market-based climate risk and scope 1 CO_2 emissions

Relationship of the firm-level market-based greenness measure with current (Column 1) and future (Columns 2-7) log(Scope 1 CO_2 emissions) at the firm level. The measure is based on CAPM abnormal returns. Panel A presents the results using the Paris-based measure as the independent variable. Panel B uses the time-varying measure as the independent variable. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.10**	-0.09**	-0.11**	-0.12***	-0.15***	-0.13***	-0.11***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
No. of obs.	1,018	1,101	1,189	1,300	1,457	1,530	1,572
R^2	0.005	0.004	0.006	0.007	0.011	0.008	0.005

Panel B: Time-varying measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.03**	-0.03**	-0.04***	-0.05***	-0.07***	-0.07***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
No. of obs.	12,506	13,646	14,750	15,450	14,772	13,672	12,407
R^2	0.000	0.000	0.001	0.001	0.002	0.002	0.001

Table 4: Predicting CO_2 with multiple measures

Correlation of the firm-level market-based greenness measure with current (Column 1) and future (Columns 2-7) log(scope 1 CO_2 emissions) at the firm level using other measures of greenness as control variables. The measure is based on CAPM abnormal returns. Panel A presents the results using the Paris-based measure as an independent variable. Panel B uses the time-varying measure as an independent variable. MSCI E-Scores, RepRisk Scores, Refinitiv's E-scores, Climate risk exposure by Sautner et al. (2023a), transition risk by Li et al. (2024), and log(market capitalization) are included as control variables. All regressions include country and sector fixed effects. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.26***	-0.24***	-0.20***	-0.17**	-0.12**	-0.10*	-0.11*
	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
Sautner et al. Measure	-74.22	-244.95	-200.60	-137.39	-123.26	-125.56	-63.29
	(226.61)	(244.98)	(230.21)	(221.54)	(167.05)	(162.47)	(171.07)
Li et al. Measure	1.06*	1.45**	1.50**	1.78***	1.92***	1.83***	1.79***
	(0.64)	(0.64)	(0.58)	(0.57)	(0.52)	(0.50)	(0.50)
MSCI E-score	-0.09	-0.08	-0.14***	-0.20***	-0.16***	-0.16***	-0.14***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Refinitiv E-score	0.02***	0.01**	0.01**	0.01**	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RepRisk	-0.08	-0.06	0.01	-0.03	0.00	-0.02	0.00
	(0.10)	(0.10)	(0.10)	(0.09)	(0.07)	(0.07)	(0.07)
log(market cap)	0.70***	0.74***	0.80***	0.73***	0.71***	0.64***	0.66***
	(0.15)	(0.14)	(0.14)	(0.12)	(0.10)	(0.10)	(0.10)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	225	246	270	300	350	363	364
R^2	0.637	0.629	0.652	0.618	0.649	0.646	0.630

Panel B: Time-varying measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.06**	-0.05**	-0.06***	-0.06***	-0.06***	-0.06***	-0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Sautner et al. Measure	271.25**	267.43**	278.59**	251.34**	225.27**	149.37	11.02
	(127.89)	(119.21)	(112.94)	(108.72)	(106.64)	(113.86)	(129.12)
Li et al. Measure	1.53***	1.58***	1.51***	1.57***	1.56***	1.62***	1.73***
	(0.33)	(0.32)	(0.30)	(0.30)	(0.31)	(0.34)	(0.37)
Refinitiv E-score	0.01***	0.01***	0.01***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MSCI E-score	-0.23***	-0.25***	-0.27***	-0.28***	-0.28***	-0.25***	-0.20***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
RepRisk	-0.16**	-0.12**	-0.10*	-0.11*	-0.08	-0.03	0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
log(market cap)	0.39***	0.42***	0.45***	0.45***	0.47***	0.55***	0.62***
	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2,526	2,782	3,048	3,273	3,341	2,970	2,565
R^2	0.446	0.448	0.454	0.451	0.467	0.511	0.568

Table 5: Greenness and any green patent

Correlation of the firm-level market-based greenness measure with current (Column 1) and future (Columns 2-7) Any Green Patent, scaled by a factor of 100. The measure is based on CAPM abnormal returns. Panel A presents the results using the Paris-based measure as an independent variable. Panel B uses the time-varying measure as an independent variable. All regressions include country and sector fixed effects. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var.:	Any Green Patent						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	1.06	1.07	1.50**	1.07	1.63**	1.10	2.44***
	(0.66)	(0.69)	(0.76)	(0.80)	(0.77)	(0.87)	(0.92)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	788	713	684	639	617	556	456
R^2	0.194	0.239	0.209	0.175	0.267	0.243	0.317

Panel B: Time-varying measure

Dep. var.:	Any Green Patent						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.06	0.04	0.03	0.11	0.14	0.02	0.21*
	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.11)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	23,110	21,935	20,812	19,681	18,559	17,559	16,522
R^2	0.146	0.145	0.146	0.147	0.149	0.151	0.154

Table 6: Correlation of market-based climate risk and implied volatility

Correlation of the firm-level market-based greenness measure with current (Column 1) and future (Columns 2-5) option-implied volatility of firms. The measure is based on CAPM abnormal returns. Panel A presents the results based on abnormal returns around the 2015 UN Climate Conference in Paris. Panel B uses the time-varying measure as the independent variable. We exclude years following the dot-com bubble (2001, 2002) and the great financial crises (2008, 2009). Implied volatilities are scaled by a factor of 100. All regressions include country and sector fixed effects. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var:	Implied volatility				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
Market-based greenness	-1.78***	-1.98***	-1.22***	-1.94***	-1.35***
	(0.38)	(0.39)	(0.35)	(0.35)	(0.31)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	526	490	446	407	374
R^2	0.358	0.411	0.358	0.441	0.450

Panel B: Time-varying measure

Dep. var:	Implied volatility				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
Market-based greenness	-0.20*	-0.16	0.16	0.09	0.00
	(0.12)	(0.13)	(0.12)	(0.10)	(0.10)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	5,900	5,803	5,596	4,971	4,399
R^2	0.202	0.200	0.189	0.195	0.219

Table 7: Greenness and firm characteristics

Correlation of the firm-level market-based greenness measure with firm-level characteristics. The measure is based on CAPM abnormal returns. All dependent variables are multiplied by 100 for better readability. Panel A presents the results using the Paris-based measure as an independent variable. Panel B uses the time-varying measure as an independent variable. All regressions include country and sector fixed effects. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var.:	Book Leverage	Cash to Assets	Investment	R&D	Log Employment
	(1)	(2)	(3)	(4)	(5)
Market-based greenness	-0.18***	0.06	-0.03**	0.57	0.17
	(0.06)	(0.04)	(0.01)	(0.63)	(0.54)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	22,673	20,926	19,900	8,742	13,554
R^2	0.124	0.214	0.136	0.139	0.337

Panel B: Time-varying measure

Dep. var.:	Book Leverage	Cash to Assets	Investment	R&D	Log Employment
	(1)	(2)	(3)	(4)	(5)
Market-based greenness	-0.04***	0.03***	-0.01***	-0.01	-0.24*
	(0.01)	(0.01)	(0.00)	(0.13)	(0.12)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	412,380	381,750	359,435	142,612	228,903
R^2	0.107	0.204	0.144	0.156	0.280

Table 8: Greenness and stock returns

Correlation between firm-level stock returns and the firm-level market-based greenness measure. We use the time-varying greenness measure constructed from CAPM abnormal returns. Monthly stock returns are from Compustat, winsorized at the 1% level, and scaled by 100 for readability. Months with UN climate conferences are excluded from the sample. Control variables are as in Bolton and Kacperczyk (2021). *BK* denotes the sample used in Bolton and Kacperczyk (2021), consisting of US firms from 2005 to 2017. Clustered standard errors at the firm and year levels in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

