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Have shifts in investor tastes led the market portfolio to capture ESG preferences?

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A B S T R A C T

Based on the growing concern about ESG issues in financial markets, in this paper we implement a generalization of the model proposed by Pástor, Stambaugh, and Taylor (2021), which predicts that when the market portfolio is not ESG-neutral and its greenness level increases, the market factor and the ESG factor become redundant, allowing the classic CAPM to account for ESG characteristics. Using market data series for the U.S. equity market, our results show that brown assets typically have negative ESG betas, the price of ESG risk is negative and progressively trends towards zero over time, and the explanatory power of the market portfolio on the ESG factor increases over time as the greenness level of the market portfolio improves. In any case, the period coinciding with the emergence of the COVID-19 pandemic implies a reversal of these trends. Our results suggest that efforts by public authorities to promote improvements in corporate ESG performance translate into lower cost of capital, especially in periods of overall declines in corporate ESG performance.

1. Introduction

Despite the important contributions and advances made by research on asset pricing in recent decades, a complete explanation of the dynamics of stock prices and the discount rates required by investors is still far from being achieved. Moreover, researchers and practitioners in this area not only have to deal with the high uncertainty surrounding stock returns in financial markets, but also with shifts in investor tastes that arise naturally over time and that can strongly influence expected returns. In this context, financial markets worldwide are experiencing an extraordinary boom in new products and practices in response to the growing demand from investors for investments labeled as 'green', that is, committed to environmental, social and corporate governance (ESG) principles and especially to the environment (Hartzmark & Sussman, 2019; Krueger, Sautner, & Starks, 2020; Venturini, 2022). Consequently, a significant portion of recent research on asset pricing and financial markets focuses on studying the effects of ESG policies on the risk and return of green investments relative to those less committed to ESG principles, often referred to as 'brown' investments.

On this basis, in this paper we study to what extent and under what circumstances shifts in investors' preferences towards sustainability are captured by the market portfolio, that is, a market-cap-weighted portfolio comprising all publicly traded risky assets, which, as is widely known, constitutes a central element in the asset pricing theory. Thus, the market portfolio is not only generally used to proxy for the wealth portfolio in the classic capital asset pricing model (CAPM) by Sharpe (1964), Lintner (1965a) and Lintner (1965b), but it is also used as a common risk factor in most contemporary asset pricing models. These aspects, together with the fact that the CAPM remains one of the most widely used asset pricing models by both researchers and practitioners in a wide range of applications (capital budgeting, performance evaluation for active asset managers, etc.), highlights the importance of the topic under study.

In this regard, a prolific part of the research in the area emphasizes the need to include additional common risk factors to consider investors' ESG preferences. Thus, building on recent findings from previous research on ESG investing, Pástor, Stambaugh, and Taylor (2021) propose a two-factor asset pricing model that includes an additional risk factor to the classic CAPM —the ESG factor—, which allows the model to explicitly account for the effect of investors' ESG tastes on asset prices. In

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any case, the model proposed by Pástor et al. (2021) relies heavily on the assumption that market participants differ in their ESG tastes, establishing two investor categories, namely investors with stronger-than-average tastes for green holdings and investors with weaker-than-average ESG preferences. As the authors state, in the case that there is no dispersion in ESG tastes, all agents hold the market portfolio and the ESG factor has no explanatory power. Moreover, if ESG tastes are strong but equal across market participants, investors just hold the market portfolio as asset prices then adjust to push the market portfolio towards greenness.

In this context, the aforementioned growing demand for green assets by investors raises questions about the explanatory power of the ESG factor over time, and its current performance in pricing equities. In particular, under the Pástor et al. (2021) setup, questions arise about the possible redundancy between the ESG factor and the market portfolio in a context of relatively high commitment to ESG principles such as the current one and, consequently, about the ability of the market portfolio to account for ESG risk. To the best of our knowledge, these important aspects remain unexplored in recent literature on the topic.

Accordingly, in order to analyze the level of redundancy of the ESG factor with the market portfolio over time, in this paper we comprehensively study the behavior over time of the risk loadings —i.e., betas— on the ESG factor across industries in the U.S. equity market, as well as the dynamics of the prices of risk that result from the Pástor et al. (2021) model, for the period from January 2001 to December 2021. Moreover, the time-varying estimates for these coefficients allow us to dynamically study the explanatory power of the market portfolio on the ESG factor and, consequently, the extent to which recent shifts in investor tastes have caused the market portfolio to subsume the ESG factor, and the classic CAPM to account for the ESG performance of firms.

