WORKING paper

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Environmental Preferences and Sector Valuations

Tristan Jourde[1] and Arthur Stalla-Bourdillon[2]

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Abstract

This paper examines the dynamic nature of pro-environmental preferences through an analysis of sector valuations in global equity markets from 2018 to 2023. We classify companies into three groups based on their business activities: green (e.g., renewables), neutral, and brown (e.g., fossil energy). We then run panel regressions to test whether being in the green or brown sectoral category affects stock valuations. We find that investors value sector affiliation, positively for green and negatively for brown, even after controlling for other firm-level financial and extra-financial characteristics. The effect is sizeable, as we report a 24% overvaluation of companies in green sectors and a 12% undervaluation of companies in brown sectors on average compared to the rest of the market. In addition, companies in green sectors have come under increased investor scrutiny since 2018 and appear increasingly overvalued relative to the rest of the market. These results suggest that, for seemingly non-financial motives, investors have developed a strong preference for stocks in green sectors over time.

Keywords: Environmental Preferences, Green Bubble, Stock Market, Stranded Assets, Valuation Ratios

JEL classification: G10, G32, Q54

[1] Banque de France, tristan.jourde@banque-france.fr
[2] Banque de France, arthur.stalla-bourdillon@banque-france.fr
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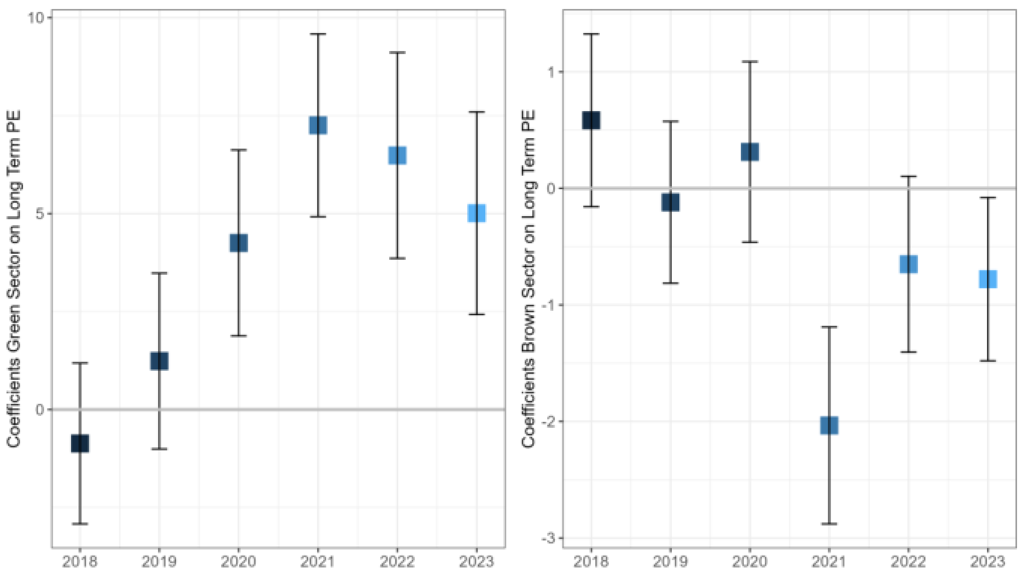
NON-TECHNICAL SUMMARY

Greening financial portfolios has become a central topic in the financial community. This has led a growing number of financial institutions to form coalitions to encourage companies to reduce their environmental footprint (e.g., Climate Action 100+) or to make net zero commitments (e.g., Glasgow Financial Alliance for Net Zero). However, there is considerable uncertainty in the assessment of the environmental status of companies, as illustrated by the significant disagreement among ESG scores (measuring their performance with respect to Environmental, Social, and Governance issues; Berg et al., 2021; Billio et al., 2021) or debatable practice from data providers (Berg et al., 2020). Importantly, the lack of a common framework and reliable information on environmental assets creates several risks, such as the dispersion of green investment flows towards non-sustainable assets (Billio et al., 2021), or over-investment in certain easily identifiable green companies that may support the emergence of a green bubble (Borio et al., 2023).

Against this background, this paper examines the dynamic nature of pro-environmental preferences by analyzing green and brown sector valuations in equity markets. We believe that the study of sector valuations is particularly appropriate given the absence of a reliable common definition of green and brown firms. Sector affiliation is arguably a more objective, consensual, and easily observable characteristic than other individual rankings based on environmental scores or carbon emissions, and less easily manipulated. Therefore, green and brown sectors are more likely to accurately reflect pro-environmental preferences than other metrics, providing a better framework for analysis. We study the effect of sector affiliation (i.e., operating in green, neutral, or brown business activity) on stock valuation, here price-earnings ratio (PER), after controlling for a large set of financial and extra-financial characteristics. We estimate this effect by running panel regressions, first over the entiresample period (2018–2023) and then separately for each year to detect possible changes in pro-environmental preferences.

Figure 1. The dynamic effect of sector affiliation on long-term PER



Note: The figure depicts the coefficients of a regression of the price-earnings ratio (PER) on green and brown sector dummies estimated dynamically every year. The regressions also include all financial and extra-financial covariates available in the paper. All regressions use country and month-year fixed effects. Standard errors are clustered at both firm and time levels. Vertical bars represent the confidence intervals at the 90% confidence level.

Figure 1 depicts the impact of green and brown sector affiliation on stock valuation over time. The figure highlights a sharp increase in the valuation of firms operating in green business activities from 2018 to 2023. Belonging to the green sectors in 2021 increases a company's PER by nearly 7.5 points compared with an average PER of 16.8 for neutral sectors (about 45% higher). In contrast, the PER of companies in brown sectors appeared higher than the rest of the market in 2018, then slowly declined and became lower than that of neutral companies in subsequent years. Overall, these results indicate that pro-environmental preferences have become more prevalent among investors.

Understanding whether pro-environmental preferences are priced at the sector level is essential for financial practitioners and regulatory authorities. First, this information can provide important insights into the effect of positive and negative screening in portfolio allocation strategies on equity valuations. Second, this research question is important for policymakers developing classification systems aimed at channeling public and private investment toward environmentally sustainable economic activities. Finally, our analysis can help identify potential financial stability risks associated with the emergence of a green bubble or a negative reassessment of the value of brown securities.

Préférences environnementales et valorisations sectorielles

Résumé

Cet article examine la nature dynamique des préférences pro-environnementales à travers une analyse des valorisations sectorielles sur les marchés boursiers mondiaux de 2018 à 2023. Nous classons les entreprises en trois groupes en fonction de leurs activités commerciales : « vertes » (par exemple, les énergies renouvelables), « neutres », et « brunes » (par exemple, celles extrayant des énergies fossiles). Nous estimons ensuite des régressions sur données de panel pour tester si l'appartenance à la catégorie sectorielle « verte » ou « brune » affecte les valorisations boursières. Nous constatons que les investisseurs valorisent l'affiliation sectorielle, positivement pour les secteurs verts et négativement pour les secteurs bruns, et ce même après avoir contrôlé d'autres caractéristiques financières et extra-financières au niveau des entreprises. Les effets estimés sont significatifs : nous observons une surévaluation de 24% pour les entreprises des secteurs verts et une sous-évaluation de 12% pour les entreprises des secteurs bruns en moyenne par rapport au reste du marché. En outre, les entreprises des secteurs verts font l'objet d'une attention accrue de la part des investisseurs depuis 2018 et apparaissent de plus en plus surévaluées par rapport au reste du marché. Ces résultats suggèrent que, pour des raisons apparemment non financières, les investisseurs ont développé au fil du temps une forte préférence pour les actions des secteurs verts.

Mots-clés : préférences environnementales, bulle verte, marché boursier, actifs échoués, ratios de valorisation

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1 Introduction

"We believe that sustainability should be our new standard for investing."

Blackrock's 2020 letter to clients

"Central banks walk the talk, increasingly integrating sustainability aspects into the investment process, within the limits of their mandate."

Sabine Mauderer, Chair of the NGFS' "Scaling-up green finance" workstream

Greening financial portfolios has become a central topic in the financial community. Along with the recent pledge by many countries to reduce greenhouse gas emissions (UNEP, 2021), pressing environmental, climate, and biodiversity issues have prompted institutional investors to become more active in monitoring the environmental impact of their portfolios. Moreover, according to the surveys of Krueger et al. (2020) and Stroebel and Wurgler (2021), investors have begun to factor the financial implications of climate change into portfolio risk management. Against this background, an increasing number of financial institutions have formed coalitions to encourage companies to reduce their environmental footprint (e.g., Climate Action 100+) or have made net zero commitments (e.g., Glasgow Financial Alliance for Net Zero).

Nevertheless, the process of greening financial portfolios might be hampered by heterogeneous preferences among investors (Pedersen et al., 2021) and uncertainty in assessing the environmental status of companies. Some papers point out that financial markets seem to remain inefficient in forecasting environmental risks and tend to under-price them (e.g., Alok et al., 2020; Hong et al., 2019; Kruttli et al., 2021), which is a key concern for public authorities (e.g., IMF, 2020; NGFS, 2022). In addition, the uncertainty in assessing the environmental status of companies is illustrated by the significant disagreement among ESG scores (Berg et al., 2021; Billio et al., 2021; Gibson et al., 2021; Krueger et al., 2021) or debatable practice from data providers (Berg et al., 2020). Importantly, the lack of a common framework and reliable information on environmental assets creates several risks, namely (i) a dispersion of green investment flows towards non-sustainable assets (Billio et al., 2021), (ii) an incentive to green signaling by firms and funds that can lead to greenwashing (Bams & van der Kroft, 2022; Dumitrescu et al., 2022; Yang, 2022; Yu et al., 2020)[1], (iii) a barrier to integrating ESG ratings into valuation processes (Bancel et al., 2023), and (iv) over-investment in certain easily identifiable green companies (e.g., Bofinger et al., 2022; Bolton & Kacperczyk, 2021) that may support the emergence of a green bubble (e.g., Borio et al., 2023).[2]

[1] The risk of "greenwashing" prompted political initiatives to improve disclosure and compliance (NGFS, 2022)

[2] See also: The Economist, *A green bubble? We dissect the investment boom.* May 2021; Project Syndicate, *The Fallacy of Climate Financial Risk.* July 2021 (by John Cochrane).

Against this background, this paper examines the dynamic nature of pro-environmental preferences by analyzing sector valuations in equity markets. We believe that the study of sector valuations is particularly appropriate given the absence of a reliable common definition of green and brown firms. Sector affiliation is arguably a more objective, consensual, and easily observable characteristic than other individual rankings based on environmental scores or carbon emissions, and less easily manipulated. Therefore, green and brown sectors are more likely to accurately reflect pro-environmental preferences than other metrics, providing a better framework for analysis. Furthermore, we focus on valuation metrics because stock prices must be compared to company fundamentals to determine whether they are overstretched, a key concept in analyzing the emergence of pro-environmental preferences and their impact on stock markets. It should be noted that we cannot discern whether the "mispricing" of green or brown sectors is driven by purely non-financial motives or whether investors are trying to hedge against a potential "green swan"[3] that would not be reflected in analysts' earnings forecasts. For this reason, we use a broad definition of environmental preferences that incorporates both taste and potential disagreement about the probability distributions of future payoffs on assets (e.g., Fama & French, 2007). The main hypothesis we test in this paper is that the development of environmental preferences has changed investor demand for green and brown stocks, leading to an increase in the valuation of green sectors and a decrease in the valuation of brown sectors, relative to the rest of the market. Next, we complement our findings by examining the degree to which investors pay attention to firms operating in green or brown sectors, based on equity turnover rates. In particular, we expect that the evolution of environmental preferences will lead to increased investor attention to both green and brown companies.