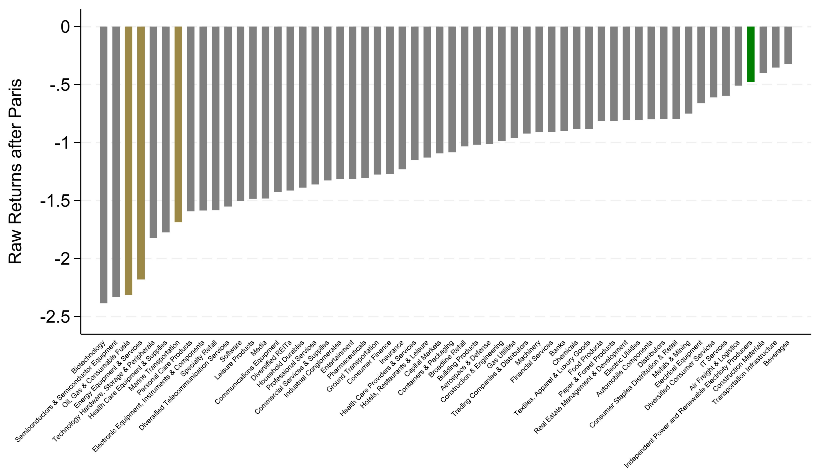
Dep. var.: Monthly returns							
	US sample				Global sample		
Indep. var.:	CO2		Market-based		Market-based		
Sample:	BK	Full	BK	Full	Full	2015-2020	pre 2015
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(CO2)	0.08**	0.03					
	(0.03)	(0.02)					
Market-based Greenness (%)			0.03	-0.00	0.05**	0.09**	0.05
			(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
LOGSIZE	0.10	0.10*	0.09*	0.10**	0.01	-0.00	0.06
	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.06)	(0.06)
BM	-2.23***	-2.95***	-2.10***	-2.19***	-0.80***	-1.02***	-0.74**
	(0.31)	(0.18)	(0.29)	(0.22)	(0.20)	(0.20)	(0.27)
LEVERAGE	-0.51	-0.76**	-0.23*	-0.01	-0.06	-0.50**	-0.56***
	(0.36)	(0.30)	(0.11)	(0.01)	(0.06)	(0.14)	(0.16)
MOM	-0.00	-0.00	-0.00	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
INVESTA	-2.73	-3.41***	-0.97	-0.00	-0.01***	-0.04	-0.01***
	(1.68)	(1.13)	(0.65)	(0.00)	(0.00)	(0.13)	(0.00)
ROE	0.01	0.00	0.00*	0.00***	0.00	0.00	0.00***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LOGPPE	-0.05	0.04	0.03	0.00	0.03	0.04	-0.00
	(0.06)	(0.05)	(0.05)	(0.04)	(0.03)	(0.05)	(0.05)
BETA	1.48	-6.15	-0.03	0.06	-0.89	0.30	-3.29
	(11.17)	(6.30)	(0.30)	(0.11)	(0.73)	(0.65)	(2.58)
VOLAT	8.38*	10.59***	-0.02	-0.04**	-0.08	-0.15	-0.19
	(4.27)	(3.56)	(0.04)	(0.01)	(0.05)	(0.27)	(0.14)
SALESGR	0.68	0.11	-0.00***	-0.00	0.00	0.00***	-0.00
	(0.45)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
EPSGR	0.00	0.00	0.00	-0.00	-0.00**	0.00***	-0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	26,393	65,582	335,056	1,027,107	2,355,543	808,070	1,206,414
R^2	0.271	0.257	0.163	0.134	0.098	0.069	0.128

A Internet Appendix figures & tables

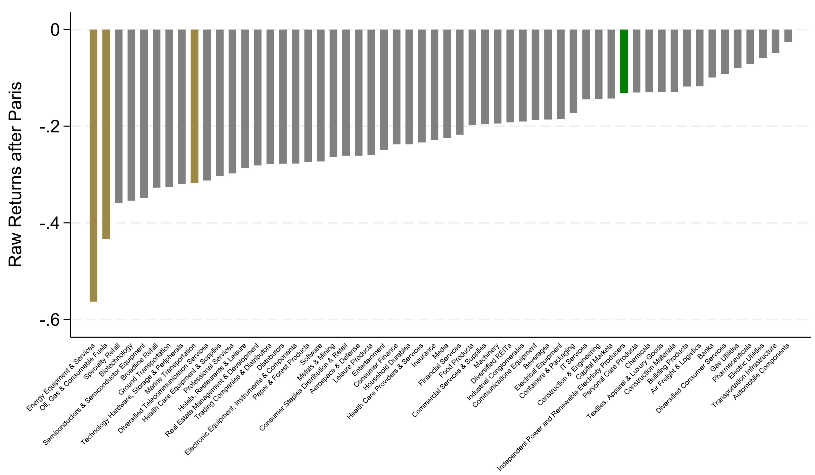
A.1 Internet Appendix figures

Figure A.1: Market-based greenness by sector: Raw returns

Panel A: Paris-based measure



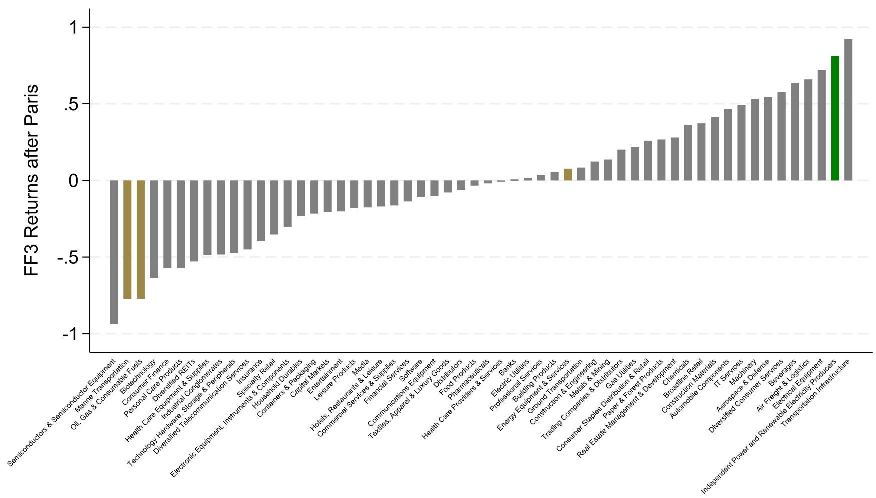
Panel B: Time-varying measure



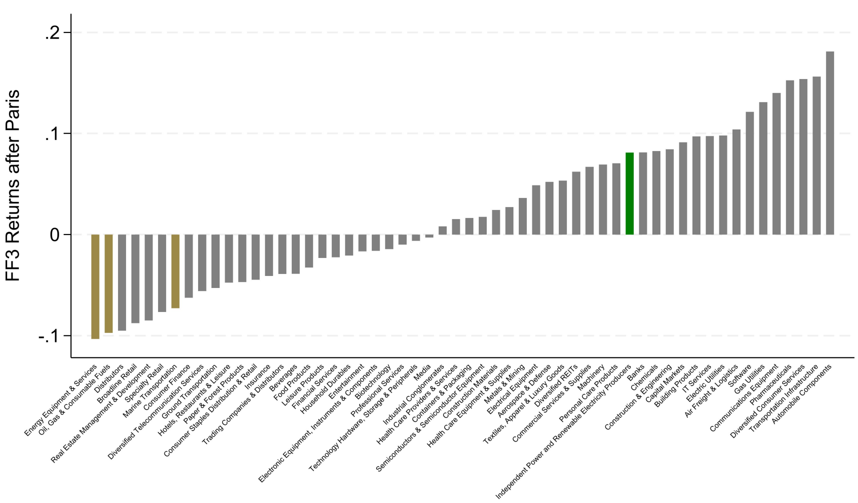
This figure shows firm-level market-based greenness based on unadjusted (raw) abnormal returns for different sectors. Panel A shows returns between the end of the 2015 UN Climate Conference in Paris, COP 21, and the next trading day (-1,0). Panel B shows the aggregated results of the time-varying measure. Sectors are classified according to the Global Industry Classification Standard (GICS). Only sectors with at least 2000 firm-year observations are displayed. Manually identified sectors with high market-based greenness are displayed in green. Manually identified sectors with low market-based greenness are displayed in brown.