For that purpose, we use market data from Refinitiv Eikon/Datastream and the Refinitiv ESG Company Scores data series to form all equal-weighted industry portfolios traded on the U.S. equity market in the period under study based on 2-digit SIC codes, as well as the ESG factor as defined by Pástor et al. (2021). Using the two-pass cross-sectional regression (CSR) methodology on these data series and a 48-month rolling window, we estimate both the portfolio betas and the prices of risk that result from the Pástor et al. (2021) model on a monthly basis. Remarkably, this procedure not only allows us to relate the behavior of risk exposures and risk premia to changes in ESG performance both at the firm level and for the entire equity market, but also to study shifts over time in the degree to which the market portfolio helps explain the ESG factor.

The contributions of this paper to the related literature are threefold. First, to the best of our knowledge, this is the first paper to use the model proposed by Pástor et al. (2021) in order to empirically study to what extent the market portfolio captures the greatest awareness of investors towards ESG issues, which is a key element for the classic CAPM to account for these aspects. In this regard, we find that, in general, the better the ESG performance of the market portfolio, the greater its explanatory power on the ESG factor, suggesting that both factors become redundant as the greenness level of the market as a whole increases. Furthermore, we find that in a context of reduced investor engagement with ESG issues, such as that occurred during the emergence of the COVID-19 pandemic, better corporate ESG performance —i.e., higher exposure to the ESG factor— helps companies mitigate increases in unconditional expected returns (i.e., discount rates) and, consequently, declines in stock prices.

In this context, it should be noted that, although the extent to which the Pástor et al. (2021) model allows the CAPM to reduce pricing errors and improve model performance is important in our research, it is not its cornerstone. In fact, from an empirical perspective, even if changes in ESG preferences lead the market portfolio to capture investors' green tastes, the prevalence of a number of market anomalies, such as the beta anomaly, the value and momentum effects, post-event drifts, insider trading or earnings quality, among many others, appear to represent characteristics that predict stock returns in ways that the CAPM cannot explain.[1] Nevertheless, regardless of these issues, the model proposed by Pástor et al. (2021) allows for an alternative explanation of CAPM alphas other than aversion to additional fundamental risks, given by heterogeneity in tastes for known ESG characteristics. Therefore, our paper contributes to related research by studying how relative consensus across investors on ESG concerns might reduce the fraction of CAPM alphas that results from heterogeneity in investor tastes.

Second, from a methodological perspective, although in deriving their two-factor asset pricing model, Pástor et al. (2021) assume that the market portfolio is ESG-neutral, in our research we relax this assumption in order to allow the model to consider shifts in the greenness level of the market portfolio. Importantly, this generalization of the Pástor et al. (2021) model allows us to directly evaluate the explanatory power of the market portfolio on the ESG factor under different levels of greenness for the entire equity market. In this regard, our time rolling window-based CSR methodology is fully aligned with the purpose of our study as it provides us with estimates for time-varying ESG betas across assets and time-varying risk prices, which allows us to dynamically study the effect of shifts in investors' ESG tastes on the power of the market portfolio to explain the ESG factor over time. This aspect is central given the strong variation experienced by investor preferences on ESG issues in recent years (Pástor, Stambaugh, & Taylor, 2022).

Third, our research provides a comprehensive analysis of the time-varying behavior of ESG betas and their significance for all industries within the U.S. equity market, which to the best of our knowledge it is unprecedented in the related literature. Furthermore, our research allows us to study specific patterns in the risk exposure of green and brown industries when they turn brown and green respectively during specific time periods. Conversely, most related research focuses on specific industries or stock categories to study the effects of ESG considerations on risk and return, as shown in detail in the literature review section.

Our findings have some important policy and practical implications. On the one hand, the fact that better corporate ESG performance appears to help companies mitigate increases in required rates of return when investor commitment to ESG principles falls, in order to increase the resilience of companies to rare events that may lead to reduced investor engagement on ESG issues (e.g., pandemics, wars, etc.), firms can benefit from corporate and government policies aimed at improving corporate ESG performance (e.g., energy use and efficiency, carbon emissions, pollution, waste and water management, community impact, board structure, etc.). Furthermore, across sectors, efforts should especially focus on those industries with poorer ESG performance and higher exposure to rare event risk.

On the other hand, from a methodological perspective, our results suggest that practitioners and researchers should explicitly account for ESG risks when performing asset pricing tasks in contexts of low to moderate investor awareness to ESG principles, for example including the ESG factor proposed by Pástor et al. (2021) as an additional common risk factor. By contrast, higher levels of investor engagement on ESG issues appear to allow asset pricing models that include the market portfolio as a common risk factor to indirectly account for ESG preferences and, consequently, provide results naturally corrected for investors' ESG tastes.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the baseline model. Section 4 describes the data and the empirical methodology. Section 5 shows and discusses the results. Section 6 concludes the paper.