To test our main hypothesis, we study the effect of sector affiliation (i.e., operating in green, neutral, or brown business activity) on stock valuation, after controlling for a large set of financial and extra-financial characteristics. We estimate this effect by running panel regressions, first over the entire sample period (2018–2023) and then separately for each year to detect possible changes in the coefficients. Dynamic estimations are useful to understand whether the valuation of green and brown sectors has evolved in recent years, a potential signal of the strengthening of pro-environmental preferences. Overall, this study can help assess whether investors use information on sector affiliation to evaluate the environmental status of companies, a critical element in designing a common taxonomy.[4] Moreover, our analysis assists in identifying where potential financial stability risks associated with overvaluation lie, which is particularly important given recent concerns about the emergence of a green bubble. Finally, our results provide some insight into the respective effects of positive and negative screening in portfolio allocation strategies, defined as the inclusion or exclusion of some assets based on environmental

[3] Bolton et al. (2020) define the green swan as "potentially extremely financially disruptive events that could be behind the next systemic financial crisis".

[4] Regulatory authorities are currently devoting resources to improving corporate environmental disclosure and to develop a common framework for identifying green assets (e.g., EU Taxonomy for sustainable activities).

characteristics, on the valuation of companies belonging to green and brown sectors.

Our empirical analysis is based on an international sample of listed firms included in the Datastream World portfolio, which we track at a monthly frequency from January 2018 to December 2023. The study begins in 2018 because of numerous indications of significant growth in the sustainable asset management industry after that date (e.g., Aramonte & Zabai, 2021; Caramichael & Rapp, 2022). We also observe a sharp increase in Internet searches for environmental, social, and governance criteria after 2018, according to Google Trends (see Figure 3). We retrieve information on business activities for each company using The Refinitiv Business Classification (TRBC) system. Then, we use this information to classify firms into green, neutral, or brown categories. Our baseline measure of equity valuation is a forward price/earnings ratio, PER, a widely used metric for equity valuation (Damodaran, 2013), calculated with three to five years ahead earnings forecasts by financial analysts from the Institutional Brokers' Estimate System (I.B.E.S.).[5]

Our selection of control variables is based on the asset pricing literature, which ties cross-sectional differences in stock returns to firm characteristics (e.g., Harvey et al., 2016; Hou et al., 2020). We include proxies for firm size (Fama & French, 1993), investment and past earnings profiles (Fama & French, 2015), payout ratio (Boudoukh et al., 2007), leverage (Bhandari, 1988), illiquidity (Amihud, 2002), systematic risk and idiosyncratic volatility (Ang et al., 2006), and extreme downside risk (Huang et al., 2012). We also control for analyst attention, an indicator of the degree of public information dissemination (e.g., Brennan et al., 1993), and analyst forecast dispersion, which reflects the degree of heterogeneity in beliefs about stock fundamentals (Diether et al., 2002; Grinblatt et al., 2016). In addition, to mitigate the risk that the technological characteristics of the green sectors (see Henriques & Sadorsky, 2008, on the technological edge of companies in the renewable energy sector) bias our estimates, we design a control variable that measures the technology component of each firm using the sensitivity of individual stock returns to a portfolio of technology firms. Finally, we account for the effect of several extra-financial characteristics on asset prices, namely environmental scores (Görgen et al., 2020), environmental score disagreements (Billio et al., 2021), the lack of ESG controversies (Aouadi & Marsat, 2018), carbon emissions (Bolton & Kacperczyk, 2021), and physical risk scores (e.g., Acharya et al., 2022). All of these individual financial and extra-financial characteristics are collected from external sources, where available, or developed using the methods described in Section 2.

Our results indicate that firms' green and brown sector affiliations are significantly priced in the global equity market. Companies operating in green business activities appear to be more highly valued, with a forward PER that is 24% higher (3.5 PER points) than that of neutral companies. The effect is quite sizeable,

[5]In our analysis, we describe PER that are higher or lower relative to other firms as indicators of "overvaluation" or "undervaluation", respectively. However, it is important to clarify that this terminology is used solely for indicative purposes within this paper. We make no final judgment as to whether such valuations represent deviations from fundamental values.

as it accounts for 41% of the standard deviation of company valuations within neutral sectors. On the other hand, companies in brown sectors are undervalued by 12% (1.7 PER points; 20% of the standard deviation within neutral sectors) compared to neutral sectors. However, this effect tends to fade once other extra-financial characteristics are taken into account, such as the carbon intensity or the physical risk of companies. Furthermore, our dynamic estimation underlines interesting patterns regarding the relative valuations of green and brown sectors. The relative PER of green stocks peaked in 2021: it was 45% higher (7.4 PER points; 80% of the standard deviation within neutral sectors in 2021) than that of neutral firms. Although this pattern moderated slightly over the next two years, green equities were still 37% more expensive than the rest of the market in 2023 (5 PER points). In contrast, the PER of companies in brown sectors appeared higher than the rest of the market in 2018, then slowly declined and became lower than that of neutral companies in subsequent years. We also find evidence that the equity turnover rate of green firms has increased in recent years. These findings imply that green firms have sparked more interest recently and suggest that pro-environmental preferences have become more widespread among investors. Overall, our results are robust to different definitions of green and brown sectors and several stock valuation measures. Our findings also remain consistent after dividing the sample into different regions.

Market-based evidence of interest and demand for green assets is mounting, from the rising prices of battery metals, such as lithium and cobalt, to the integration of environmental considerations in the price of equity markets (e.g., Ardia et al., 2023; Bolton & Kacperczyk, 2021; Chini & Rubin, 2022; Choi et al., 2020; Engle et al., 2020; Jourde & Moreau, 2022; Pástor et al., 2021), CDS spreads (Blasberg et al., 2021), bond markets (e.g., Flammer, 2021; Kim & Pouget, 2023; Zerbib, 2019), and real estate (e.g., Baldauf et al., 2020; Bernstein et al., 2019; Giglio et al., 2021). Papers also report massive inflows into sustainable funds (e.g., GSIA, 2020; Hartzmark & Sussman, 2019) despite poor performance (El Ghoul & Karoui, 2017) and show that investors are willing to pay more to invest in a fund with an ESG mandate (Baker et al., 2022). Finally, Edmans (2023) argues that ESG has moved from a niche subfield to a mainstream practice. These developments have fueled narratives about a green bubble (e.g., Borio et al., 2023; Jourde & Stalla-Bourdillon, 2021) and a potential undervaluation of brown companies (see Cornell & Damodaran, 2020, for evidence based on companies with low ESG ratings).

Our main contributions to the literature are twofold. While some papers study the effect of ESG or climate characteristics on stock valuation (e.g., Bofinger et al., 2022; Bolton & Kacperczyk, 2021; Chava, 2014; Gao & Zhang, 2015; Giese et al., 2019; Krueger, 2015; Marsat et al., 2013; Pástor et al., 2022), our article is to our knowledge the first to analyze the valuation of stocks belonging to green and brown sectors. Since several definitions of green and brown can coexist, we believe it is important to fill this gap and test whether investors price the affiliation to green and brown sectors.[6] Our interest in sector affiliation is related to the seminal work of

[6] In a different setting, the recent paper of Fliegel (2023) also uses sector affiliation to build green-minus-brown factors and finds that green stocks tend to outperform brown stocks after controlling for well-established risk factors.

Hong and Kacperczyk (2009), who analyze moral preferences through the lens of the valuation of "sin" companies belonging to the alcohol & tobacco or gambling sectors. As noted above, we believe that green and brown sectors are more consensual and easily observable than other environmental metrics, hence more likely to accurately reflect pro-environmental preferences. Another advantage of our framework is that we can disentangle investor preferences for green and brown assets, which, from an asset management perspective, helps to better understand the respective effects of positive and negative screening in asset allocation strategies. Finally, unlike previous studies, we account for potential correlations among green characteristics by incorporating several environmental features as control variables in our model.[7] In some respects, this point is related to papers that examine the effect of corporate social responsibility (CSR) on stock valuation conditional on other variables, such as institutional ownership and economic conditions (Buchanan et al., 2018) or investor protection (Breuer et al., 2018). Wong and Zhang (2022) also find that market reactions to adverse ESG disclosures are sector-dependent (e.g., no effect on "sin" stocks), but they do not distinguish between green, brown, and neutral sectors as we do.

Second, we complement the literature by studying the dynamic nature of pro-environmental preferences, allowing us to capture potential paradigm shifts in investor behavior. This approach is also useful for identifying the potential emergence of a green bubble. Our measure of overvaluation focuses on the valuation of the green and brown sectors relative to neutral sectors. It therefore differs from papers that identify speculative bubbles from time series, exploring the behavior of stock prices from a historical perspective (e.g., Jordà et al., 2015; Phillips et al., 2015) with applications to green indices (see Ghosh et al., 2022; Lehnert, 2022). We consider that our approach is better suited to examining sector valuation, as our diagnosis is less conditioned by the common factor structure of stock prices. In particular, given the overall rise in equity valuations after the COVID-19 crisis, it seems more appropriate to adopt a relative approach by comparing sector valuations at each date in cross-section, rather than analyzing the time series of valuations for each sector. In addition, we extend our main approach based on stock valuation to other features that reflect investors' attention to green and brown stocks, based on stock turnover rates. This approach relates to previous work on the relationship between attention and mispricing. Hong and Stein (2007) highlight that "glamour" stocks (with high market value relative to fundamentals) have high turnover rates, especially during the Internet bubble. Xiong and Yu (2011) find similar evidence in the context of the Chinese warrants bubble.

The rest of the study is structured as follows: Section 2 describes the data and methodology; Section 3 presents the results of the empirical analysis; Section 4 details the robustness tests; Section 5 concludes.

[7] Bolton and Kacperczyk (2021) show that including industry fixed effects in their model specification alters the effect of carbon emissions on stock prices. However, they do not examine whether green and brown industries tend to be over or undervalued in the market.

2 Data and Methodology

2.1 Model

We study the effect of environmental preferences on sector valuation using a panel regression framework. Our dependent variable is the valuation of each stock included in the Datastream World portfolio between January 2018 and December 2023 at monthly frequency. We regress stock valuation ratios on dummy variables that indicate whether the firm operates in green, neutral, or brown business activity and a set of controls based on financial and extra-financial firm characteristics (see Equation 1). This approach is related to the characteristic-based asset pricing model of Daniel and Titman (1997). We use the valuation ratios of the companies (see Equation 2) as the dependent variable instead of returns, which seems more appropriate to determine whether equity prices are overstretched over a relatively short time. Our main model is determined by the following equation:

$$PER_{i,t} = \alpha + \beta_g Green_i + \beta_b Brown_i + \sum_{f=1}^{F} \lambda_f FIN_{i,t-1}^{f} + \sum_{e=1}^{E} \lambda_e ENV_{i,t-1}^{e} + \gamma_{country,i} + \gamma_t + \epsilon_{i,t} \quad (1)$$

where $Green_i$ and $Brown_i$ are dummy variables that take the value 1 when the company operates in a green or brown business activity. The coefficients of interest are β_g and β_b, which are expressed in PER units and can be interpreted as the overvaluation or undervaluation associated with the firm's affiliation to a green or brown sector, conditional on the other covariates. FIN and ENV are all variables representing the financial and environmental characteristics of each firm. Covariates are lagged by one month to alleviate potential endogeneity issues. Finally, α is the constant term, and $\gamma_{country,i}$ and γ_t represent country and time fixed effects. All non-binary variables are winsorized at the 5% level to mitigate the effect of potential outliers on our estimates. Following Petersen (2009) and Thompson (2011), we cluster the standard errors by firm and by time to control for simultaneous correlation across both dimensions. The variables and their construction are described in the rest of the section and summarized in Table 3.