Figure A.2: Market-based greenness by sector: FF3 returns

Panel A: Paris-based measure



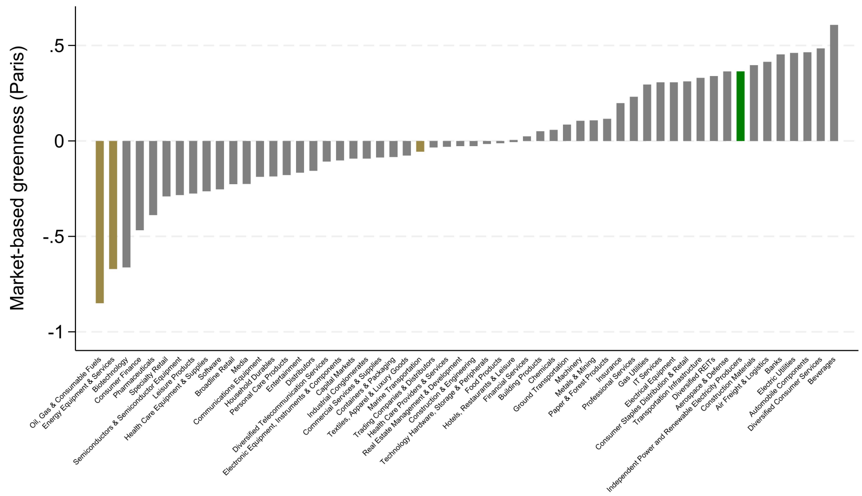
Panel B: Time-varying measure



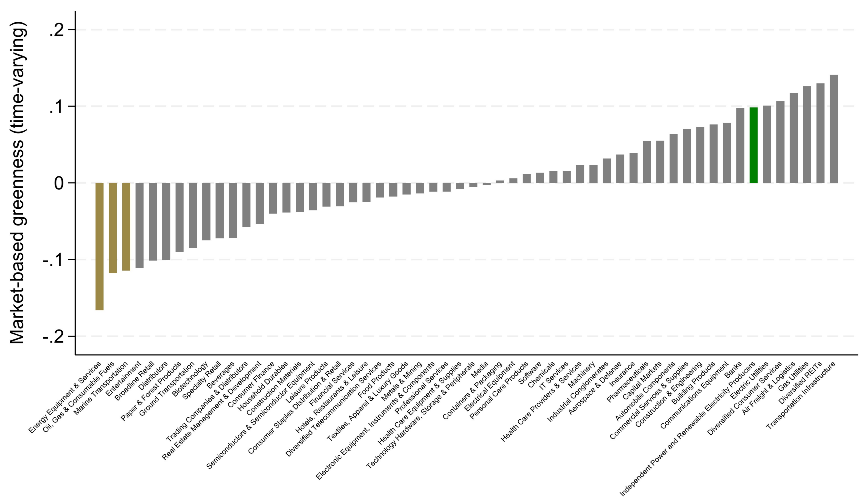
This figure shows firm-level market-based greenness based on Fama-French 3-factor adjusted abnormal returns for different sectors. Panel A shows returns between the end of the 2015 UN Climate Conference in Paris, COP 21, and the next trading day (-1,0). Panel B shows the aggregated results of the time-varying measure. Sectors are classified according to the Global Industry Classification Standard (GICS). Only sectors with at least 2000 firm-year observations are displayed. Manually identified sectors with high market-based greenness are displayed in green. Manually identified sectors with low market-based greenness are displayed in brown.

Figure A.3: Market-based greenness by sector: Country demeaned

Panel A: Paris-based measure

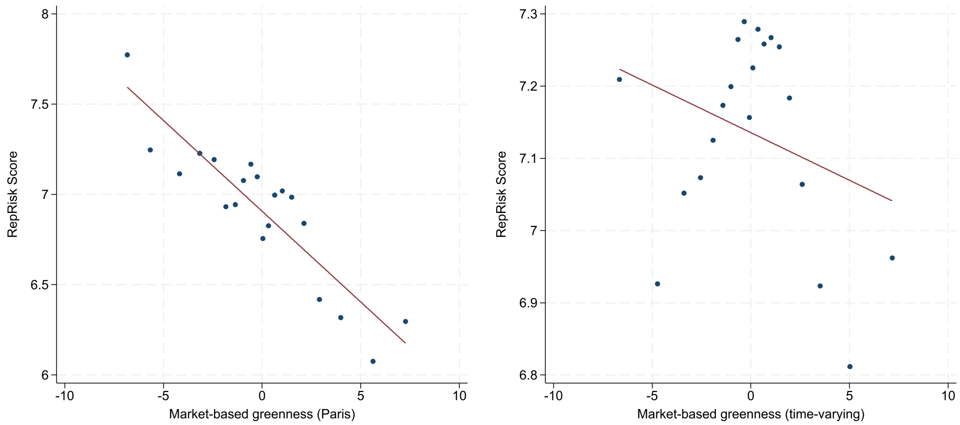


Panel B: Time-varying measure



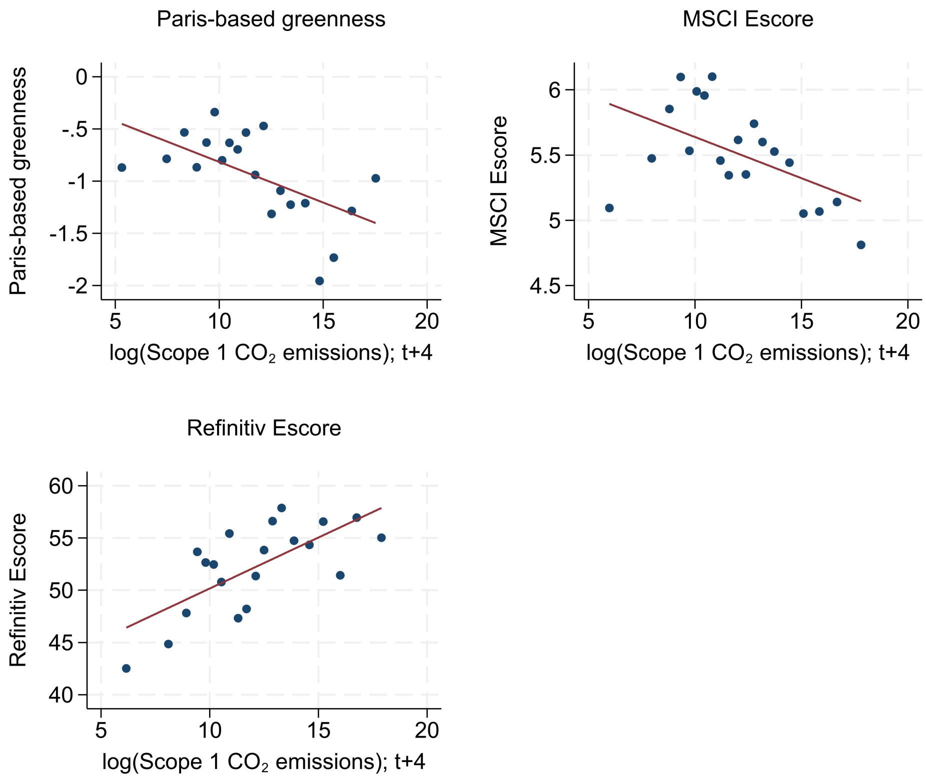
This figure shows firm-level market-based greenness based on cumulative CAPM abnormal returns for different sectors, demeaned by country. Panel A shows returns between the end of the 2015 UN Climate Conference in Paris, COP 21, and the next trading day (-1,0). Panel B shows the aggregated results of the time-varying measure. Sectors are classified according to the Global Industry Classification Standard (GICS). Only sectors with at least 2000 firm-year observations are displayed. Manually identified sectors with high market-based greenness are displayed in green. Manually identified sectors with low market-based greenness are displayed in brown.

Figure A.4: Market-based greenness and RepRisk



This figure provides binscatter plots of firm-level market-based greenness (%; x-axis) and RepRisk. In the first column the market-based greenness is constructed based on returns between the end of the 2015 UN Climate Conference in Paris, COP 21, and the next trading day (Paris-based measure). In the second column market-based greenness is time-varying. Fitted linear regression lines are depicted in red.

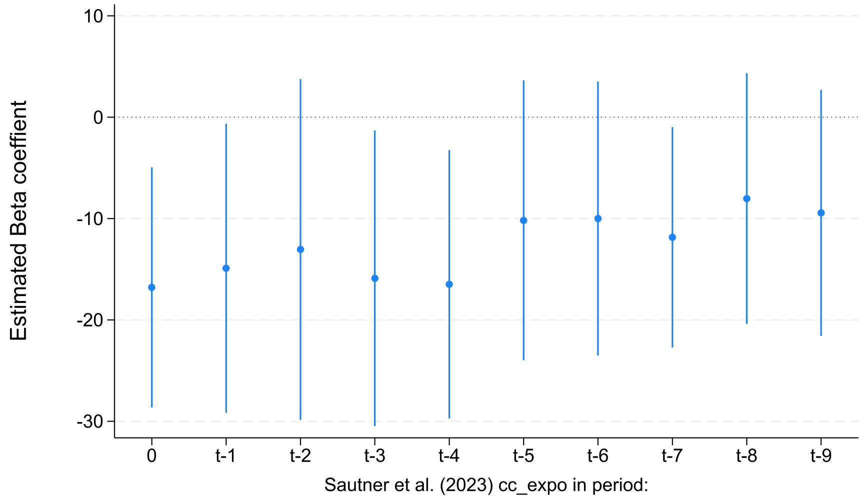
Figure A.5: CO_2 emissions, market-based greenness, and E-Scores