[1] This literature is too large to summarize here. Campbell (2018, pp. 66-72) provides an excellent summary of the state of the art on these aspects.

2. Literature review

Previous research on the effects of ESG preferences on asset prices largely emphasizes the importance of heterogeneity in ESG tastes across economic agents on expected returns. Thus, Heinkel, Kraus, and Zechner (2001) establish two types of investors, one of which —green investors— avoids stock holdings in polluting companies. On this basis, the authors show that exclusionary ethical investing leads to lower stock prices for polluting companies and, consequently, a higher cost of capital. Similarly, Baker, Bergstresser, Serafeim, and Wurgler (2018) assume two types of investors with mean-variance preferences, one of which displays green tastes. Focusing on the prices and ownership patterns of U.S. corporate and municipal green bonds, the authors find that green assets have lower expected returns and more concentrated ownership. By contrast, Pedersen, Fitzgibbons, and Pomorski (2021) add a third type of investor who is unaware of the ESG performance of companies. The authors find that, depending on the wealth of this third type of investor, better corporate ESG performance can imply either higher or lower expected returns.

As noted in the previous section, Pástor et al. (2021) also assume two types of investors —investors with stronger-than-average and weaker-than-average ESG tastes— to develop an equilibrium model that allows explaining stock returns based on two market factors, namely, the return on the market portfolio as in the classic CAPM, and an ESG factor composed of a position in the stock portfolio that maximizes the level of greenness attainable in the market. Under this equilibrium model, green assets have positive betas on the new ESG factor and brown assets have negative ESG betas. Furthermore, the model predicts that green assets underperform brown assets in the long run due to the effects of ESG concerns on investor utility, which means that green assets provide lower unconditional expected returns than brown assets and the new ESG factor has a negative price of risk.

Nevertheless, as noted above, the fact that the ESG factor requires the presence of heterogeneity in investors' ESG tastes raises questions about the importance of this new factor at different levels of market-wide ESG commitment. In this regard, Pástor et al. (2022) compare the unconditional expected returns of green stocks with those of brown stocks both ex ante and ex post, finding that while green assets have outperformed brown assets in recent years, this does not mean that their expected returns are higher. In fact, in analogy to the results of recent research on green bonds (Baker et al., 2018; Larcker & Watts, 2020; Zerbib, 2019), the authors show that just the opposite is true, with green stocks having lower unconditional expected returns than brown stocks, even when this is not necessarily the case on a conditional basis (Rojo-Suárez & Alonso-Conde, 2023). Importantly, Pástor et al. (2022) state that these results are mainly due to shifts in investors' tastes towards green assets caused by increased concerns about climate change, consistent with other research in the area (Avramov, Cheng, Lioui, & Tarelli, 2022; Baker et al., 2018; Fama & French, 2007; Pedersen et al., 2021; Zerbib, 2022).

These aspects are directly related to recent research studying the shifts in the explanatory power of the classic CAPM in recent years, primarily caused by the mitigation of market anomalies due to increased trading activity in financial markets worldwide. In this context, Chordia, Roll, and Subrahmanyam (2011) find that the intraday volatility of equity markets and the level of predictability of stock returns have decreased significantly in recent years, enhancing market efficiency. Furthermore, Chordia, Subrahmanyam, and Tong (2014) show that increased trading activity in financial markets has significantly attenuated most market anomalies. These conclusions are shared by a lot of recent research analyzing specific market anomalies, with McLean and Pontiff (2016) finding that the predictive power of 97 market anomalies in forecasting stock returns is 58% lower after publication in peer-reviewed finance, accounting, and economics journals. Remarkably, Bornholt (2013) states that if market anomalies are temporary, then the CAPM may recover its past explanatory power.[2] In fact, based on these contributions and using market data for the period from January 1989 to December 2018, Rojo-Suárez, Alonso-Conde, and Ferrero-Pozo (2022) show that the classic CAPM performs satisfactorily in pricing different market anomaly portfolios on the London Stock Exchange. Despite this, to the best of our knowledge, the effects of shifts in investors' ESG tastes on the explanatory power of the CAPM remain largely unexplored by research on the area.

In addition to this, it should be noted that most research on the topic focuses on the study of specific sectors or stock categories rather comprehensively analyzing all industries within the economy. Thus, Hong and Kacperczyk (2009) focus on 'sin' stocks, that is, firms involved in producing alcohol, tobacco, and gaming, concluding that these assets are less held by norm-constrained investors such as pension plans, which leads to sin stocks having higher expected returns than other comparable stocks. This conclusion is fully shared by Fabozzi, Ma, and Oliphant (2008) and also by Blitz and Fabozzi (2017), who find that the sin stock anomaly can be largely explained by the profitability and investment factors in the Fama-French five-factor model (Fama & French, 2015). On the other hand, Hong, Li, and Xu (2019) study the effects of climate risk on the stock prices of food producers, while Bolton and Kacperczyk (2021) sort companies based on their total carbon dioxide emissions to conclude that investors demand higher returns on carbon-intensive firms. Accordingly, in order to provide a comprehensive overview of the effects of corporate ESG performance on ESG risk across sectors, in this paper we perform our analysis using all industries traded on the U.S. equity market, using 2-digit SIC codes for that purpose.