2.2 Variables

2.2.1 Valuation and investors' attention measures

Our baseline measure of equity valuation is a long-term forward PER, such as:

$$PER_{i,t} = \frac{P_{i,t}}{E_{i,t}} \quad (2)$$

with $P_{i,t}$ the price of stock i at the end of the month t and $E_{i,t}$ the average of the earnings forecasts by financial analysts 3 to 5 years ahead, retrieved from I.B.E.S. To test the robustness of our findings, we also build three alternative valuation measures: the short-term forward PER based on the average of the earnings forecasts over a 1-2 year horizon, the trailing PER that focuses on the latest earnings, and the book-to-market ratio.

To explore investors' attention to environmental issues, we also compute the monthly turnover rate for each stock, which is based on the sum of daily traded volumes ($V_{i,t}$), the price of the stock at the end of the month ($P_{i,t}$) and its market value ($MV_{i,t}$), all expressed in US dollars, such as:

$$TR_{i,t} = \frac{V_{i,t}.P_{i,t}}{MV_{i,t}} \tag{3}$$

2.2.2 Sector affiliation

We collect information on sector affiliation for each company using the TRBC system. TRBC covers over 250,000 securities in 130 countries to 5 levels of granularity. The information comes from local language-speaking analysts who utilize company filings, Reuters news, and corporate action services to assign and maintain a company's activity. This is a key advantage over the NACE and NAICS classifications, in which the identification of the company's main activity is declared by the company itself, leaving space for more subjectivity that could affect our assessment of green and brown firms (Battiston et al., 2022). However, a potential limitation of the TRBC system is that only companies' most recent sector affiliations are available, which prevents any further analysis based on changes in affiliation.

We classify firms into green, neutral, and brown categories based on the most granular TRBC classification that contains more than 600 business activities. First, we define two baseline lists of green and brown business activities (see Tables 4 and 5). These lists are quite restrictive, as they are intended to focus on business activities that are most easily identified by investors as green or brown. Our baseline lists include only business activities in two key economic sectors for the environmental transition[8], namely the energy and utilities sectors. Specifically, we exploit intrasectoral divergences by classifying business activities as green (e.g., renewable energy and alternative electric utilities) or brown (e.g., oil & gas and fossil fuel electric utilities) within the same economic sectors. This approach facilitates the comparison of results for green and brown firms and allows us to alleviate the risk that our results are affected by a structural difference in valuation across economic sectors. Our baseline lists identify 63 green companies, 265 brown companies, and 3,342 neutral companies in 69 countries for which data is available. We provide information on the ten largest green and brown companies in Table 6 and on the distribution of green and brown firms by region in Table 7.

As a robustness test (Section 4.2), we propose two extensions to these initial lists. The first one classifies business activities within the basic materials sector: paper and forest products are considered green, while metals and mining and construction

[8]see e.g., IPCC (Intergovernmental Panel on Climate Change) (2022). Climate Change 2022: Impacts, Adaptations and Vulnerability. Working Group II Contribution to the IPCC Sixth Assessment Report.

materials are defined as brown. Based on this definition, 35 and 271 additional companies are considered green and brown, respectively. The second extension incorporates electric vehicles and environmental services as green, whereas it defines automobiles and truck manufacturers and some transportation services as brown. This leads us to add 31 and 93 firms to our initial lists of green and brown companies, respectively.

Our classification is related to the Sustainable Industry Classification System (SICS) of the Sustainability Accounting Standards Board, which classifies companies based on common sustainability issues. Our brown list matches closely with the Extractives & Minerals Processing SICS category and our green list shares strong similarities with the Renewable Resources & Alternative Energy SICS category. Note that we do not directly rely on the Climate Policy Relevant Sectors of Battiston et al. (2017) for two reasons: they do not distinguish between green and brown business activities and they may not be easily identified by investors since the list of sectors is quite extensive. However, following their approach, we classify the finance, health, and technology sectors as neutral. While these sectors are not carbon-intensive, the financial sector is heavily involved in financing polluting companies, and the health and technology sectors are unlikely to be considered key economic sectors for the ecological transition by investors.

2.2.3 Financial characteristics

We collect a large set of financial variables based on the characteristics that are associated with cross-sectional stock return differences (e.g., Harvey et al., 2016; Hou et al., 2020). To control for firm size, we use the natural logarithm of companies' total assets denominated in USD. Alternatively, we also confirm that our results are robust to other lagged size indicators, such as market capitalization and company sales (unreported). Following Fama and French (2015), firm investment is calculated as the annual growth rate in total assets. Profitability is defined as the firms' net income after preferred dividends divided by common equity. We also control in our regressions by the past earning growth, computed as the annual growth rate of realized earnings per share, and by the payout ratio, computed as the ratio of distributed dividends on earnings. Firm leverage is proxied by the total debt of the company divided by common equity. We estimate analyst attention by the total number of analyst estimates for expected earnings per share. Finally, the analyst forecast dispersion is based on the standard deviation of the expected earnings per share.

We also build several market-based variables for each stock, including several measures of risk. We use the Amihud indicator to measure stock illiquidity. For each trading day, we calculate the ratio of the absolute value of the daily return of each stock ($r_{i,t}$) to the daily traded volume of that same stock ($V_{i,t}$, expressed in dollars). For each stock, we aggregate the data by month based on the median value to deal with potential outliers in daily volumes.

$$ILLIQ_{i,t} = median_{t=1}^{T} \frac{|r_{i,t}|}{V_{i,t}} \tag{4}$$

We then estimate dynamic measures of systematic risk (beta) and idiosyncratic volatility (see Equation 5). We regress the daily returns of each stock on the returns of the global market portfolio from Refinitiv Datastream. Due to differences in trading hours across markets, stock returns on one day are potentially correlated with global market portfolio returns on the previous, current, and next day. Following Hollstein (2020), we adjust the beta estimator to account for this lead-lag structure in Equation 5. We estimate the model dynamically based on a rolling-window framework. The systematic risk at month t is $\beta_{i,t}^{M}$ estimated over the twelve past months (see Equation 6). We use weighted regressions based on an exponentially decaying factor that gives more weight to the more recent observations. The idiosyncratic risk measure at month t is computed from the standard deviation of $\epsilon_{i,t}$ over the estimation period.

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M(-1)} MKT_{t-1} + \beta_{i,t}^{M(0)} MKT_t + \beta_{i,t}^{M(+1)} MKT_{t+1} + \epsilon_{i,t} \tag{5}$$

$$\beta_{i,t}^{M} = \beta_{i,t}^{M(-1)} + \beta_{i,t}^{M(0)} + \beta_{i,t}^{M(+1)} \tag{6}$$

Given the apparent link between environmental profile and extreme risk reduction (Ilhan et al., 2021; Lins et al., 2017), we construct a measure of extreme risk based on a monthly 5% parametric Value-at-Risk (VaR, see Equation 7). To account for the non-normality of returns, we estimate the VaR using the Cornish and Fisher (1937, see Equation 8) expansion that adjusts the traditional parametric normal VaR for the skewness and kurtosis of the empirical distribution:

$$VaR = \mu + \Omega(\alpha) * \sigma \tag{7}$$

$$\Omega(\alpha) = z(\alpha) + \frac{1}{6}(z(\alpha)^2 - 1)S + \frac{1}{24}(z(\alpha)^3 - 3z(\alpha))K - \frac{1}{36}(2z(\alpha)^3 - 5z(\alpha))S^2 \tag{8}$$

where μ is the mean, σ is the standard deviation of the returns over the entire period, and $\Omega(\alpha)$ is the critical value based on the loss probability level, skewness, and kurtosis (Equation 8). Specifically, z(α) is the critical value from the normal distribution for probability (1-α), S is the skewness, and K is the excess kurtosis. We set the parameter α to 5%. For the sake of consistency with other risk measures, we modify the sign of VaR so that a high value means that the company is exposed to a substantial downside risk.

Finally, to account for the effect of the technology characteristics of the green firms (see Henriques & Sadorsky, 2008) on stock valuation, we design a control variable that captures the technology component of each firm using the sensitivity of individual stock returns to a portfolio of technology firms. The technology portfolio is based on the world technology index of Refinitiv Datastream. We regress the daily returns of each stock on the returns of the technology portfolio, those of the global market portfolio, and the returns of the value (HML) and size (SMB) factors (see Fama & French, 1992) from 2018 to 2023.[9]. We approximate the technology component of each firm by the coefficient associated with the returns of the technology portfolio using a framework similar to that presented in Equation (5)

2.2.4 Environmental characteristics

We collect additional environmental variables to control for the effect of various extra-financial characteristics on stock returns (see e.g., Acharya et al., 2022; Aouadi & Marsat, 2018; Billio et al., 2021; Bolton & Kacperczyk, 2021; Görgen et al., 2020) and potential correlation among green characteristics. We construct a composite environmental measure based on "E" (from ESG) scores from four data providers: CDP, Refinitiv ESG, S&P Global, and Sustainalytics. More specifically, we standardize the scores to ensure the data is on a consistent scale, ranging from 0 to 100, then calculate the cross-sectional average of the scores for each company. A high environmental score means that the company outperforms its peers in terms of ecological responsibility. Based on standardized E scores, we also construct a measure of environmental score disagreement for each company using the standard deviation between the scores of the different data providers.

Then, we download a variable for the lack of ESG controversies from Refinitiv Datastream, which measures a company's exposure to environmental, social, and governance controversies and negative events reflected in global media. The score ranges between 0 and 100, with the upper bound indicating that the firm is not subject to ESG controversies. We also design a carbon intensity measure for each firm based on both reported and estimated emissions, Scopes 1 & 2, divided by net sales, from Refinitiv Datastream. Finally, we use the physical risk score of ISS-ESG, which represents the fraction of the value of each company susceptible to being lost due to physical climate risks by 2050 in a likely climate-change scenario.

2.2.5 Descriptive statistics

We compare the average value of various financial and extra-financial characteristics for our baseline lists of green, brown, and neutral companies (see Table 8). First, based on all valuation measures, we observe that the stock valuation of green firms is higher than that of neutral firms, while brown companies appear less valued than the rest of the market. However, this finding might be driven by structural differences between the characteristics of green, brown, and neutral firms.

Regarding financial characteristics, we show that green firms tend to be smaller, invest more, and have more debt than neutral firms. The inverse holds for brown companies. While green companies are generally less profitable and have a lower payout ratio than brown and neutral companies on average, their annual earnings growth rate is around twice that of other companies. Furthermore, both green and brown stocks are more illiquid and volatile than neutral companies.

[9]We use HML and SMB factors for developed markets, available on Kenneth R. French website

Regarding extra-financial characteristics, firms in green sectors surprisingly have a lower environmental score (although there is more disagreement among data providers) than the rest of the market. This finding can be explained by the fact that E scores are industry-adjusted ("best-in-class approach"). Moreover, the way the ESG score measures corporate sustainability tends to favor larger companies, in our case brown firms, that have more resources for providing ESG data (Drempetic et al., 2020). The existence of carbon-intensive green companies also suggests that existing environmental characteristics may not be able to fully capture certain sectoral aspects, such as green innovation (e.g., Cohen et al., 2020) or positive externalities, for example, the fact that companies are allowed to use renewable energy certificates to report emission reductions from electricity purchases (Bjørn et al., 2022). Finally, firms in green sectors also appear to be less concerned by ESG controversies and less exposed to physical risks.