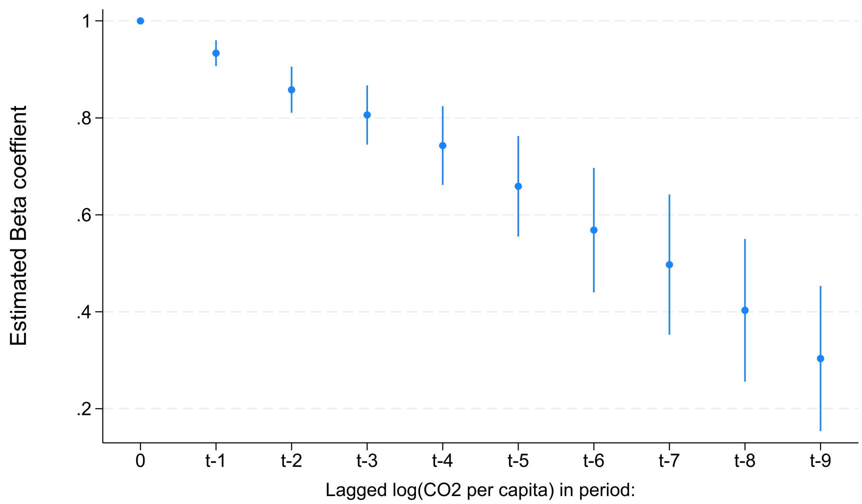
This figure provides a binscatter plot of firm-level greenness measures (market-based and E-scores) (y-axis) and the log of Scope 1 CO_2 emissions in $t+4$ (x-axis). Fitted linear regression lines are depicted in red.

Figure A.6: Alternative measures of climate risk and country-level emissions

Panel A: Sautner et al. (2023a)



Panel B: Lagged log(CO_2 per capita) emissions

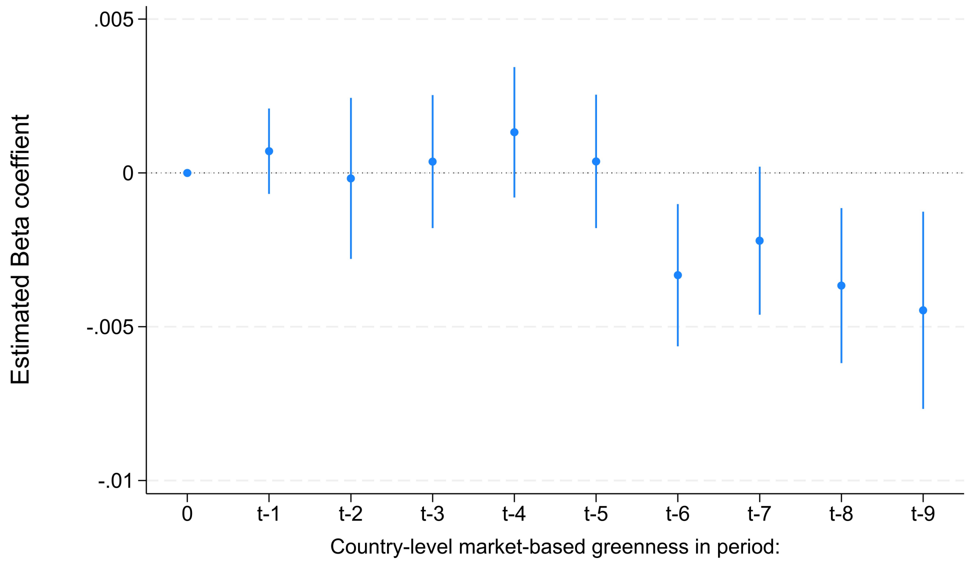


This figure plots beta coefficients of the following regression:

$$log(\text{Emissions})_{i,t} = \beta \text{ alternative\_greenness}_{i,t-k} + \gamma \text{ macro\_controls}_{i,t} + \alpha_i + \epsilon_{i,t}$$

With countries i at year t, with lag k. Beta coefficients of the resulting regression and 90% confidence intervals are displayed on the y-axis. Different instances of $t-k$ are displayed on the x-axis. In Panel A alternative_greenness$_{i,t-k}$ is defined as cc_expo from Sautner et al. (2023a). In Panel B it is defined as lagged log(CO_2 per capita). In both Panels, emissions$_{i,t}$ are characterized as CO_2 per capita. Data on emissions is from the World Bank.

Figure A.7: Relationship between market-based greenness and country-level emissions: Controlling for lagged emissions



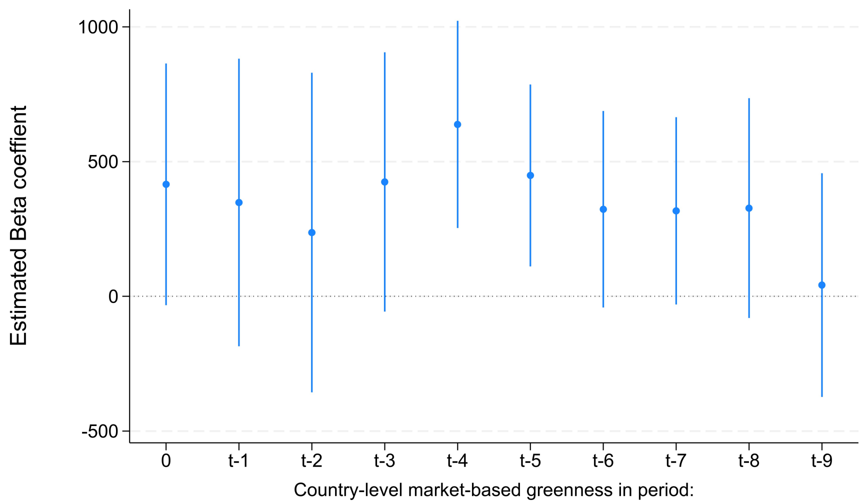
This figure plots beta coefficients of the following regression:

$log(CO_2 \text{ per capita})_{i,t} = \beta \text{ market-based greenness}_{i,t-k} + \gamma \text{ macro\_controls}_{i,t} + log(CO_2 \text{ per capita})_{i,t-k} + \alpha_i + \epsilon_{i,t}$

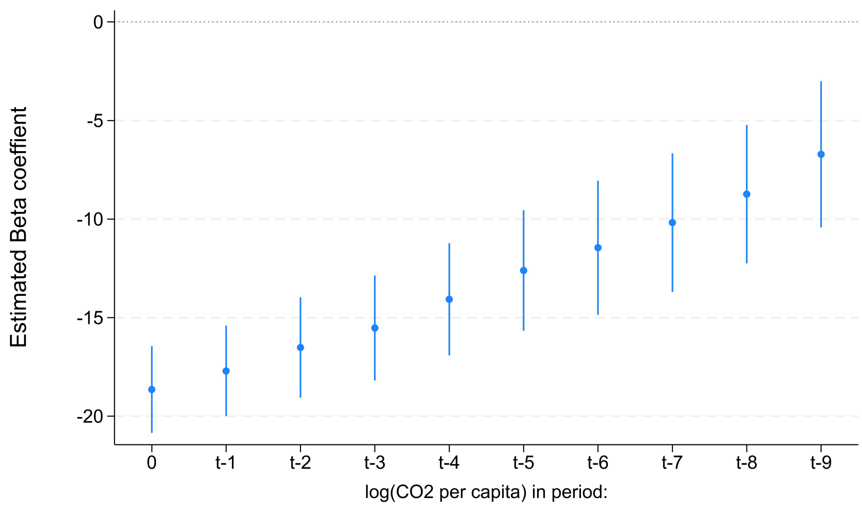
With countries i at year t, with lag k. Beta coefficients of the resulting regression and 90% confidence intervals are displayed on the y-axis. Different instances of $t - k$ are displayed on the x-axis. Data on emissions is from the World Bank.