Finally, our research is also related to the literature analyzing the relationship between climate risk and stock prices in the presence of rare events. In this regard, Dhifaoui, Khalfaoui, Ben Jabeur, and Abedin (2023) study the effects of climate risk on agricultural and food stock prices, concluding that climate shocks affect global agricultural stock prices. Moreover, the authors warn of the convenience for investors of hedging this risk, especially in the presence of rare events such as the conflict in Ukraine, where food prices reach their highest level ever. Similarly, Khalfaoui et al. (2022) find that the dependence of U.S. stock returns on climate change-related risks is greater in extreme market scenarios, where clean energy-related indexes and climate policy uncertainty are key drivers of climate risk and clean energy spillovers on stock returns. In this regard, while Chai, Chu, Zhang, Li, and Abedin (2022) find that the relationship between green bonds, clean energy and stock prices exhibits different dynamics before, during and after the emergence of the COVID-19 pandemic, Dhifaoui, Khalfaoui, Abedin, and Shi (2022) show that the causal information flow between different energy and precious metals markets is most pronounced at high frequencies, mainly due to the immediate impact of specific events such as the 2016 Brexit referendum, the 2018 U.S.-China trade war, or the COVID-19 pandemic, among others.

3. The model

In this section we summarize the main elements of the theoretical framework that guides our study, which heavily relies on the equilibrium model proposed by Pástor et al. (2021), but with some generalization that allows us to straightforwardly highlight the implications of shifts in investor tastes pushing the market portfolio towards greenness. Thus, based on Pástor et al. (2021), we assume that every economic agent i has exponential utility as follows:

$$U(W_{1i}, \mathbf{X_i}) = -e^{-A_i W_{1i} - \mathbf{b}_i' \mathbf{X_i}} \tag{1}$$

where W_{ti} is the agent's wealth at time t, $\mathbf{X_i}$ is the N-dimensional vector

[2] See Appendix in Cochrane (2011) for an interesting comparative analysis of the CAPM performance before and after 1963 in pricing value portfolios.

of wealth fractions allocated in N stocks, A_i is the absolute risk aversion coefficient, and $\mathbf{b_i}$ is the N-dimensional vector of nonpecuniary benefits from stock holdings, following:

$$\mathbf{b_i} = d_i \mathbf{g} \tag{2}$$

where $d_i \geq 0$ is a score that measures the ESG tastes of agent i (with $d_i = 0$ representing an agent not committed to ESG principles), and $\mathbf{g}$ is the N-dimensional vector of observable scores that measure the ESG performance of firms. Therefore, in addition to usual risk and return considerations, each firm j is also characterized by its positive ($g_j > 0$) or negative ($g_j < 0$) social impact. Based on Eq. (1), the first-order condition of agent i for $\mathbf{X_i}$ can be written as follows:

$$\mathbf{X_i} = \frac{1}{a_i}\mathbf{\Sigma}^{-1}\left(\boldsymbol{\mu} + \frac{1}{a_i}\mathbf{b_i}\right) \tag{3}$$

where $a_i = A_i W_{0i}$ is the relative risk aversion coefficient, $\mathbf{\Sigma}$ is the $N \times N$ covariance matrix of stock returns, and $\boldsymbol{\mu}$ is the N-dimensional vector of expected returns in excess of the risk-free rate r_f. For tractability, Pástor et al. (2021) make three main assumptions in relation to Eq. (3), namely: (i) all agents have identical relative risk aversion ($a_i = a$), (ii) the risk-free asset is in zero net supply, and (iii) the market portfolio is ESG-neutral. Importantly, the first and second assumptions allow us to determine the N-dimensional vector of weights in the market portfolio $\mathbf{w_m}$ as follows:

$$\mathbf{w_m} = \frac{1}{a}\mathbf{\Sigma}^{-1}\boldsymbol{\mu} + \frac{\overline{d}}{a^2}\mathbf{\Sigma}^{-1}\mathbf{g} \tag{4}$$

where $\overline{d}$ is the wealth-weighted average of ESG tastes d_i across economic agents. Eq. (4) implies that the vector of expected excess returns $\boldsymbol{\mu}$ and the equity premium $\mu_m = \mathbf{w}_\mathbf{m}'\boldsymbol{\mu}$ can be determined respectively as follows:

$$\boldsymbol{\mu} = a\mathbf{\Sigma}\mathbf{w_m} - \frac{\overline{d}}{a}\mathbf{g} \tag{5}$$

$$\mu_m = a\sigma_m^2 - \frac{\overline{d}}{a}\mathbf{w}_\mathbf{m}'\mathbf{g} \tag{6}$$

where $\sigma_m^2 = \mathbf{w}_\mathbf{m}'\mathbf{\Sigma}\mathbf{w_m}$ is the variance of the return on the market portfolio. On the other hand, the assumption that the market portfolio is ESG-neutral implies that the vector of weights $\mathbf{w_m}$ satisfies:

$$\mathbf{w}_\mathbf{m}'\mathbf{g} = g_m = 0 \tag{7}$$

where g_m represents the greenness of the market portfolio. Combining Eq. (5) with Eqs. (6) and (7), the vector of expected excess returns in equilibrium can be written as follows:

$$\boldsymbol{\mu} = \mu_m\boldsymbol{\beta}_\mathbf{m} - \frac{\overline{d}}{a}\mathbf{g} \tag{8}$$

where $\boldsymbol{\beta}_\mathbf{m} = (1/\sigma_m^2)\mathbf{\Sigma}\mathbf{w_m}$ is the N-dimensional vector of market betas. Remarkably, the second term on the right-hand side of Eq. (8) represents the vector of alphas that results from the classic CAPM, where green stocks have negative alphas ($g_j > 0$) and brown stocks have positive alphas ($g_j < 0$).

Regarding investors' portfolio choices, under the Pástor et al. (2021) setup, each agent i allocates the initial wealth across the risk-free asset, the market portfolio and an ESG portfolio, where the fractions of wealth channeled to risky assets (i.e., the components of the market portfolio and the ESG portfolio) follow:

$$\mathbf{X_i} = \mathbf{w_m} + (\delta_i/a^2)\mathbf{\Sigma}^{-1}\mathbf{g} \tag{9}$$

The second term on the right-hand side of Eq. (9) represents the fraction of wealth allocated to the ESG portfolio, that is, a stock portfolio formed as a function of the covariance matrix $\mathbf{\Sigma}$ and the vector of ESG scores $\mathbf{g}$, where $\delta_i = d_i - \overline{d}$ is the difference between the ESG tastes of agent i and the average ESG tastes. Operating on Eq. (9), the N-dimensional vector of weights in the ESG portfolio can be determined as follows:

$$\mathbf{w_g} = \frac{\mathbf{1}}{\boldsymbol{\iota}'\mathbf{\Sigma}^{-1}\mathbf{g}}\mathbf{\Sigma}^{-1}\mathbf{g} \tag{10}$$

where $\boldsymbol{\iota}$ is an N-dimensional vector of ones. Importantly, using Eqs. (7), (8) and (10), Pástor et al. (2021) show that when the market portfolio is ESG-neutral —i.e., when Eq. (7) is exactly satisfied—, the ESG portfolio's market beta is zero and its alpha is negatively proportional to its greenness. Specifically:

$$\mathbf{w}_\mathbf{g}'\boldsymbol{\beta}_\mathbf{m} = 0 \tag{11}$$

$$\alpha_g = -\frac{\overline{d}}{a}\mathbf{w}_\mathbf{g}'\mathbf{g} = -\frac{\overline{d}}{a}g_g \tag{12}$$

where g_g represents the greenness of the ESG portfolio. In this context, Eq. (8) naturally results in the following two-factor asset pricing model:

$$\boldsymbol{\mu} = \mu_m\boldsymbol{\beta}_\mathbf{m} + \mu_g\boldsymbol{\beta}_\mathbf{g} \tag{13}$$

where $\mu_g = \mathbf{w}_\mathbf{g}'\boldsymbol{\mu} = \alpha_g$ is the expected excess return on the ESG portfolio, and $\boldsymbol{\beta}_\mathbf{g} = \mathbf{g}/g_g$ is the vector of univariate betas with respect to the excess return of the ESG portfolio, which means that ESG betas are proportional to the ESG scores at the firm level. At this point, it is important to note that in the case where ESG tastes are equal across market participants (regardless of whether they are weaker or stronger), then δ_i=0 and, according to Eq. (9), all investors allocate their initial wealth across the risk-free asset and the market portfolio, ignoring the ESG portfolio. Therefore, under the Pástor et al. (2021) setup, a zero dispersion in ESG tastes across agents implies that the market portfolio captures all the relevant ESG information and, consequently, Eq. (13) converges to the classic CAPM:

$$\boldsymbol{\mu} = \mu_m\boldsymbol{\beta}_\mathbf{m} \tag{14}$$

However, an important assumption in the derivation of the two-factor model in Eq. (13) is given by Eq. (7), that is, the fact that the market portfolio is ESG-neutral. In this context, the current interest in ESG issues and the growing demand for investments committed to ESG principles call into question this assumption imposed by Pástor et al. (2021). Consequently, relaxing the constraint in Eq. (7) to allow the market portfolio to have any ESG profile, and operating on Eqs. (5) and (6), Eq. (8) can be rewritten as follows:

$$\boldsymbol{\mu} = \mu_m\boldsymbol{\beta}_\mathbf{m} - \frac{\overline{d}}{a}(\mathbf{g} - g_m\boldsymbol{\beta}_\mathbf{m}) \tag{15}$$

Remarkably, the new form of the second term on the right-hand side of Eq. (15) together with the possible positive or negative value of g_m allows the ESG portfolio to have a non-zero market beta and an alpha different from its expected excess return, depending on the greenness level of the market portfolio. Specifically, premultiplying both sides of Eq. (15) by $\mathbf{w}_\mathbf{g}'$:

$$\mathbf{w}_\mathbf{g}'\boldsymbol{\mu} = \mu_g = \mu_m\mathbf{w}_\mathbf{g}'\boldsymbol{\beta}_\mathbf{m} - \frac{\overline{d}}{a}\mathbf{w}_\mathbf{g}'(\mathbf{g} - g_m\boldsymbol{\beta}_\mathbf{m}) \tag{16}$$

where the CAPM alpha of the ESG portfolio is given by the second term on the right-hand side of Eq. (16):

$$\alpha_g = -\frac{\overline{d}}{a}\mathbf{w}_\mathbf{g}'(\mathbf{g} - g_m\boldsymbol{\beta}_\mathbf{m}) \tag{17}$$

Of course, Eq. (17) mechanically converges to Eq. (12) when the market portfolio is ESG-neutral (i.e., $g_m = 0$). On the other hand, in the specific case that the ESG portfolio is correctly priced by the classic CAPM, then $\alpha_g = 0$ and both the market portfolio and the ESG portfolio are fully redundant, implying that Eq. (17) satisfies:

$$\mathbf{w}_{\mathbf{g}}^{'}(\mathbf{g} - g_m \boldsymbol{\beta}_{\mathbf{m}}) = 0 \tag{18}$$

Hence, Eq. (18) implies that when the ESG portfolio is correctly explained by the market portfolio, the ESG portfolio's market beta is proportional to its relative greenness with respect to that of the market portfolio:

$$\mathbf{w}_{\mathbf{g}}^{'}\boldsymbol{\beta}_{\mathbf{m}} = \frac{g_g}{g_m} \tag{19}$$

At this point it should be noted that, according to Eqs. (10) and (13), the ESG portfolio maximizes the ESG score attainable in the market for β_g=1, thus imposing an upper bound for the ESG score. This means that an increasing commitment to ESG principles by investors that pushes the greenness of the market portfolio (g_m) towards the greenness of the ESG portfolio (g_g) will simultaneously push the ESG portfolio's market beta towards 1. In this case, the market portfolio will coincide with the ESG portfolio and, according to the basic setup defined by Pástor et al. (2021), the market alphas in Eq. (15) will be zero:

$$\boldsymbol{\alpha} = -\frac{\overline{d}}{a}(\mathbf{g} - g_m \boldsymbol{\beta}_{\mathbf{m}}) = \mathbf{0}_N \tag{20}$$

which implies that market betas are proportional to the vector of ESG scores $\mathbf{g}$:

$$\boldsymbol{\beta}_{\mathbf{m}} = \frac{\mathbf{g}}{g_m} \tag{21}$$

Therefore, when the ESG portfolio is correctly priced by the classic CAPM and its market beta is equal to 1, the fact that $g_m = g_g$ necessarily implies that market betas $\boldsymbol{\beta}_{\mathbf{m}}$ in Eq. (21) are identical to ESG betas $\boldsymbol{\beta}_{\mathbf{g}}$ in Eq. (13). Furthermore, according to Eq. (16), in this case, the expected excess return of the ESG portfolio μ_g is equal to the equity premium μ_m, which means that investor preferences pushing the market portfolio towards greenness lead the market portfolio to subsume the ESG portfolio.

Based on this rationale, in the next sections we study the effects of the recent trend of agents to invest in firms committed to ESG principles on betas, risk prices and the market portfolio, according to the Pástor et al. (2021) model.