3 Results

3.1 The pricing of pro-environmental preferences in sector valuation

In this section, we explore whether being in the green or brown sector category affects firm valuations in global equity markets. We use panel regressions based on the full sample and proceed in two steps. First, we regress the firm-specific PER on the green and brown sector dummies and company financial characteristics. Second, we add the extra-financial variables as control variables to assess if the information on green and brown sectors is priced above and beyond other firm-level environmental characteristics (environmental scores, carbon intensity, etc.).

Our first regression, estimated from 2018 to 2023, is therefore:

$$PER_{i,t} = \alpha + \beta_g Green_i + \beta_b Brown_i + \sum_{f=1}^{F} \lambda_f FIN_{i,t-1}^{f} + \gamma_{country,i} + \gamma_t + \epsilon_{i,t} \quad (9)$$

The results are presented in Table 1. One finding that stands out from the analysis is that the coefficient associated with the green sector is significantly positive in all four distinct specifications. The magnitude of the effect is substantial: operating in a green sector increases the PER of firms by 2 to 3.6 points (+24%) compared to the average PER of the neutral sectors (14.5). Symmetrically, the coefficient related to the brown sector appears significantly negative in all specifications. Although the scale of the discount for brown sectors is smaller in absolute terms than the premium for green sectors, it is still sizeable. Operating in a brown business activity reduces firms' PER by 1.8 to 2.7 points (approximately -12% based on column 4) compared to neutral sectors.

Concerning financial variables, we show that companies with limited total assets, high investment, earnings growth, and payout ratio, as well as low debt tend to be more valued in equity markets. Furthermore, all market-based risk indicators appear to be priced by investors: companies exposed to liquidity, idiosyncratic, systematic (beta), or extreme risks tend to have lower PER on average. We also find that stocks with greater analyst coverage tend to be more expensive. Finally, the technology component of companies tends to drive down their valuations. This can be explained by the fact that we control for the HML factor, which captures the characteristics of growth and value stocks when estimating the technology beta (see Section 2). When we remove this control, we find a positive effect of a firm's technology component on its stock valuation (unreported).

The R-squared of the regressions is between 14% and 29%, which is in line with the related literature (e.g., Bolton & Kacperczyk, 2021). However, one potential limitation of this approach is the omission of certain extra-financial variables that could be correlated with the classification of companies in green or brown sectors (see Table 8). Indeed, alternative environmental characteristics, namely E scores, E score disagreements, the lack of ESG controversies, carbon emission intensity, and physical risk scores, have been found to have significant effects on stock returns or valuations (see e.g., Acharya et al., 2022; Aouadi & Marsat, 2018; Billio et al., 2021; Bolton & Kacperczyk, 2021; Görgen et al., 2020). To take these characteristics into account, we add the corresponding variables as covariates, and estimate the regression detailed in Equation 1. We report the results in Table 2.

We find that the green sector premium outlined above is robust to the inclusion of the various extra-financial variables. In the five different specifications, the coefficient associated with the green sector dummy is significantly positive, and of the same order of magnitude as in Table 1. Additionally, in four out of five specifications, the coefficient for brown sectors is, as before, significantly negative. Interestingly, the effect of brown sectors on equity valuation becomes non-significant after controlling for both carbon intensity and physical risk. This suggests that investors may prioritize more granular environmental characteristics over brown sector affiliation when evaluating companies. Nevertheless, we show in a dynamic setting that the coefficient associated with brown sectors turns significantly negative at the end of the period, even after controlling for all alternative environmental characteristics (see Section 3.2).

After including additional extra-financial variables, the R-squared of the estimations increases from 29% to 30%–34%. The results for alternative environmental characteristics indicate that firms with high carbon emission intensity, high exposure to physical risk, low "E" scores, and subject to ESG controversies tend to exhibit lower valuation in equity markets. These are several indications that environmental concerns and potential green opportunities are being reflected in stock prices. This evidence supports the view that investors believe that greening companies can create long-term shareholder value (see e.g., Cornell & Shapiro, 2021; Edmans, 2023; Gillan et al., 2021). Moreover, unlike Billio et al. (2021), we do not find that inconsistencies in environmental ratings, which may result from difficulties in assessing firms' environmental performance and the risk of greenwashing, tend to dilute green investment flows.

Table 1: PER on sectoral and financial variables

	(1)	(2)	(3)	(4)
Green Sector	3.605***	1.998*	2.982***	3.544***
	(1.039)	(1.038)	(0.997)	(1.030)
Brown Sector	−2.681***	−2.382***	−2.052***	−1.795***
	(0.349)	(0.312)	(0.319)	(0.311)
Assets_{t-1}		−1.250***	−1.554***	−1.833***
		(0.060)	(0.061)	(0.073)
Earnings growth_{t-1}		0.004***	0.002	0.003**
		(0.001)	(0.001)	(0.001)
Payout_{t-1}		0.031***	0.013***	0.006*
		(0.003)	(0.003)	(0.003)
Investment_{t-1}		8.267***	8.484***	8.632***
		(0.416)	(0.413)	(0.427)
Leverage_{t-1}		−0.006***	−0.004***	−0.004***
		(0.001)	(0.001)	(0.001)
Illiquidity_{t-1}			−3.299***	−2.957***
			(0.392)	(0.428)
Idio. risk_{t-1}			−2.626***	−2.803***
			(0.891)	(0.883)
Beta_{t-1}			−1.158***	−0.670***
			(0.219)	(0.225)
Extreme risk_{t-1}			-12.417***	-12.995***
			(1.640)	(1.680)
$\text{Profitability}_{t-1}$				−0.766
				(0.597)
Analyst disp._{t-1}				0.002
				(0.008)
Analyst cov._{t-1}				0.151***
				(0.017)
Tech_{t-1}				−2.624***
				(0.291)
Observations	401,367	386,306	377,282	354,317
R^2	0.143	0.246	0.266	0.293
Adjusted R^2	0.143	0.246	0.266	0.293

Note: This table presents estimates of the effect of sectoral affiliation on firms' long-term PER. The control variables are detailed in Table 3. We use the lagged values of all covariates to alleviate potential endogeneity issues. All regressions use country and month-year fixed effects. Standard errors are clustered at firm and time levels and reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2: PER on sectoral, financial and extra-financial variables

	(1)	(2)	(3)	(4)	(5)
Green Sector	3.157^{***}	3.584^{***}	3.640^{***}	3.207^{***}	4.161^{***}
	(1.034)	(1.020)	(1.228)	(1.055)	(1.274)
Brown Sector	-1.712^{***}	-1.305^{***}	-1.290^{***}	-1.650^{***}	-0.622
	(0.318)	(0.352)	(0.351)	(0.342)	(0.384)
E score$_{t-1}$	0.009^{*}				0.001
	(0.005)				(0.006)
E disag.$_{t-1}$	-0.003				-0.012
	(0.011)				(0.012)
GES intensity$_{t-1}$		-1.509^{***}			-1.337^{***}
		(0.218)			(0.228)
Physical risk$_{t-1}$			-0.311^{***}		-0.271^{***}
			(0.041)		(0.045)
Lack of ESG controv.$_{t-1}$				0.008^{***}	0.005
				(0.003)	(0.003)
Assets$_{t-1}$	-1.899^{***}	-1.985^{***}	-1.930^{***}	-1.947^{***}	-2.073^{***}
	(0.079)	(0.079)	(0.082)	(0.081)	(0.093)
Earnings growth$_{t-1}$	0.003^{***}	0.003^{**}	0.003^{**}	0.003^{**}	0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Payout$_{t-1}$	0.005^{*}	0.002	0.005	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Investment$_{t-1}$	8.834^{***}	9.023^{***}	9.620^{***}	9.124^{***}	9.513^{***}
	(0.437)	(0.467)	(0.459)	(0.464)	(0.481)
Leverage$_{t-1}$	-0.004^{***}	-0.005^{***}	-0.004^{***}	-0.004^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Illiquidity$_{t-1}$	-3.218^{***}	-2.948^{***}	-3.081^{***}	-2.830^{***}	-3.622^{***}
	(0.447)	(0.547)	(0.509)	(0.544)	(0.591)
Idio. risk$_{t-1}$	-2.721^{***}	-3.981^{***}	-2.147^{**}	-3.919^{***}	-3.813^{***}
	(0.890)	(0.937)	(0.961)	(0.938)	(1.050)
Beta$_{t-1}$	-0.728^{***}	-0.718^{***}	-0.808^{***}	-0.706^{***}	-0.830^{***}
	(0.229)	(0.236)	(0.246)	(0.237)	(0.253)
Extreme risk$_{t-1}$	-12.530^{***}	-13.875^{***}	-10.399^{***}	-14.820^{***}	-11.882^{***}
	(1.741)	(1.884)	(1.981)	(1.893)	(2.160)
Profitability$_{t-1}$	-0.720	-1.289^{**}	-0.939	-0.955	-1.059
	(0.614)	(0.644)	(0.685)	(0.639)	(0.712)
Analyst disp.$_{t-1}$	0.003	0.004	0.010	0.003	0.006
	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)
Analyst cov.$_{t-1}$	0.140^{***}	0.130^{***}	0.160^{***}	0.142^{***}	0.144^{***}
	(0.019)	(0.018)	(0.019)	(0.018)	(0.021)
Tech$_{t-1}$	-2.617^{***}	-2.411^{***}	-2.662^{***}	-2.256^{***}	-2.286^{***}
	(0.295)	(0.321)	(0.315)	(0.323)	(0.340)
Observations	341,933	293,549	286,073	294,528	242,982
R^2	0.300	0.317	0.319	0.310	0.340
Adjusted R^2	0.300	0.316	0.319	0.310	0.339

Note: This table presents estimates of the effect of sectoral affiliation on firms' long-term PER. The control variables are detailed in Table 3. We use the lagged values of all covariates to alleviate potential endogeneity issues. All regressions use country and month-year fixed effects. Standard errors are clustered at firm and time levels and reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

3.2 The build-up of pro-environmental preferences

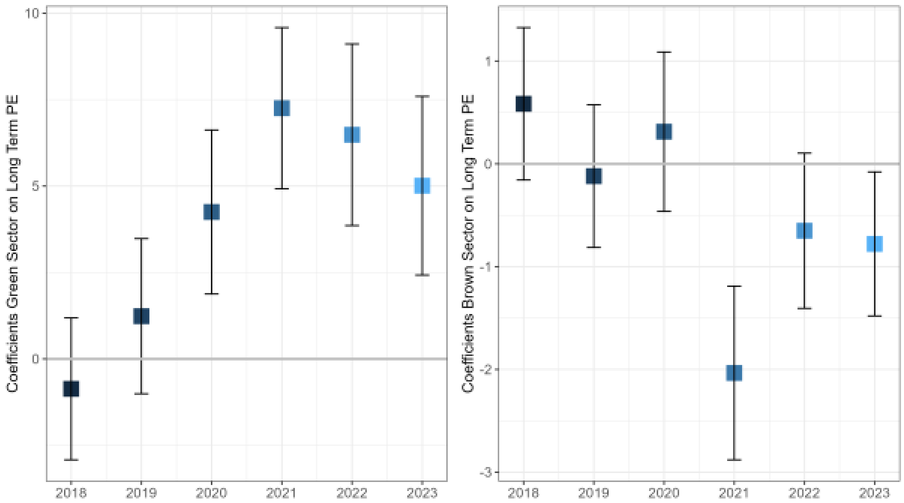
The previous analysis is conducted over the entire period covered by our dataset (2018-2023). To evaluate whether investors' environmental preferences have strengthened over time, we split our monthly dataset year by year and run the estimations again. Our main regression reflects Equation 1 and includes all our financial and extra-financial covariates, as in the last column of Table 2. Figure 1 depicts the coefficients associated with the green and brown sector dummies along with the corresponding confidence intervals at the 90% confidence levels.