Figure A.8: Relationship between alternative greenness measures and the share of renewable energy

Panel A: Sautner et al. (2023a) measure



Panel B: log(CO_2 per capita)



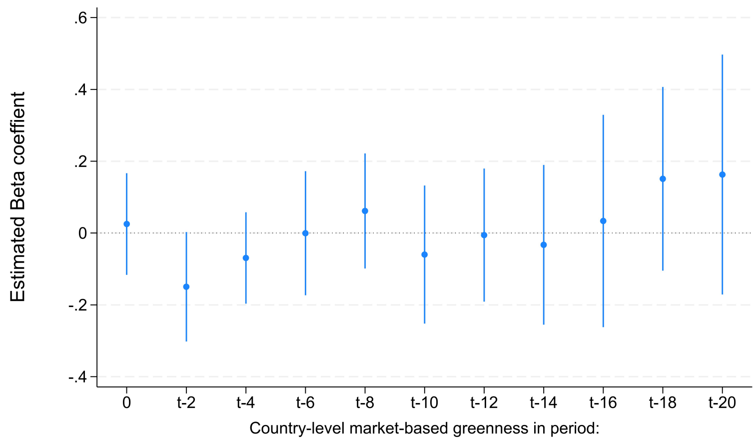
This figure plots beta coefficients of the following regression:

$$log(\text{share of renewable energy})_{i,t} = \beta \text{ other climate risk indicator}_{i,t-k} + \gamma \text{ macro\_controls}_{i,t} + \alpha_i + \epsilon_{i,t}$$

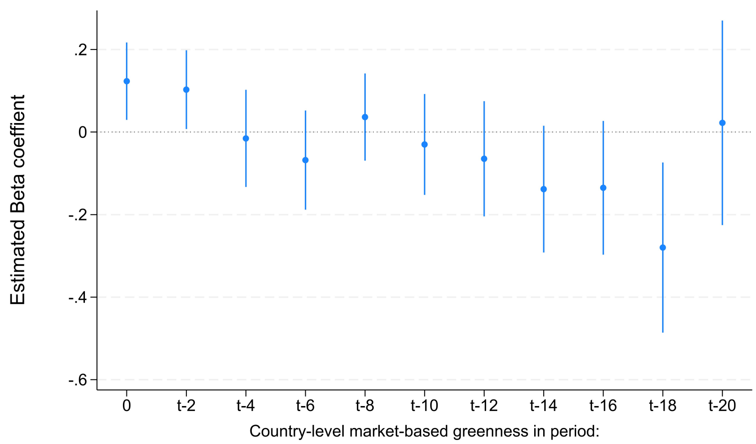
With countries i at year t, with lag k. Beta coefficients of the resulting regression and 90% confidence intervals are displayed on the y-axis. Different instances of $t-k$ are displayed on the x-axis. In Panel A, other climate risk indicator$_{i,t-k}$ is the climate risk exposure from Sautner et al. (2023a) at the country level. In Panel B, other climate risk indicator$_{i,t-k}$ is log(CO_2 per capita) at the country level. Data on renewable energy is from the Green Growth Indicators provided by the OECD.

Figure A.9: Relationship between market-based greenness and physical risk: Natural disasters

Panel A: log(total disaster damages)



Panel B: log(number of people affected)



This figure plots beta coefficients of the following regression:

$$log(\text{disaster losses})_{i,t} = \beta \text{ market-based greenness}_{i,t-k} + \gamma \text{ macro\_controls}_{i,t} + \alpha_i + \epsilon_{i,t}$$

With countries i at year t, with lag k. Beta coefficients of the resulting regression and 90% confidence intervals are displayed on the y-axis. Different instances of $t-k$ are displayed on the x-axis. In Panel A, disaster losses$_{i,t}$ is defined as the monetary damage caused by disasters in USD. In Panel B, disaster losses$_{i,t}$ is defined as the number of people affected by disasters.

A.2 Internet Appendix tables

Table A.1: Variable definitions

Variable	Definition
Market-based greenness variables	
Market-based greenness	CAPM abn. returns; (-1, 0) event window around climate change conference. Own Calculations.
Market-based greenness, raw	Raw abn. returns; (-1, 0) event window around climate change conference. Own Calculations.
Market-based greenness, FF3	Fama-French 3-factor adjusted abn. returns; (-1, 0) event window around climate change conference. Own Calculations.
Other firm-level variables	
GICS sectors	MSCI Global Industry Classification Standard sectors.
MSCI E-score	Environmental pillar score. Source: MSCI
RepRisk score	Reputation risk rating. Rescaled to a 1-10 scale. Lower scores mean higher reputational risk. Source: RepRisk
E-score	Environmental Score of the ESG score. Source: Refinitiv.
cc_expo	Firm-level climate change exposure based on text from firms' earnings calls. Source: Sautner et al. (2023a).
Transition risk	Firm-level measure of transition risk based on text from firms' earnings calls. Source: Li et al. (2024).
Scope 1 CO_2 emissions (kt)	Scope 1 CO_2 emissions in metric kilo tons. Source: Refinitiv. Used as log(Scope 1 CO_2 emissions) in the regressions.
Total CO_2 emissions (kt)	Total CO_2 emissions in metric kilo tons. Source: Refinitiv. Used as log(Total CO_2 emissions) in the regressions.
Any green patent ($\cdot$100)	Indicator for a firm filing at least one patent, conditional on filing any patent. Source: UPSTO.
Implied volatility (%)	Forward 365-day implied volatility measure in % built from OptionMetrics at-the-money options. Source: Alfaro et al. (2024).

Variable definitions (cont.)

Variable	Definition
Other firm-level variables (cont.)	
Cash to assets	Cash holdings scaled by total assets. Source: Compustat.
Book leverage	Total debt scaled by total assets. Source: Compustat.
Investment	Capital expenditures scaled by total assets. Source: Compustat
R&D	R&D expenditures scaled by sales. Source: Compustat
Log employment	Log number of employees (in thousands). Source: Compustat
Main country-level variables	
CO_2 emissions per capita	CO_2 emissions per capita in metric tons. Source: World Development Indicators, World Bank.
CO_2 emission intensity	CO_2 emission intensity (kg per 2021 PPP $ of GDP). Source: World Bank.
Share of renewable energy	Share of renewable sources (hydro, geothermal, solar, wind & biomass) in total energy supply. Source: OECD Green Growth Indicators.
GDP per capita	GDP per capita (current US$). Source: World Bank.
GDP growth	GDP growth (annual %). Source: World Bank.
Country-level control variables	
GNI per capita	GNI per capita, PPP (current international $). Source: World Bank.
Inflation	Inflation, GDP deflator (annual %). Source: World Bank.
Population	Total Population. Source: World Bank.
WGI indicators	World Governance Indicators: Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law, Control of Corruption. Source: World Bank.

Table A.2: Correlation of firm-level market-based greenness measures with other existing measures of climate risk

Panel A uses market-based greenness based on the Paris Climate Agreement. Panel B uses the time-varying measure. Correlations are displayed with MSCI E-Scores (Column 1), Refinitiv's E-score (Column 2), Climate risk exposure (cc_expo x 1000) by Sautner et al. (2023a) (Column 3), and transition risk (x100) by Li et al. (2024) (Column 4). The greenness measures are based on CAPM abnormal returns. Firm-level clustered standard errors in parentheses. Significance Levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dependent variable:	E-Scores		Text-based Measures	
Source:	MSCI	Refinitiv	Sautner et al.	Li et al.
	(1)	(2)	(3)	(4)
Market-based greenness	0.048***	0.121	-0.160***	-0.298*
	(0.014)	(0.261)	(0.041)	(0.156)
No. of obs.	3,304	1,789	3,532	1,945
R^2	0.003	0.000	0.005	0.002

Panel B: Time-varying measure

Dependent variable:	E-Scores		Text-based Measures	
Source:	MSCI	Refinitiv	Sautner et al.	Li et al.
	(1)	(2)	(3)	(4)
Market-based greenness	0.018***	0.010	-0.014	-0.018
	(0.005)	(0.076)	(0.010)	(0.037)
No. of obs.	31,745	26,084	56,733	31,720
R^2	0.000	0.000	0.000	0.000

Table A.3: Correlation of market-based climate risk and scope 1 CO_2 emissions: Harmonized sample

Correlation of the firm-level market-based greenness measure with current (Column 1) and future (Columns 2-7) log(scope 1 CO_2) emissions. Different from Table 3, the results presented here are based on a harmonized sample. The measure is based on CAPM abnormal returns. Panel A presents the results using the Paris-based measure as the independent variable. Panel B uses the time-varying measure as the independent variable. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.12**	-0.11**	-0.12**	-0.12**	-0.12**	-0.11**	-0.11**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
No. of obs.	830	830	830	830	830	830	830
R^2	0.008	0.007	0.007	0.008	0.008	0.007	0.006

Panel B: Time-varying measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.04**	-0.04**	-0.04**	-0.04**	-0.04**	-0.04**	-0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
No. of obs.	6,023	6,023	6,023	6,023	6,023	6,023	6,023
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Table A.4: Market-based climate risk and CO_2 emissions: Different returns