Our dynamic framework highlights a sharp increase in the valuation of firms operating in green business activities in the early years of our sample, and a persistence in positive territory of the green sector coefficient at the end of our estimation period. Although non-significant at the beginning of the sample, the coefficient associated with the green sector dummy becomes significant in 2020. Moreover, the effect appears quite substantial after this date. Belonging to the green sectors in 2021 increases a company's PER by nearly 7.5 points compared with an average PER of 16.8 for neutral sectors (about 45% higher). For brown sectors, the coefficient appears positive in 2018, then slowly falls into negative territory in subsequent years. While the coefficient remains non-significant in the first three years, it becomes significantly negative in the year 2021, despite the inclusion of carbon intensity and physical risk as independent variables in the underlying regression. This finding contrasts with the results of the static regressions (see Table 2) and underlines that there is a material discount for firms belonging to brown sectors, but only in years 2021 and 2023.

As illustrated in Figure 1, the green premium and the brown discount both exhibit significant levels in 2023, but reach their peaks in 2021. This observed reduction can be attributed to a confluence of factors. Among other things, the period marking the end of our sample is characterized by relatively high interest rates, a response from central banks to inflationary pressures, and increased energy prices, consequent to the Ukrainian conflict. Higher interest rates tend to discount future earnings more heavily, which could harm the valuations of green companies, as they are more dependent on future cash flows associated with expected stricter environmental regulations. Conversely, the rise in energy prices is likely to have benefited the fossil fuel companies, which predominantly make up our brown sector category. This may elucidate the observed decline in the brown discount after 2021.

Overall, we conclude that both green and brown sector characteristics are priced by investors. Given that we control for other extra-financial variables, such as environmental scores or carbon emissions at the firm level, our findings indicate that investors take sector affiliation into account over and above other environmental criteria. The emergence of both a green premium and a brown discount also suggests that the need for investors to "green" financial portfolios manifests itself in both positive and negative screening in asset allocation strategies, namely the inclusion of green sectors and the exclusion of brown sectors in financial portfolios.

Fig. 1: The dynamic effect of sector affiliation on long-term PER

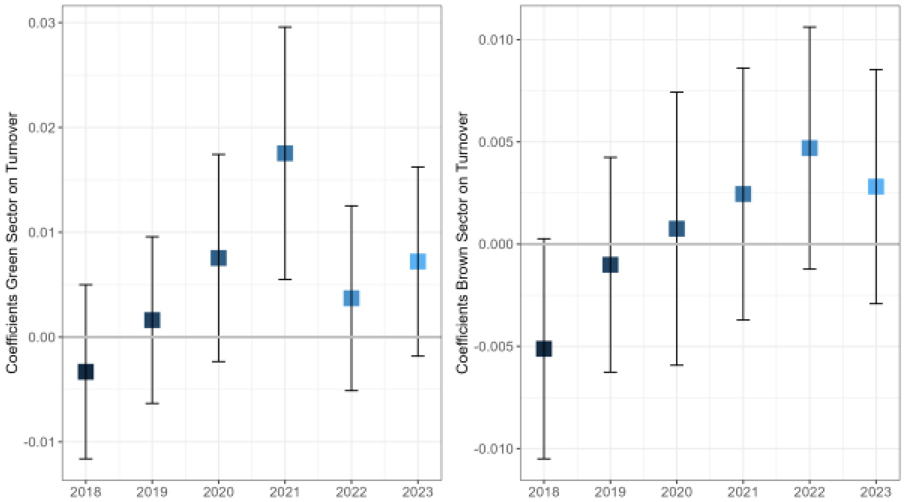


Note: The figure depicts the coefficients associated with the green and brown sector dummies from Equation (1), estimated dynamically every year. The regressions include all financial and extra-financial covariates, as in the last column of Table 2. All regressions use country and month-year fixed effects. Standard errors are clustered at both firm and time levels. Vertical bars represent the confidence intervals at the 90% confidence level.

Finally, to better grasp the growing attention of investors for firms operating in green and brown business activities, we complement the above findings with similar regressions using the firm-specific turnover rates as a dependent variable. Turnover rates are defined as the volumes traded for a stock divided by the outstanding shares. We believe that this metric usefully complements our core approach based on valuation measures to capture the degree of interest in green and brown sector characteristics. The results are presented in Figure 2. Again, the underlying regressions include all our financial and extra-financial variables as regressors.

We find that the coefficient associated with the green sector dummy is non-significant in the first years of the sample, but turns significantly positive in 2021. Although the coefficient loses its significance in 2022-2023, this finding underlines that investors' attention to firms operating in green business activities has increased over time. This result can be compared with those of Hong and Stein (2007) and Xiong and Yu (2011), which highlight high turnover rates for certain stocks during the Internet bubble and the Chinese warrant bubble, respectively. This increase in the turnover rate of green stocks is also consistent with the theory of Pedersen et al. (2021), which assumes the co-existence of different types of investors with heterogeneous (environmental) preferences. Based on the resale option theory (Scheinkman & Xiong, 2003), such a divergence in investor preferences can also help to drive up the price of green stocks. While we do not consider this to be sufficient

Fig. 2: The dynamic effect of sector affiliation on turnover rate



Note: The figure depicts the coefficients associated with the green and brown sector dummies from Equation (1), estimated dynamically on a yearly basis. The dependent variable is the firm-specific turnover rate instead of PER. The regressions include all financial and extra-financial covariates, as in the last column of Table 2. All regressions use country and month-year fixed effects. Standard errors are clustered at both firm and time levels. Vertical bars represent the confidence intervals at the 90% confidence level.

evidence to support the thesis of a green bubble in the equity markets, it is a further sign of the rapid build-up of pro-environmental preferences among investors.

Conversely, although it tends to increase over time, the coefficient associated with the brown sector dummy remains non-significant, even at the end of the sample. The fact that we find no significant relationship between firms' affiliation to brown sectors and turnover rates may explain why evidence of a brown discount is less salient than for the green premium in previous analyses.

4 Robustness tests and extensions

4.1 Valuation metrics

Our main conclusions are based on a long-term forward PER defined, in Section 2.2.1, as the ratio of the current price of the stock divided by the earning forecasts over a 3-5 year horizon. As the earning forecasts made by I.B.E.S analysts may be biased, we replicate the same analysis with different valuation ratios. More specifically, we test the robustness of our findings to the use of a short-term forward PER (with earning forecasts over a 1-2 year horizon), a trailing PER (with, as the denominator, the latest earnings of the company), and a book-to-market ratio. We perform the same analysis as in Figure 1 but with the aforementioned alternative valuation ratios. The results are outlined in Figures 4 to 6.

For green sectors, our results appear robust to alternative valuation measures. In all three cases, the coefficient associated with the green sector dummy increases in the early years of our estimation period (or decreases in the case of the book-to-market ratio) and remains significantly positive (negative) in the last year of the sample. In contrast, for brown sectors, the coefficient declines in the first years in all cases (or increases in the case of the book-to-market ratio). However, the brown coefficient is only significant in 2021 for the book-to-market ratio. This indicates, in line with our previous analysis, that the brown discount is likely to be less pronounced, and thus harder to detect than the green premium.

4.2 Definitions of green and brown sectors

As indicated in Section 2.2.2, selecting business activities to build the lists of green and brown sectors remains, to some extent, arbitrary, as there is no consensual classification of this sort in the literature. Our main specification, which we label "Main list", is the most restrictive one and focuses only on the energy and utilities sectors. We also consider two potential extensions of this list. The first one classifies business activities within the basic materials sector: paper and forest products are considered green, while metals and mining and construction materials are defined as brown. The second extension incorporates electric vehicles and environmental services as green, whereas it defines automobiles and truck manufacturers and some transportation services as brown. More details on these two extensions, "Extended 1" and "Extended 2", can be found in Tables 4 and 5 in the Appendix.

We check whether our main results are robust to variations in the definition of green or brown sectors. To that end, we try to consider as many potential definitions as possible and replicate our analysis with three different classifications: Main list with Extension 1, Main list with Extension 2, and Main list with Extensions 1 & 2. We report in Table 9 the results of the different regressions using the long-term forward PER as the dependent variable, and, as regressors, the sector, financial, and extra-financial variables (as in the last column of Table 2). In all the different cases, we observe a gradual emergence over time of a green premium on the one hand and a brown discount on the other. Indeed, for the three alternative sectoral definitions, the coefficient associated with the green (brown) sector dummy tends to increase (decrease) in the first years of our sample, and remains significantly positive (negative) afterward. This finding highlights that our results do not depend on a specific sector classification.

4.3 Regional analysis

A natural extension of our analysis is to combine our sectoral focus with a geographical dimension. To that aim, we split our sample into three regions, Asia, Europe, and North America. These three different regions cover close to 90% of the companies in our sample. The distribution of green, brown, and neutral companies by region is detailed in Table 7. We replicate in Table 10 the same exercise as in Section 2.2.2 and evaluate whether our results are sensible to specific geographical locations.

We confirm that the green premium documented above is present in each of the three regions. Although the magnitudes may vary across areas, all three coefficients associated with the green sector dummy are significantly positive at least in 2021 and 2022. Interestingly, the green premium in Europe became positive and significant from 2020 onwards, a year before North America and Asia. Rather counterintuitively, the scale of the green premium appears to be greater in North America than in Europe after 2021. This contrasts with Amel-Zadeh and Serafeim (2018), who highlights that European investors tend to have stronger environmental concerns than their US counterparts.[10] Nevertheless, European investors also invest to a large extent in US securities, which could push up the valuation of green stocks in North America.

Concerning the brown sectors, our analysis reveals that the associated coefficients are lower from 2019 to 2023 compared to their 2018 levels, reaching their lowest points in 2021-2022 across all three regions. In Europe and North America, the coefficients for the year 2021 are significantly negative. Before this date, we note that brown companies in North America had slightly higher multiples than neutral companies. Finally, Asian stocks do not show a significant brown discount. This finding may help explain the more mixed evidence of the brown discount observed in prior analyses.

Ultimately, one plausible explanation for our findings related to the observed green premium and brown discount may reside in the progressively stricter regulatory environment faced by companies in brown sectors. To illustrate this, we propose a targeted examination of the regulatory stringency in the United States (see Appendix C). Using the regulatory stringency indices from Al-Ubaydli and McLaughlin (2017), the analysis suggests that regulatory pressures have intensified more significantly for brown firms than for green firms in recent times (see Figure 8). However, due to the limitations in the data described in Appendix C, we leave it to future research to investigate whether there is a formal relationship between environmental regulatory stringency and stock valuation.

4.4 Matching

We test the robustness of our findings by using a pre-regression matching approach. Preprocessing data with matching methods can help improve parametric statistical models for estimating treatment effects, producing inferences that are more robust and less sensitive to modeling assumptions (Ho et al., 2007). In particular, matching can mitigate asymptotic biases arising from endogeneity (Roberts & Whited, 2013). The objective of matching is to achieve a balance in covariates, ensuring that the distributions of these variables in both the treatment and control groups are roughly equivalent.

[10] See also the 2021 report from the Global Alliance for Sustainable Investment. The proportion of sustainable investments (relative to total assets under management) has been consistently higher in Europe than in the US over the 2014–2020 period.

As we are dealing with a panel dataset, we need to calculate the average value of all numerical financial and extra-financial covariates from the years 2018 to 2023. We then use 3:1 nearest neighbor propensity score matching without replacement. To estimate the propensity score, we use logistic regression of the treatment on the numerical covariates. As the number of green (63) and brown (265) firms is limited in comparison with neutral firms (3342), we match each firm in the green and brown sectors to the three nearest neighbors within neutral companies. This matching specification yields adequate covariate balance, both for brown and green sectors: for most of the covariates, standardized mean differences are below the threshold of 0.1. All green and brown firms have been successfully matched to neutral firms.

Using the previously described matched samples, we separately (to maximize covariate balance) estimate the effect of belonging to a green or brown sector on stock valuation by fitting the following fixed-effect panel regressions:

$$PER_{i,t} = \alpha + \beta_g Green_i + \sum_{f=1}^{F} \lambda_f FIN_{i,t-1}^{f} + \sum_{e=1}^{E} \lambda_e ENV_{i,t-1}^{e} + \gamma_{country,i} + \gamma_t + \epsilon_{i,t} \quad (10)$$

$$PER_{i,t} = \alpha + \beta_b Brown_i + \sum_{f=1}^{F} \lambda_f FIN_{i,t-1}^{f} + \sum_{e=1}^{E} \lambda_e ENV_{i,t-1}^{e} + \gamma_{country,i} + \gamma_t + \epsilon_{i,t} \quad (11)$$

These post-matching regressions confirm prior findings, indicating that firms belonging to a green (brown) sector have shown significantly higher (lower) multiples than neutral firms since 2021 (see Figure 7).

5 Conclusion

In this paper, we explore the dynamic nature of pro-environmental preferences among investors through the lens of sector valuations in global equity markets from 2018 to 2023. We argue that sector affiliation is a more objective, consensual, and easily observable characteristic than other environmental measures. Therefore, sector valuations are likely to provide a reliable framework for studying the evolution of environmental preferences.

Understanding whether pro-environmental preferences are priced at the sector level is essential for financial practitioners and regulatory authorities. First, this information can provide important insights into the effect of positive and negative screening in portfolio allocation strategies on equity valuations. Second, this research question is important for policymakers developing classification systems aimed at channeling public and private investment toward environmentally sustainable economic activities. This is particularly relevant in Europe where corporate alignment with EU Taxonomy is based on business activities. Additionally, our analysis can help identify potential financial stability risks associated with the emergence of a green bubble or a negative reassessment of the value of brown securities.

Based on panel regressions, we find that firms' sector affiliations are significantly priced in the global equity market, positively for green sectors and negatively for brown sectors. Furthermore, companies operating in green sectors have gradually become overvalued relative to the rest of the market between 2018 and 2023, and vice versa for those operating in brown sectors, implying that pro-environmental preferences have become more prevalent among investors. However, despite this evidence, we believe that the green bubble narrative may be overstated, given that the overvaluation of companies operating in green business activities is quite substantial, but not extreme. In the same vein, while firms belonging to brown sectors appear slightly undervalued, they are still far from becoming stranded assets.

Since our baseline valuation measure relies on long-term analyst forecasts, our results suggest that the mispricing of green or brown sectors is driven by purely non-financial motives. However, we cannot exclude the fact that investors' demand for green firms is intended to hedge against a potential "green swan." It might also reflect a divergence between the beliefs of investors and financial analysts. Such divergence could stem from the uncertainty surrounding the effect of environmental risks or opportunities on future earnings profiles. Distinguishing between these effects is a promising avenue for future research.

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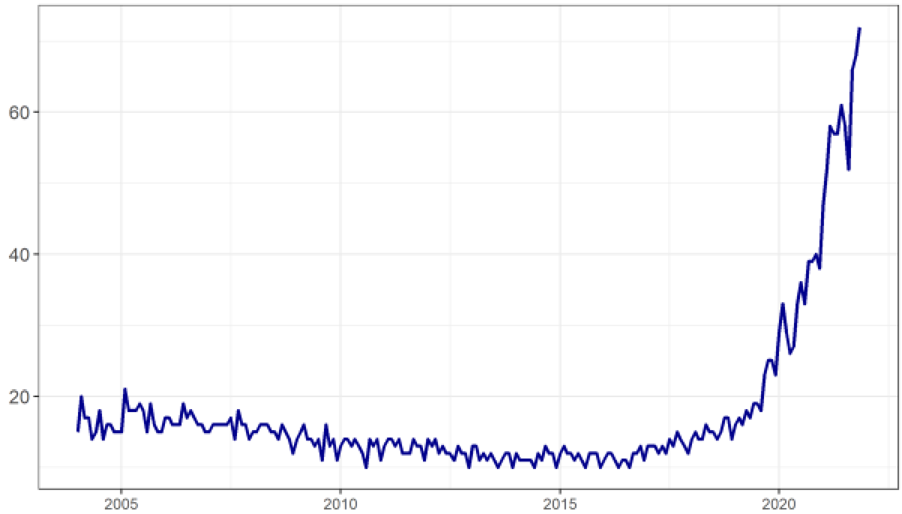
Appendix A: Variables

Fig. 3: Internet searches for environmental, social, and governance criteria based on Google trends



Note: The figure shows the evolution of internet searches for ESG criteria based on Google trends from 2004 to 2023 at a monthly frequency. The score is normalized between 0 and 100, with the upper bound indicating a historically high level of internet searches.

Table 3: Variable description

Type	Variables	Definition	Sources
Valuation measures	Long-term PER	Stock price divided by expected earnings per share (EPS3MN, EPS4MN, EPS5MN), denominated in USD	Refinitiv Datastream, I.B.E.S, authors' computation
	Short-term PER	Stock price divided by expected earnings per share (EPS1MN, EPS2MN), denominated in USD	Refinitiv Datastream, I.B.E.S, authors' computation
	Trailing PER	Stock price divided by current earnings per share (EPS1TR12), denominated in USD	Refinitiv Datastream, authors' computation
	Book-to-Market ratio	Common equity (WC03501) of firms divided by market capitalization (MV)	Refinitiv Datastream, authors' computation
Financial variables	Assets	Logarithm of total assets (WC02999) of firms, denominated in USD	Refinitiv Datastream
	Investment	Annual growth in total assets (WC02999)	Refinitiv Datastream, authors' computation
	Profitability	Net income after prefered dividends (WC01706) divided by common equity (WC03501)	Refinitiv Datastream, authors' computation
	Earnings growth	Growth rate of current earnings per share (EPS1TR12) over the last 12 months	Refinitiv Datastream, authors' computation
	Payout ratio	Ratio of dividends per share to earnings per share (WC09504)	Refinitiv Datastream
	Leverage	Total debt of the company divided by common equity, expressed in percentage (WC08231)	Refinitiv Datastream
	Analyst coverage	Total number of analyst estimates for expected earnings per share (EPS1NE)	Refinitiv Datastream, I.B.E.S
	Analyst dispersion	Standard deviation of the expected earnings per share (EPS3SD, EPS4SD, EPS5SD)	Refinitiv Datastream, I.B.E.S, authors' computation
	Illiquidity	Amihud indicator; ratio of the absolute value of the daily return of each stock to the daily traded volume (VO) of that same stock	Refinitiv Datastream, authors' computation
	Turnover rate	Sum of daily traded volumes in amount (VO*P) divided by the market value (MV)	Refinitiv Datastream, authors' computation
	Beta	Dynamic beta from the regression of firm returns on market returns (TOTMKWD)	Refinitiv Datastream, authors' computation
	Idiosyncratic risk	Standard deviation of the residual of the regression used to estimate the systematic risk (Beta)	Refinitiv Datastream, authors' computation
	Extreme risk	Cornish-Fisher 5% monthly Value-at-Risk	Refinitiv Datastream, authors' computation
	Technology component	Beta from the regression of firm returns on the returns of a technology portfolio (TECNOWD)	Refinitiv Datastream, authors' computation
Environmental variables	Environmental score	Measure based on the "E" scores of four data providers	CDP, Refinitiv ESG, S&P Global, and Sustainalytics, authors' computation
	Environmental disagreement	Standard deviation between the environmental scores of the different data providers	CDP, Refinitiv ESG, S&P Global, and Sustainalytics, authors' computation
	Lack of ESG controversies	Company's exposure to environmental, social and governance controversies and negative events reflected in global media (TRESGCCS)	Refinitiv Datastream
	Carbon intensity	A carbon intensity measure for each firm based on both reported and estimated emissions, Scopes 1 & 2 (ENERDP123), divided by net sales (WC01001)	Refinitiv Datastream, authors' computation
	Physical risk score	The physical risk score represents the fraction of each issuer value susceptible of being lost due to physical climate risks by 2050 in a likely climate-change scenario.	ISS-ESG

Note: This table describes the variables we use in our empirical analysis. We report in parentheses the Datastream identifiers used to download or construct the main variables. Variables are grouped into three categories: valuation measures, financial variables, and environmental variables. The construction of green and brown sector dummies is detailed in Tables 4 and 5

Table 4: List of green sectors

List	Business Sector	Industry Group	Industry	Business Activity	TRBC ID
	Renewable Energy				5020
		Renewable Energy			502010
			Equipment & Services	All	50201010
			Renewable Fuels	All	50201020
	Utilities				5910
		Electric Utilities & IPPs			591010
			Electric Utilities		59101010
Main list				Power Charging Stations	5910101014
				Alternative Electric Utilities	5910101020
				Hydroelectric & Tidal Utilities	5910101021
				Solar Electric Utilities	5910101022
				Wind Electric Utilities	5910101023
				Biomass & Waste to Energy	5910101024
				Geothermal Electric Utilities	5910101025
			Independent Power Producers		59101020
				Renewable IPPs	5910102012
	Applied Resources				5130
Extended 1		Paper & Forest Products			513010
			Forest & Wood Products	All	51301010
			Paper Products	All	51301020
	Automobiles & Auto Parts				5310
		Automobiles & Auto Parts			531010
			Auto & Truck Manufacturers		53101010
Extended 2				Electric (Alternative) Vehicles	5310101014
	Industrial & Comm Services				5220
		Pro & Comm Services			522030
			Environmental Serv. & Equip.	All	52203010

Note: This table describes the business activities included in our lists of green sectors. This selection is based on The Refinitiv Business Classification (TRBC) which contains more than 600 business activities. We define a main list based solely on business activities in the energy and utilities sector and two extensions. The TRBC methodology used to assign an industry to firms is described here.

Table 5: List of brown sectors

List	Business Sector	Industry Group	Industry	Business Activity	TRBC ID
Main list	Fossil Fuels				5010
		Coal			501010
			Coal	All	50101010
		Oil & Gas			501020
			Integrated Oil & Gas	All	50102010
			Oil & Gas Explo. and Prod.	All	50102020
			Oil & Gas Refin. and Mark.	All	50102030
		Oil & Gas Equip. & Serv.			501030
			Oil & Gas Drilling	All	50103010
			Oil Related Serv. and Equip.	All	50103020
			Oil & Gas Transport. Serv.	All	50103030
	Utilities				5910
		Electric Utilities & IPPs			591010
			Electric Utilities		59101010
				Fossil Fuel Electric Utilities	5910101012
			Independent Power Producers		59101020
				Fossil Fuel IPPs	5910102011
		Natural Gas Utilities			591020
			Natural Gas Utilities	All	59102010
Extended 1	Mineral Resources				5120
		Metals & Mining			512010
			Precious Metals & Minerals	All	51201010
			Iron & Steel	All	51201020
			Aluminum	All	51201030
			Specialty Mining & Metals	All	51201050
			Diversified Mining	All	51201080
		Construction Materials			512020
			Construction Materials	All	51202010
Extended 2	Automobiles				5310
		Automobiles & Auto Parts			531010
			Auto & Truck Manufac.	All (without Electric Vehicles)	53101010
	Transportation				5240
		Freight & Logistics Serv.			524050
			Air Freight & others		52405010
				Air Freight	5240501012
			Ground Freight & Logis.		52405030
				Freight Trucking	5240503012
		Passenger Transport. Serv.			524060
			Airlines	All	52406010

Note: This table describes the business activities included in our lists of brown sectors. This selection is based on The Refinitiv Business Classification (TRBC) which contains more than 600 business activities. We define a main list based solely on business activities in the energy and utilities sector and two extensions. The TRBC methodology used to assign an industry to firms is described here.