This table shows the results of a regression of carbon emissions on the firm-level market-based climate risk measure. Panel A shows results using the measure based on abnormal returns around the 2015 UN Climate Conference in Paris. Panel B uses the time-varying climate risk measure. The dependent variables are log(scope 1 CO_2 emissions) in t+4 (Columns 1-3) and log(total CO_2 emissions) in t+4 (Columns 4-6). The calculation of the climate risk measures are abnormal returns based on CAPM in columns 1 and 4, raw returns in columns 2 and 5, and abnormal returns based on the Fama-French three factor model in columns 3 and 6. Firm-level clustered standard errors in parentheses. Significance Levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dependent variable:	log(Scope 1 CO_2 emissions (t+4))			log(Total CO_2 emissions (t+4))		
AR calculation:	CAPM	Raw	FF3	CAPM	Raw	FF3
	(1)	(2)	(3)	(4)	(5)	(6)
Market-based greenness, CAPM	-0.068***			-0.038***		
	(0.013)			(0.009)		
Market-based greenness, raw		-0.040***			-0.015*	
		(0.011)			(0.008)	
Market-based greenness, FF3			-0.048***			-0.026***
			(0.013)			(0.010)
No. of obs.	14,772	14,772	14,772	16,468	16,468	16,468
R^2	0.002	0.001	0.001	0.001	0.000	0.000

Panel B: Time-varying measure

Dependent variable:	log(Scope 1 CO_2 emissions (t+4))			log(Total CO_2 emissions (t+4))		
AR calculation:	CAPM	Raw	FF3	CAPM	Raw	FF3
	(1)	(2)	(3)	(4)	(5)	(6)
Market-based greenness, CAPM	-0.07***			-0.04***		
	(0.01)			(0.01)		
Market-based greenness, raw		-0.04***			-0.02*	
		(0.01)			(0.01)	
Market-based greenness, FF3			-0.05***			-0.03***
			(0.01)			(0.01)
No. of obs.	14,772	14,772	14,772	16,468	16,468	16,468
R^2	0.002	0.001	0.001	0.001	0.000	0.000

Table A.5: Predicting CO_2 with multiple measures: Harmonized sample

Correlation of the firm-level market-based greenness measure with current (Column 1) and future (Columns 2-7) log(scope 1 CO_2 emissions) at the firm level using other measures of greenness as control variables, keeping a harmonized sample. The measure is based on CAPM abnormal returns. Panel A presents the results using the Paris-based measure as an independent variable. Panel B uses the time-varying measure as an independent variable. MSCI E-Scores, RepRisk Scores, Refinitiv's E-scores, Climate risk exposure by Sautner et al. (2023a), transition risk by Li et al. (2024), and log(market capitalization) are included as control variables. All regressions include country and sector fixed effects. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.27***	-0.26***	-0.28***	-0.27***	-0.26***	-0.24***	-0.24**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Sautner et al. Measure	-269.35	-310.40	-314.13	-293.34	-301.69	-235.32	-241.17
	(270.20)	(278.32)	(276.49)	(281.06)	(269.03)	(252.58)	(258.75)
Li et al. Measure	1.22*	1.32*	1.39*	1.40**	1.39**	1.27**	1.48**
	(0.74)	(0.73)	(0.71)	(0.71)	(0.67)	(0.63)	(0.66)
MSCI E-score	-0.09	-0.09	-0.08	-0.08	-0.08	-0.10	-0.10
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Refinitiv E-score	0.02**	0.01**	0.01**	0.01**	0.02**	0.01**	0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
RepRisk	-0.08	-0.07	-0.07	-0.04	-0.07	-0.09	-0.09
	(0.11)	(0.11)	(0.12)	(0.12)	(0.10)	(0.10)	(0.10)
log(market cap)	0.72***	0.72***	0.71***	0.72***	0.69***	0.65***	0.63***
	(0.18)	(0.18)	(0.18)	(0.18)	(0.16)	(0.16)	(0.16)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	185	185	185	185	185	185	185
R^2	0.634	0.625	0.630	0.622	0.636	0.640	0.629

Panel B: Time-varying measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.09***	-0.09***	-0.09***	-0.09***	-0.09***	-0.08***	-0.08***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Sautner et al. Measure	-128.27	-121.34	-141.80	-155.26	-155.87	-137.97	-141.13
	(204.23)	(203.04)	(204.29)	(206.78)	(207.36)	(205.61)	(206.86)
Li et al. Measure	1.67***	1.67***	1.66***	1.68***	1.64***	1.62***	1.64***
	(0.49)	(0.48)	(0.48)	(0.47)	(0.47)	(0.47)	(0.47)
MSCI E-score	-0.19***	-0.18***	-0.18***	-0.18***	-0.18***	-0.18***	-0.18***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Refinitiv E-score	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RepRisk	-0.03	-0.02	-0.02	-0.01	-0.01	-0.00	-0.00
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)
log(market cap)	0.60***	0.62***	0.63***	0.63***	0.63***	0.64***	0.62***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	1,264	1,264	1,264	1,264	1,264	1,264	1,264
R^2	0.549	0.548	0.552	0.552	0.554	0.554	0.556

Table A.6: Predicting CO_2 with other measures

Correlation of the firm-level market-based greenness measure with current (Column 1) and future (Columns 2-7) log(scope 1 CO_2 emissions) at the firm level using other measures of greenness as control variables. The measure is based on CAPM abnormal returns. Panel A presents the results using the Paris-based measure as an independent variable. Panel B uses the time-varying measure as an independent variable. Different from Table 4, we use MSCI Climate Change Theme Scores, and the regulatory Climate risk exposure by Sautner et al. (2023a) as alternative control variables while all other controls are the same. All regressions include country and sector fixed effects. Firm-level clustered standard errors in parentheses.

Panel A: Paris-based measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.23***	-0.25***	-0.21***	-0.19***	-0.13**	-0.11**	-0.12**
	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Sautner (regulatory)	988.72	1680.58	1935.78	2481.31	1611.21	2145.16	1300.69
	(2035.68)	(2132.48)	(2133.92)	(2160.86)	(1932.45)	(1919.62)	(1896.26)
Li et al. Measure	0.92*	0.93*	1.04**	1.37***	1.78***	1.63***	1.73***
	(0.51)	(0.48)	(0.46)	(0.45)	(0.45)	(0.42)	(0.42)
MSCI CC-score	-0.29***	-0.28***	-0.29***	-0.30***	-0.24***	-0.24***	-0.23***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Refinitiv E-score	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RepRisk	-0.04	-0.02	0.03	-0.03	-0.00	-0.03	0.00
	(0.10)	(0.09)	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)
log(market cap)	0.84***	0.90***	0.92***	0.84***	0.78***	0.70***	0.72***
	(0.16)	(0.15)	(0.14)	(0.12)	(0.10)	(0.10)	(0.10)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	224	245	268	299	345	359	361
R^2	0.668	0.663	0.686	0.656	0.672	0.669	0.652

Panel B: Time-varying measure

Dep. var.:	log(Scope 1 CO_2 emissions)						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	-0.09***	-0.08***	-0.08***	-0.07***	-0.08***	-0.10***	-0.14***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Sautner (regulatory)	4470.94***	4605.14***	4482.39***	4567.09***	4244.70***	3214.04***	1647.76
	(1093.14)	(1050.28)	(1055.35)	(1070.42)	(1044.29)	(1160.05)	(1249.48)
Li et al. Measure	1.38***	1.55***	1.53***	1.60***	1.58***	1.48***	1.38***
	(0.32)	(0.30)	(0.28)	(0.28)	(0.27)	(0.30)	(0.35)
MSCI CC-score	-0.34***	-0.34***	-0.33***	-0.32***	-0.31***	-0.29***	-0.26***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Refinitiv E-score	0.01***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RepRisk	-0.22***	-0.18***	-0.17***	-0.19***	-0.17***	-0.10*	-0.04
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
log(market cap)	0.41***	0.43***	0.41***	0.38***	0.40***	0.50***	0.61***
	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	1,568	1,745	1,955	2,172	2,223	1,847	1,419
R^2	0.419	0.417	0.416	0.411	0.421	0.463	0.551

Table A.7: Correlation of implied volatility using market-based greenness, harmonized sample