Table 6: Ten largest firms belonging to green and brown sectors

Name	Symbol	Size	Business Activity	Country
		Green sectors		
Vestas Windsystems	DK:VEW	32.1	Wind Systems & Equip.	Denmark
Adani Green Energy	IN:AG	30.4	Renewable IPPs	India
First Solar	@FSLR	18.4	Photovoltaic Solar Syst.	USA
Enphase Energy	@ENPH	18.0	Photovoltaic Solar Syst.	USA
Centrais Eletr Bras	BR:EL3	17.7	Hydroelectric & Tidal Util.	Brazil
Siemens Gamesa RE	E:GAM	13.6	Wind Systems & Equip.	Spain
Siemens Energy	D:ENR	10.6	Renewable Energy Equip.	Germany
Meridian Energy	Z:MELZ	9.1	Hydroelectric & Tidal Util.	New Zealand
NHPC	IN:NHD	8.0	Hydroelectric & Tidal Util.	India
Brookfield Ren. Part.	C:BEP.UN	7.6	Hydroelectric & Tidal Util.	Canada
		Brown sectors		
Saudi Arabian Oil	SA:ARO	2,132.8	Integrated Oil & Gas	Saudi Arabia
Exxon Mobil	U:XOM	399.6	Oil & Gas Refin. & Mark.	USA
Chevron	U:CVX	280.7	Oil & Gas Explo. & Prod.	USA
Reliance Industries	IN:REL	210.6	Oil & Gas Refin. & Mark.	India
Total	F:FP	164.1	Integrated Oil & Gas	France
Conocophillips	U:COP	137.8	Oil & Gas Explo. & Prod.	USA
BP	BP.	102.1	Oil & Gas Refin. and Mark.	UK
Equinor	N:EQNR	95.3	Integrated Oil & Gas	Norway
Royal Dutch Shell	RDSB	85.8	Integrated Oil & Gas	UK
Enbridge	C:ENB	76.9	Oil & Gas Transport. Serv.	Canada

Note: This table details the ten largest companies, by market capitalization in December 2023, for our main lists of green and brown sectors, detailed in Tables 4 and 5. Company market capitalization (Size) is expressed in billions of US dollars. The countries indicated correspond to the company's main trading market.

Table 7: Distribution of green and brown firms by region

	Green sectors								
	Main list			Main list with 1			Main list with 1&2		
Regions	#N firms	Market value	%	#N firms	Market value	%	#N firms	Market value	%
Europe	29	91	32	47	157	39	59	186	13
Asia	17	92	33	24	105	26	32	122	9
North Am.	12	72	26	18	91	23	29	1,078	75
Other	5	26	9	9	49	12	9	48	3
Total	63	281	100	98	402	100	129	1,436	100

	Brown sectors								
	Main list			Main list with 1			Main list with 1&2		
Regions	#N firms	Market value	%	#N firms	Market value	%	#N firms	Market value	%
Asia	80	803	12	177	1,648	19	225	2,465	24
Europe	65	798	12	119	1,380	16	136	1,610	16
North Am.	60	2,232	35	118	2,829	32	136	3,108	30
Other	60	2,634	41	122	3,002	34	132	3,041	30
Total	265	6,468	100	536	8,859	100	629	10,224	100

Note: This table details the geographical distribution of green and brown companies, based on our main list of green and brown sectors and the extensions described in Tables 4 and 5. For each region, we report the number of companies, their cumulative market capitalization in billions of US dollars, and as a percentage of the global market value of the green and brown sectors, respectively.

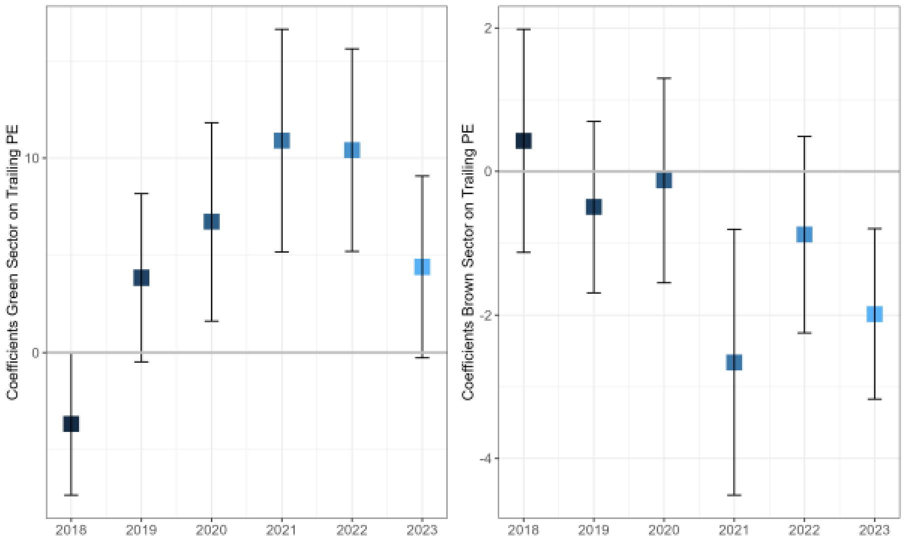
Table 8: Descriptive statistics

	Green sectors			Brown sectors			Neutral sectors		
Variables	Q25	Mean	Q75	Q25	Mean	Q75	Q25	Mean	Q75
Long-term PER	9.1	18.3	27.2	6.1	10.9	13.5	8.3	14.5	18.5
Short-term PER	10.0	23.4	36.9	6.7	13.5	17.1	9.7	18.1	23.0
Trailing PER	9.2	25.3	44.0	6.3	13.8	18.6	9.8	19.2	25.4
Book-to-Market	0.23	0.59	0.78	0.45	0.86	1.19	0.26	0.69	0.98
Turnover rate	0.01	0.07	0.09	0.01	0.07	0.09	0.02	0.07	0.10
Assets	13.5	14.7	15.7	14.6	15.7	16.9	14.0	15.2	16.4
Investment	-0.01	0.15	0.22	-0.04	0.06	0.11	-0.03	0.08	0.13
Profitability	0.01	0.08	0.14	0.04	0.12	0.20	0.05	0.11	0.18
Earnings growth	-25.1	8.2	37.5	-31.5	4.66	31.9	-13.6	5.8	22.5
Payout ratio	0.00	25.1	46.6	13.5	40.5	63.4	8.7	34.4	53.7
Analyst cov.	3.0	7.3	9.0	2.0	9.2	14.0	3.0	8.8	13.0
Analyst disp.	0.07	4.36	0.48	0.15	6.73	2.44	0.14	7.12	4.28
Leverage	33	134	214	26	93	131	19	94	123
Illiquidity	0.001	0.197	0.104	0.000	0.107	0.013	0.000	0.100	0.017
Idiosyn. risk	0.28	0.40	0.51	0.26	0.36	0.45	0.24	0.33	0.40
Beta	0.69	1.12	1.51	0.59	1.01	1.38	0.60	0.99	1.34
Extreme risk	0.3	2.6	1.0	0.2	5.4	1.5	0.2	5.5	1.5
Technology	-0.50	-0.20	0.02	-0.25	-0.01	0.21	-0.37	-0.10	0.11
GES intensity	0.01	0.39	0.67	0.120	0.50	0.74	0.01	0.16	0.10
E score	14.3	32.9	48.4	16.2	40.8	62.0	19.0	40.2	61.0
Environ. disagr.	12.3	16.9	21.1	10.6	14.7	17.3	10.1	14.7	18.1
Lack of ESG controv.	100	93	100	77	85	100	100	90	100
Physical risk	0.03	1.36	1.17	0.20	2.37	3.38	0.16	1.87	2.42

Note: This table reports the descriptive statistics for our baseline lists of green, neutral, and brown sectors. We compute the mean and quantiles for each of the variables we use in our empirical analysis.

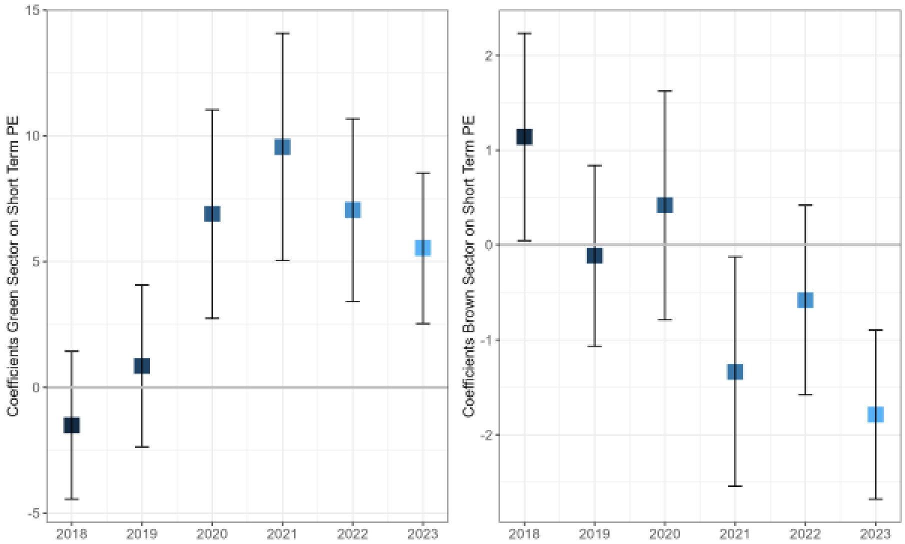
Appendix B: Dynamic regressions

Fig. 4: The dynamic effect of sector affiliation on trailing PER



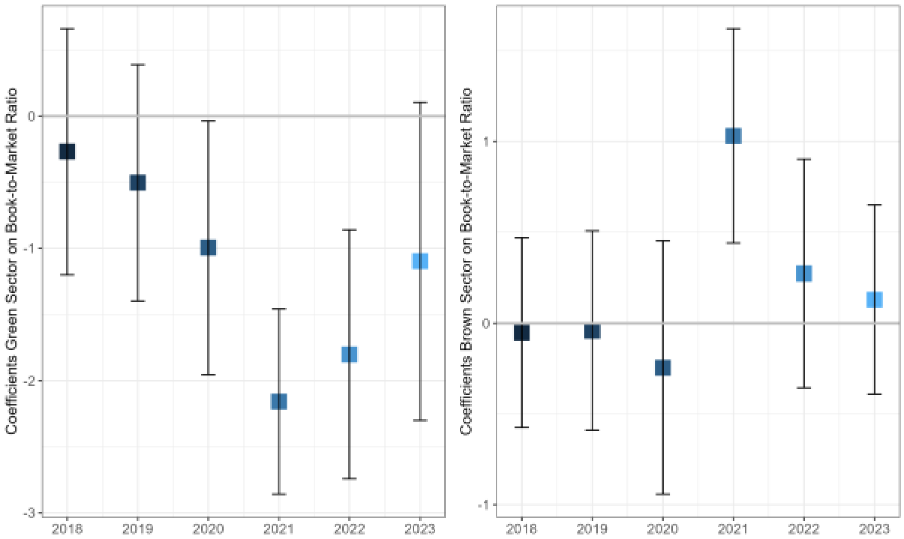
Note: The figure depicts the coefficients associated with the green and brown sector dummies from Equation (1), estimated dynamically on a yearly basis. The dependent variable is the firm-specific trailing PER. The regressions include all financial and extra-financial covariates, as in the last column of Table 2. All regressions use country and month-year fixed effects. Standard errors are clustered at both firm and time levels. Vertical bars represent the confidence intervals at the 90% confidence level.

Fig. 5: The dynamic effect of sector affiliation on short-term forward PER



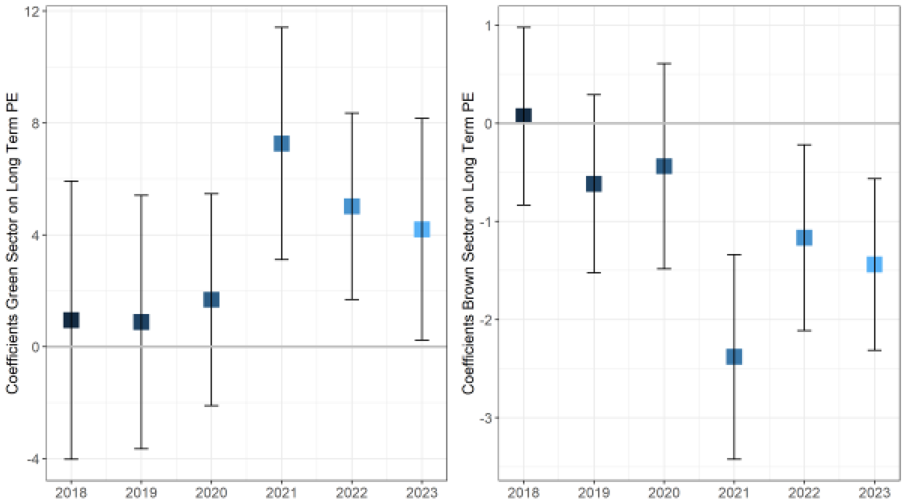
Note: The figure depicts the coefficients associated with the green and brown sector dummies from Equation (1), estimated dynamically on a yearly basis. The dependent variable is the firm-specific short-term forward PER. The regressions include all financial and extra-financial covariates, as in the last column of Table 2. All regressions use country and month-year fixed effects. Standard errors are clustered at both firm and time levels. Vertical bars represent the confidence intervals at the 90% confidence level.

Fig. 6: The dynamic effect of sector affiliation on book-to-market ratio



Note: The figure depicts the coefficients associated with the green and brown sector dummies from Equation (1), estimated dynamically on a yearly basis. The dependent variable is the firm-specific book-to-market ratio. The regressions include all financial and extra-financial covariates, as in the last column of Table 2. All regressions use country and month-year fixed effects. Standard errors are clustered at both firm and time levels. Vertical bars represent the confidence intervals at the 90% confidence level.

Fig. 7: Post-matching regressions



Note: We use propensity score matching to match each firm in the green/brown sector group to three firms in the control group (without replacement) based on their propensity score. The matching procedure is based on the average value of the covariates from 2018 to 2023. After matching, we run fixed-effect panel regressions in matched samples to estimate the effect of green/brown sector affiliation on stock valuation. This procedure reduces the dependence of the validity of the estimated treatment effect on the correct specification of the model (Ho et al., 2007). The regressions include all financial and extra-financial covariates, as in the last column of Table 2. All regressions use country and month-year fixed effects. Standard errors are clustered by matched company groups. Vertical bars represent the confidence intervals at the 90% confidence level.

Table 9: Dynamic regressions based on alternative sector definitions

	2018	2019	2020	2021	2022	2023
Green - Main with 1	-0.764	-0.254	1.741*	3.335***	2.911**	1.839*
	(0.807)	(0.834)	(0.906)	(1.055)	(1.089)	(1.015)
Green - Main with 2	-0.701	0.494*	2.306***	4.573***	4.786***	3.914***
	(0.870)	(0.981)	(1.132)	(1.203)	(1.203)	(1.137)
Green - Main with 1 and 2	-0.800	-0.472	1.059	2.542**	2.642**	1.883*
	(0.667)	(0.714)	(0.810)	(0.931)	(0.923)	(0.858)
Brown - Main with 1	0.197	-0.210	-0.403	-1.994***	-1.415***	-0.735*
	(0.356)	(0.343)	(0.376)	(0.424)	(0.371)	(0.340)
Brown - Main with 2	-0.760*	-1.281**	-0.321	-2.238***	-1.449***	-1.474***
	(0.359)	(0.342)	(0.412)	(0.442)	(0.398)	(0.361)
Brown - Main with 1 and 2	-0.646*	-1.011***	-0.725*	–2.253***	-1.879***	-1.254***
	(0.324)	(0.312)	(0.350)	(0.397)	(0.344)	(0.315)

*Note: Each sectoral coefficient stems from a regression with, as dependent variable, the long-term forward PER, and, as independent variables, all the financial and extra-financial characteristics of our dataset, as in the last column of Table 2. The first column of the table indicates which definition is considered for the construction of the green and brown sectors. "Main with 1" refers to the Main list with Extension 1, as detailed in Table 4 and 5. All regressions use country and month-year fixed effects. Standard errors are clustered at firm and time levels and reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Table 10: Dynamic regressions by regions

	2018	2019	2020	2021	2022	2023
Green sector - North America	0.453	2.859	4.979	9.094***	9.089*	6.710*
	(3.424)	(3.344)	(2.875)	(1.884)	(4.328)	(3.338)
Green sector - Europe	0.108	0.818	6.777**	7.289**	6.961**	6.181*
	(1.586)	(1.635)	(1.960)	(2.040)	(1.962)	(2.096)
Green sector - Asia	-1.343	1.512	1.374	6.884**	5.271*	3.344
	(2.093)	(2.456)	(2.435)	(2.807)	(2.838)	(3.080)
Brown sector - North America	1.994*	1.318	1.327	-3.086***	-1.105	-1.273*
	(0.621)	(0.610)	(0.593)	(0.643)	(0.696)	(0.638)
Brown sector - Europe	0.376	-0.315	-0.324	-2.713***	-0.578	-0.384
	(0.621)	(0.610)	(0.593)	(0.643)	(0.696)	(0.638)
Brown sector - Asia	-0.277	-0.241	-0.572	-0.849	-0.980	-0.947
	(0.882)	(0.943)	(1.046)	(1.263)	(1.022)	(1.053)

*Note: Each sectoral coefficient stems from a regression with, as dependent variable, the long-term forward PER, and, as independent variables, the lagged value of all the financial and extra-financial characteristics of our dataset, as in the last column of Table 2. The first column of the table indicates which region is considered for the analysis. All regressions use country and month-year fixed effects. Standard errors are clustered at firm and time levels and reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.*

Appendix C: US Stringency Indices

To assess the potential influence of increased regulatory stringency on sectoral equity valuations, we utilize the RegData regulatory stringency indices developed by the Mercatus Center. These indices quantify individual regulatory restrictions found within the Code of Federal Regulations, assigning them to the respective authoring agencies and departments, as well as to the industries impacted. Consequently, using the North American Industry Classification System (NAICS), we obtain sector-level regulatory stringency indices. Further details on this methodology can be found in Al-Ubaydli and McLaughlin (2017).

We employ these indices to analyze changes in regulatory stringency over time, aggregating them through a simple average to create distinct "brown stringency index" and "green stringency index." This methodology, however, is not without limitations. First, RegData exclusively offers metrics of stringency for the United States, omitting other nations represented in our study. Additionally, sector-specific data are confined to the years 2019 to 2021, and are available only on a yearly basis. Second, the dataset adheres to the NAICS, whereas our analysis is based on the TRBC system. Consequently, to construct these brown and green stringency indices, it is necessary to establish a correspondence between our sectoral classification, detailed in Tables 4 and 5, and the NAICS classification. Although an exact correspondence between the two classification systems is not possible, the NAICS sectors considered are specified in Table 11. Third, RegData does not exclusively focus on environmental regulation; therefore, the proxies utilized here reflect the general regulatory stringency, which may not directly pertain to environmental concerns. Lastly, using a simple average to aggregate different sectoral stringency indices can give excessive weight to certain sectors. Despite these limitations, we believe that this approach serves as a valuable initial indicator of the changes in regulatory stringency within green and brown sectors.

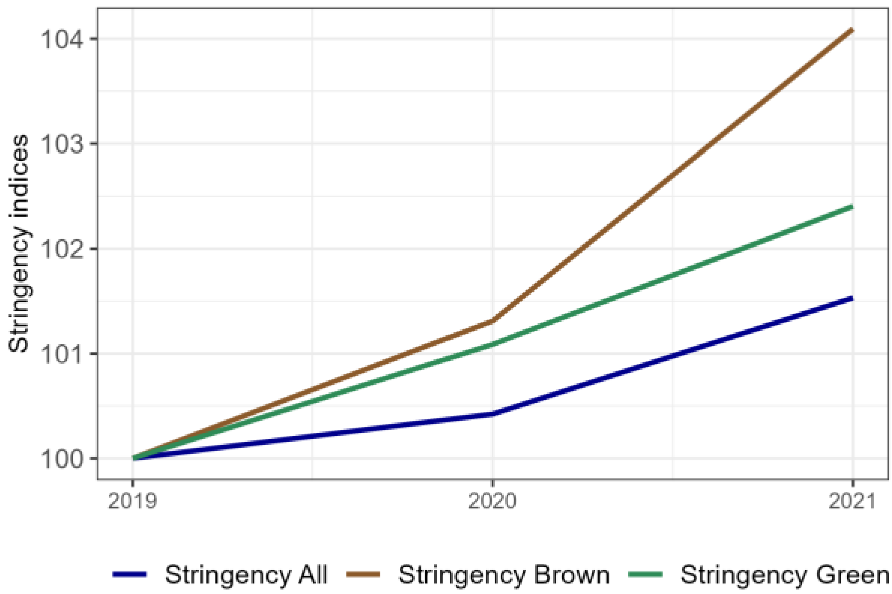
The outcomes of our analysis are presented in Figure 8. The blue line illustrates the overall stringency index for all sectors within the U.S. economy, while the brown and green lines depict the respective indices for the brown and green sectors, as per the methodology previously outlined. Each index has been normalized to a baseline value of 100 in 2019. The analysis reveals that, although the stringency in green sectors has increased more than the overall economy's stringency, the stringency in brown sectors has risen significantly more, particularly between 2020 and 2021. This notable increase in brown sector stringency may help explain the emergence of a significant brown discount after 2021 in the United States.

Table 11: Green and Brown sectors based on NAICS classification

	NAICS code	NAICS title
Green Sector	221114	Solar Electric Power Generation
	221115	Wind Electric Power Generation
	221116	Geothermal Electric Power Generation
	221117	Biomass Electric Power Generation
	33591	Battery Manufacturing
Brown Sector	2111	Oil and Gas Extraction
	2121	Coal Mining
	2212	Natural Gas Distribution
	3241	Petroleum and Coal Products Manufacturing
	4247	Petroleum and Petroleum Products Merchant Wholesalers
	4571	Gasoline Stations
	4572	Fuel Dealers
	4861	Pipeline Transportation of Crude Oil
	4862	Pipeline Transportation of Natural Gas

Note: In this table, we establish a correspondence between our green and brown sector classification, detailed in Tables 4 and 5, and the NAICS classification. Note that an exact match between the TRBC and the NAICS systems is unattainable.

Fig. 8: Evolution of Stringency Indices



Note: The blue line on this graph illustrates the overall stringency index for all sectors within the U.S. economy, while the brown and green lines depict the respective indices for the brown and green sectors, as per the methodology outlined in Appendix C, with a sectoral allocation detailed in Table 11.