Correlation of the firm-level market-based greenness measure with current (Column 1) and future (Columns 2-5) option-implied volatility of firms. The measure is based on CAPM abnormal returns. Panel A presents the results based on abnormal returns around the 2015 UN Climate Conference in Paris. Panel B uses the time-varying measure as the independent variable. We exclude years following the dot-com bubble (2001, 2002) and the great financial crises (2008, 2009). We use a harmonized sample, i.e. the same set of observations for each regression. Implied volatilities are scaled by a factor of 100. All regressions include country and sector fixed effects. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var:	Implied volatility				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
Market-based greenness	-1.51***	-2.23***	-1.55***	-1.57***	-1.47***
	(0.29)	(0.42)	(0.33)	(0.35)	(0.33)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	347	347	347	347	347
R^2	0.429	0.479	0.470	0.420	0.446

Panel B: Time-varying measure

Dep. var:	Implied volatility				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
Market-based greenness	-0.06	-0.35**	-0.32**	-0.31**	-0.32**
	(0.15)	(0.17)	(0.16)	(0.14)	(0.13)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	2,793	2,793	2,793	2,793	2,793
R^2	0.260	0.253	0.231	0.249	0.255

Table A.8: Correlation of implied volatility with multiple measures

This table shows regressions with current (Column 1) and future (Columns 2-5) option-implied volatility of firms as dependent variable. Independent variables are the firm-level market-based greenness based on CAPM abnormal returns, the measures by Sautner et al. (2023a) and Li et al. (2024), Refinitiv and MSCI E-Scores as well as Rep Risk scores. Panel A presents the results based on abnormal returns around the 2015 UN Climate Conference in Paris. Panel B uses the time-varying measure. We exclude years following the dot-com bubble (2001, 2002) and the great financial crises (2008, 2009). Implied volatilities are scaled by a factor of 100. All regressions include country and sector fixed effects. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var:	Implied volatility				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
Market-based greenness	-0.95**	-1.83***	-1.50***	-1.31***	-1.18***
	(0.38)	(0.43)	(0.36)	(0.39)	(0.42)
Sautner et al. Measure	-388.58	-753.33	216.12	-86.24	-1,863.78
	(1,637.96)	(2,821.82)	(2,556.92)	(2,030.14)	(2,128.63)
Li et al. Measure	-15.36**	-12.52	-10.61	-3.42	-7.63
	(7.54)	(8.22)	(7.21)	(5.26)	(6.72)
Refinitiv E-score	-0.08**	-0.05	-0.06	-0.06	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
MSCI E-score	-0.53	-0.92	-0.63	-1.03	-1.12
	(0.57)	(0.72)	(0.71)	(0.78)	(0.72)
RepRisk	-0.63	0.73	0.76	1.18	1.54
	(0.86)	(1.24)	(1.18)	(1.12)	(1.08)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Observations	96	83	77	73	72
R^2	0.652	0.731	0.738	0.779	0.855

Panel B: Time-varying measure

Dep. var:	Implied volatility				
	t+0	t+1	t+2	t+3	t+4
	(1)	(2)	(3)	(4)	(5)
Market-based greenness	-0.24	-0.16	0.23	-0.43***	-0.30*
	(0.19)	(0.20)	(0.25)	(0.15)	(0.16)
Sautner et al. Measure	78.56	-10.81	-541.09	-2,111.73**	-455.19
	(615.13)	(820.32)	(876.99)	(830.51)	(985.58)
Li et al. Measure	-0.05	-1.65	-3.39*	-0.89	0.81
	(1.73)	(1.93)	(2.02)	(2.48)	(2.46)
Refinitiv E-score	-0.11***	-0.13***	-0.14***	-0.10***	-0.06***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
MSCI E-Score	-0.26	-0.19	-0.33	-0.51**	-0.88***
	(0.23)	(0.25)	(0.26)	(0.26)	(0.29)
RepRisk	0.20	0.18	-0.13	0.04	0.28
	(0.43)	(0.53)	(0.64)	(0.56)	(0.55)
Country FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Observations	1,029	948	716	522	380
R^2	0.208	0.232	0.270	0.417	0.562

Table A.9: Greenness and any green patent, harmonized sample

Correlation of the firm-level market-based greenness measure with current (Column 1) and future (Columns 2-7) Any Green Patent, scaled by a factor of 100. The measure is based on CAPM abnormal returns. Panel A presents the results using the Paris-based measure as an independent variable. Panel B uses the time-varying measure as an independent variable. All regressions include country and sector fixed effects. Firm-level clustered standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Paris-based measure

Dep. var.:	Any Green Patent						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	1.94	1.77	0.85	-0.06	2.10*	1.11	1.89
	(1.30)	(1.26)	(1.27)	(1.31)	(1.20)	(1.28)	(1.23)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	347	347	347	347	347	347	347
R^2	0.269	0.279	0.287	0.228	0.284	0.273	0.312

Panel B: Time-varying measure

Dep. var.:	Any Green Patent						
	t+0	t+1	t+2	t+3	t+4	t+5	t+6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market-based greenness	0.08	0.27*	0.27*	0.32**	0.34**	0.10	0.26*
	(0.14)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	10,662	10,662	10,662	10,662	10,662	10,662	10,662
R^2	0.172	0.169	0.170	0.167	0.166	0.162	0.156

B Proofs

B.1 Proof of Proposition 1

Following Kacperczyk et al. (2016), we solve the model by performing a change of variables. We create linear combinations of assets (synthetic assets) such that the payoff of each synthetic asset is determined only by one shock (either aggregate or idiosyncratic). This allows us to characterize the investors' quantity choice of these synthetic assets, and price them. After we have a solution to the synthetic asset problem, we can invert the linear transformation to back out the prices of the original assets.

B.1.1 Synthetic assets

Recall that z_i, $i \in \{1, ..., n\}$ denotes the n risk factors. For notational ease, let us denote by $\mu_{n-1} = \mu_m$ and $\mu_n = \mu_c$, respectively. Consider n synthetic assets with payoffs $\tilde{f}_i$, $i \in \{1, \ldots, n\}$:

$$\tilde{f}_i = \tilde{\mu}_i + z_i, \tag{18}$$

where

$$\tilde{\mu}_i = \begin{cases} \mu_i - b_i\mu_m - g_i\mu_c, & \text{for } i = 1, \ldots, n-2; \\ \mu_i, & \text{for } i = n-1, n, \end{cases} \tag{19}$$

It is immediate that each synthetic asset is a payoff to a particular portfolio of assets. We will henceforth work with risk factor payoffs, $\tilde{f}_i$, and their prices, $\tilde{p}_i$ in order to solve the model in a tractable way.

We can rewrite the budget constraint given in (5) in terms of risk factor prices and quantities as

$$\pi_j = \sum_{i=1}^{n} \tilde{q}_{ij}(\tilde{f}_i - \tilde{p}_i) \tag{20}$$

by defining

$$\tilde{p}_i \equiv \begin{cases} p_i - b_i p_{n-1} - g_i p_n & \text{for } i = 1, \ldots, n-2, \\ p_i, & \text{for } i = n-1, n. \end{cases} \tag{21}$$

$$\tilde{q}_{ij} \equiv \begin{cases} q_{ij}, & \text{for } i = 1, \ldots, n-2; \\ q_{n-1j} + \sum_{k=1}^{n-2} b_k q_{kj}, & \text{for } i = n-1, \\ q_{nj} + \sum_{k=1}^{n-2} g_k q_{kj}, & \text{for } i = n. \end{cases} \tag{22}$$

B.1.2 Equilibrium portfolio choices and asset prices at $t = 1$

We begin by working through the mechanics of Bayesian updating. There are three types of information that are aggregated in $t = 1$ posterior beliefs: prior belief, price information, and (private) signals. For notational brevity, let us denote by K_i the precision of investors' private signals about factor i:

$$K_i \equiv \begin{cases} K_s, & \text{for } i = 1, \ldots, n-2, \\ K_m, & \text{for } i = n-1, \\ K_c, & \text{for } i = n. \end{cases} \tag{23}$$

We conjecture and later verify that a transformation of prices $\tilde{p}_i$ generates an unbiased signal about the risk factor payoff, $\hat{z}_i = z_i + \nu_{ip}$, where $\nu_{ip} \sim N(0, \tau_{ip}^{-1})$. Then, by Bayes' law, the posterior beliefs about z are normally distributed with mean

$$E_j[z_i] = \frac{K_i \eta_{ij} + \tau_{ip} \hat{z}_i}{\tau_i + K_i + \tau_{ip}}, \tag{24}$$

where τ_i denotes the prior precision of the risk factor i (i.e., the inverse of its prior variance), and variance

$$V_j[z_i] = \frac{1}{\tau_i + K_i + \tau_{ip}}. \tag{25}$$

Next, we derive the investors' portfolio choices. Substituting the budget constraint (20) into the objective function (4), we obtain the following first-order condition with respect to $\tilde{q}_{ij}$:

$$\tilde{q}_{ij} = \frac{E_j[\tilde{f}_i] - \tilde{p}_i}{\rho V_j[\tilde{f}_i - \tilde{p}_i]}. \tag{26}$$

We then characterize the equilibrium prices. Following Admati (1985), we know that the equilibrium price is linear in z_i and ℓ_i and therefore we conjecture an equilibrium price of the form

$$\tilde{p}_i = A_i + B_i(C_i z_i - \ell_i). \tag{27}$$

The transformation of the price in (27) then yields an unbiased signal about z_i that is

$$\eta_{ip} = \frac{\tilde{p}_i - A_i}{B_i C_i}, \tag{28}$$

implying that the signal noise is $\nu_{ip} = -\frac{\ell_i}{C_i}$ and that

$$\tau_{ip} = C_i^2 \tau_\ell, \tag{29}$$

where $\tau_\ell = \frac{1}{\sigma_\ell^2}$. Substituting (24)–(25) and (28)–(29) into the investor j's optimal portfolio (26), after collecting terms, we obtain

$$\tilde{q}_{ij} = \frac{(\tilde{\mu}_i - \tilde{p}_i)(\tau_i + K_i + C_i^2 \tau_\ell) + K_i \eta_{ij} + C_i^2 \tau_\ell \frac{\tilde{p}_i - A_i}{B_i C_i}}{\rho}. \tag{30}$$

Substituting (30) into the market-clearing condition in (6) yields

$$\frac{(\tilde{\mu}_i - \tilde{p}_i)(\tau_i + K_i + C_i^2 \tau_\ell) + K_i z_i + C_i^2 \tau_\ell \frac{\tilde{p}_i - A_i}{B_i C_i}}{\rho} = \ell_i. \tag{31}$$

After collecting terms and comparing to (27), we have

$$A_i = \tilde{\mu}_i, \tag{32}$$

$$B_i = \frac{\rho}{K_i} \frac{K_i + \tau_{ip}}{\tau_i + K_i + \tau_{ip}}, \tag{33}$$

$$C_i = \frac{K_i}{\rho}. \tag{34}$$

We derive the equilibrium abnormal return r_i given in (8). First, it follows from (21) that

$$p_i = \tilde{p}_i + b_i \tilde{p}_m + g_i \tilde{p}_c, \tag{35}$$

where equilibrium prices $\tilde{p}_i$ and $\tilde{p}_c$ are given by (27) and (32)–(34). After some algebraic manipulation, we then obtain (8), where

$$\gamma_c = \gamma(\frac{1}{\sigma_c^2}, K_c), \tag{36}$$

$$\gamma_s = \gamma(\frac{1}{\sigma_s^2}, K_s), \tag{37}$$

and

$$\gamma(\tau, K) = \frac{K + \left(\frac{K}{\rho}\right)^2 \tau_\ell}{\tau + K + \left(\frac{K}{\rho}\right)^2 \tau_\ell}. \tag{38}$$

The properties of $\gamma(\cdot)$ then follows.

B.2 Proof of Corollary 1

From (8), we have that $E[\hat{r}_i \mid \hat{z}_c] = g_i \gamma_c |\hat{z}_c|$, which is increasing in g_i.

B.3 Proof of Corollary 2

This result follows immediately from (10).

B.4 Proof of Corollary 3

This result follows from (36)–(38).

B.5 Proof of Proposition 2

We first compute the investor's ex ante expected utility for a given information choice, and then solve for the optimal information choice at $t = 0$.

Substituting the optimal risky asset holdings from (26) into the budget constraint (20), we have that the investor's expected utility at $t = 1$, given by (4), is equal to

$$U_j = \frac{1}{2} \sum_{i=1}^{n} \frac{\left(E_j[\tilde{f}_i] - \tilde{p}_i\right)^2}{V_j[\tilde{f}_i]}. \tag{39}$$

From the $t = 0$ perspective, $E_j[\tilde{f}_i] - \tilde{p}_i$ is normally distributed, and $V_j[\tilde{f}_i]$ is a constant.

As a result, $E[U_j]$ is the expectation of the sum of squared normal variables and we only need to know the $t = 0$ expectation and variance of $E_j[\tilde{f}_i] - \tilde{p}_i$, By the law of iterated expectation, and using (27), we have $E\left[E_j[\tilde{f}_i] - \tilde{p}_i\right] = E[f_i - \tilde{p}_i] = 0$.

It then remains to compute the variance of $E_j[\tilde{f}_i] - \tilde{p}_i$. We write $E_j[\tilde{f}_i] - \tilde{p}_i = E_j[\tilde{f}_i] - \tilde{f} + \tilde{f} - \tilde{p}_i$, and express the variance as

$$V\left[E_j[\tilde{f}_i] - \tilde{p}_i\right] = V\left[E_j[\tilde{f}_i] - \tilde{f}\right] + V\left[\tilde{f} - \tilde{p}_i\right] + 2Cov\left[E_j[\tilde{f}_i] - \tilde{f}, \tilde{f} - \tilde{p}_i\right]. \qquad (40)$$

Using (24), we can express

$$E_j[\tilde{f}_i] - \tilde{f} = E_j[z_i] - z_i = \frac{-\tau_i z_i + K_{ij} \upsilon_{ij} + \tau_{ip} \upsilon_{ip}}{\tau_i + K_{ij} + \tau_{ip}}, \qquad (41)$$

whose variance coincides with $V_j[z_i]$ given by (25). Using (27), we can express

$$\tilde{f}_i - \tilde{p}_i = \frac{\tau_i z_i + \frac{\rho}{K_i}\left(K_i + \tau_{ip}^2\right)\ell_i}{\tau_i + K_i + \tau_{ip}}, \qquad (42)$$

whose variance is equal to

$$V\left[\tilde{f}_i - \tilde{p}_i\right] = \frac{\tau_i + \left[\frac{\rho}{K_i}\left(K_i + \tau_{ip}\right)\right]^2 / \tau_\ell}{\left(\tau_i + K_i + \tau_{ip}\right)^2} = \frac{\left(\tau_i + K_i + \tau_{ip}\right) + K_i + \rho^2/\tau_\ell}{\left(\tau_i + K_i + \tau_{ip}\right)^2}. \qquad (43)$$

The covariance term is equal to

$$Cov\left[E_j[\tilde{f}_i] - \tilde{f}, \tilde{f} - \tilde{p}_i\right] = Cov\left[\frac{-\tau_i z_i + \tau_{ip}\nu_{ip}}{\tau_i + K_{ij} + \tau_{ip}}, \frac{\tau_i z_i - (K_i + \tau_{ip})\nu_{ip}}{\tau_i + K_i + \tau_{ip}}\right] = -V_j[z_i]. \qquad (44)$$

The variance of $E_j[\tilde{f}_i] - \tilde{p}_i$ is thus given by

$$V\left[E_j[\tilde{f}_i] - \tilde{p}_i\right] = V\left[\tilde{f}_i - \tilde{p}_i\right] - V_j[z_i], \qquad (45)$$

where $V\left[\tilde{f}_i - \tilde{p}_i\right]$ is given by (43) and $V_j[z_i]$ is given by (25).

We can now compute the the investor's ex ante expected utility. Using (4) and the fact that the expectation of $E_j[\tilde{f}_i] - \tilde{p}_i = 0$, we have

$$E\left[U_j\right] = \frac{1}{2}\sum_{i=1}^{n} \frac{V\left[E_j[\tilde{f}_i] - \tilde{p}_i\right]}{V_j[z_i]} = \frac{1}{2}\sum_{i=1}^{n}\left(\frac{V\left[\tilde{f}_i - \tilde{p}_i\right]}{V_j[z_i]} - 1\right), \tag{46}$$

Collecting terms that depends on K_{ij}, we have that the investor's optimal attention allocation problem is equivalent to

$$\max_{\{K_{ij}\}_{i=1}^{n}} \quad \sum_{i=1}^{n} \lambda_i K_{ij}, \tag{47}$$

subject to the information capacity constraint (11), where

$$\lambda_i = V\left[\tilde{f}_i - \tilde{p}_i\right] = \frac{(\tau_i + K_i + \tau_{ip}) + K_i + \rho^2/\tau_\ell}{(\tau_i + K_i + \tau_{ip})^2}. \tag{48}$$

It follows that the solution is given by $K_{ij} = K_i$ if $\lambda_i = \max_k \lambda_k$, and $K_{ij} = 0$ otherwise.