4. Data and empirical methodology

4.1. Data and variables

In order to evaluate the effects from shifts in ESG tastes on the behavior of stock returns based on the model described in the previous section, we compile monthly market data for all stocks traded on the U. S. equity market in the period from January 2001 to December 2021 from Refinitiv Eikon/Datastream. In this regard, it should be noted that the U.S. equity market not only constitutes the largest stock exchange in the world by market capitalization, but also has the largest number of listed firms comprising a large portion of industries based on 2-digit SIC codes. Accordingly, our research focuses on this equity market in order to consider as many companies and sectors as possible, simultaneously promoting consistency and reliability of estimates. Therefore, considering that we use the Refinitiv ESG Company Scores to estimate the ESG scores $\mathbf{g}$, our sample comprises those U.S. publicly traded firms for which the Refinitiv ESG Company Scores are available, totaling 3149 companies. For each company, we compile monthly data series for its total return index ('RI' series), which shows the growth in value of a share holding assuming that dividends are re-invested to purchase additional stocks, and its market value ('MV' series). Additionally, we collect the SIC codes from Refinitiv Eikon/Datastream for the companies under study.

Regarding the ESG scores, although Refinitiv reports environmental, social and corporate governance indicators at a high level of detail, we use the ESG Combined Score ('TRESGCS' series) to estimate $\mathbf{g}$. This indicator is an overall company score based on reported information about the ESG pillars (which are considered in the basic ESG Score provided by Refinitiv), but including an ESG Controversies overlay that discounts the ESG performance score based on negative events in the media. The ESG Combined Score ranges from 0 to 100, with 0 representing the worst performing companies and 100 the best performers. Considering that the model proposed by Pástor et al. (2021) requires unbounded ESG scores $\mathbf{g}$ ranging from $-\infty$ to $+\infty$, we transform the ESG Combined Score into a normally distributed variable with mean zero and standard deviation one, thus ensuring consistency with the Pástor et al. (2021) model.

We use the total return index data series and the risk-free rate provided by Kenneth R. French on his website to determine the excess returns of all companies under study on a monthly basis. Based on these excess returns, we use the firms' 2-digit SIC codes to determine the equal-weighted excess returns for all industry portfolios in the U.S. equity market for the period considered, totaling 69 industry portfolios comprising 3130 stocks due to missing SIC codes for 19 companies in our sample. Additionally, we determine the equal-weighted ESG score for each industry portfolio each month, which provides us with a vector of ESG scores for each portfolio.

We use the excess return on the U.S. equity market, as provided by Kenneth R. French on his website, to proxy for the pricing factor that corresponds to the excess return on the market portfolio (hereafter denoted by f_m). In this regard, it should be noted that, although the return on the equity market reported by Kenneth R. French comprises the returns of the vast majority of U.S. firms incorporated in the Center for Research in Security Prices (CRSP) and listed on the NYSE, AMEX, or NASDAQ, it provides essentially the same results in our study as the value-weighted return of the 3149 firms under consideration (see results in the next section and Section A1 in the Appendix, respectively), which is proof of the representativeness of our sample. Consequently, each month we estimate the greenness of the market portfolio g_m as the value-weighed ESG score of the companies that constitute our sample.

Regarding the ESG factor (hereafter denoted by f_g), although it can be determined as the excess return on a position in the ESG portfolio (i. e., the portfolio that results from the vector of weights $\mathbf{w}_{\mathbf{g}}$ in Eq. (10), under the assumption that the market portfolio is ESG-neutral), to improve tractability, we follow Pástor et al. (2021) to consider that the ESG factor f_g is proportional to the difference between returns on green-stock and brown-stock portfolios:

$$f_g \propto r_{\{g_j>0\}} - r_{\{g_j<0\}} \tag{22}$$

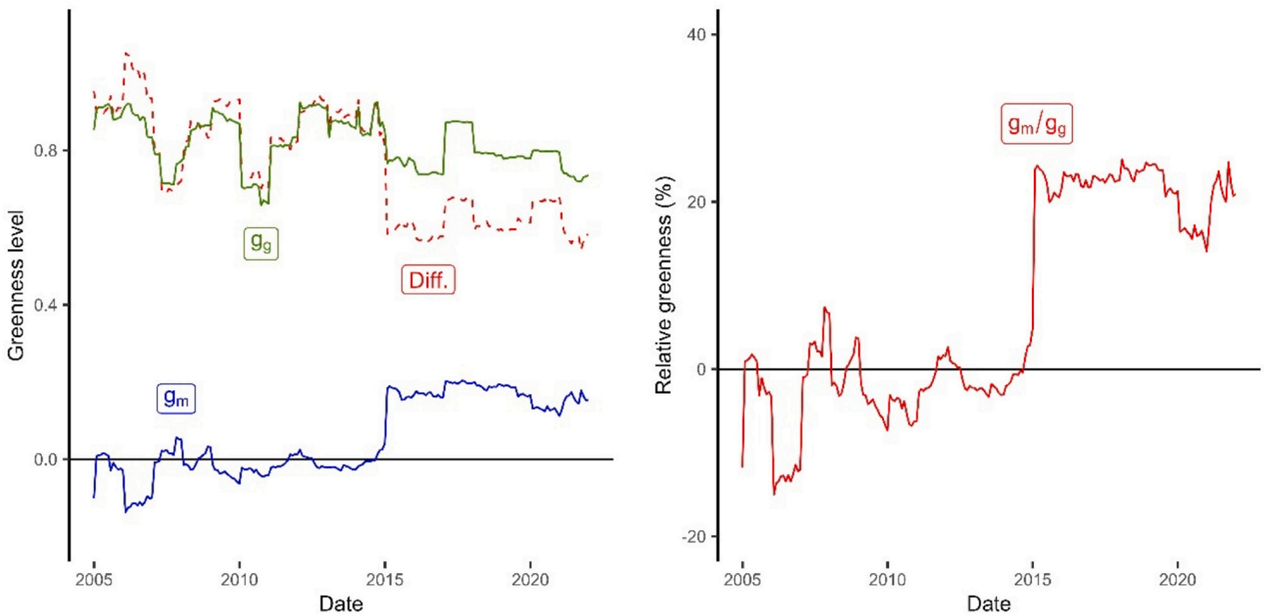
where $r_{\{g_j>0\}}$ and $r_{\{g_j<0\}}$ denote the weighted-average returns of green stocks and brown stocks, respectively, using the ESG scores within the vector $\mathbf{g}$ as portfolio weights. Additionally, we estimate the greenness of the ESG portfolio g_g as the ESG-weighted average ESG score of a zero-cost portfolio formed by a long position in green stocks ($g_j > 0$) and a short position in brown stocks ($g_j < 0$).

Based on these data series, Table 1 shows the main summary statistics of the industry portfolios in our sample for the entire time period under analysis. Additionally, Fig. 1 depicts the values for g_m and g_g over time, as well as their relationship measured by g_m/g_g, which corresponds to the inverse of the result of Eq. (19). As shown in Table 1, the industry portfolios with the highest average returns in the period are those with 2-digit SIC codes 10 (metal mining), 41 (local & suburban transit & interurban highway transportation), 75 (automotive repair, services and parking) and 89 (services, not elsewhere classified). In any case, it should be noted that some industry portfolios comprise a single company, which leads us to take the results for these portfolios with caution

Table 1
Summary statistics.

2-digit SIC	No.	μ_j	sd_j	Avg.g_j	*Max* g_j	*Min* g_j	$\beta_{m,j}$	$\beta_{g,j}$	$t(\beta_{m,j})$	$t(\beta_{g,j})$
01	6	1.27	7.33	−0.33	0.01	−0.60	0.84	−0.68	10.14	−4.66
02	1	2.04	13.37	−0.63	0.20	−1.06	0.37	−0.43	1.99	−1.31
07	1	−0.44	12.27	−0.73	−0.31	−1.40	1.41	0.37	4.95	0.78
10	18	2.69	12.02	−0.05	0.69	−1.25	1.25	−0.79	8.75	−3.11
12	9	1.98	11.65	−0.23	0.19	−0.68	0.80	−0.83	5.25	−3.08
13	72	1.52	11.03	−0.54	−0.36	−0.94	1.45	−1.15	12.72	−5.69
14	9	1.40	8.52	−0.62	−0.35	−1.35	1.00	−0.60	10.24	−3.45
15	19	1.49	10.07	−0.62	−0.24	−1.28	1.41	−0.71	13.54	−3.86
16	15	1.54	7.74	−0.30	0.58	−1.02	1.12	−0.58	14.53	−4.23
17	8	1.81	9.49	−0.62	−0.28	−0.97	1.34	−0.69	13.74	−4.01
20	56	1.26	3.90	−0.17	0.39	−1.52	0.63	−0.09	17.46	−1.48
21	6	1.67	8.13	0.12	0.64	−0.48	0.75	−0.20	7.30	−1.08
22	5	1.32	9.26	−0.15	0.36	−0.89	1.42	−0.57	16.21	−3.65
23	11	1.54	7.70	−0.10	0.27	−0.74	1.12	−0.44	14.51	−3.18
24	14	1.75	8.31	−0.01	0.99	−1.31	1.33	−0.48	17.69	−3.64
25	14	1.46	8.34	−0.12	0.27	−0.91	1.28	−0.39	15.66	−2.67
26	12	1.18	6.17	−0.06	0.44	−0.94	1.01	−0.33	18.42	−3.44
27	13	0.85	6.99	−0.31	0.02	−1.02	1.11	−0.38	16.96	−3.33
28	281	1.52	6.70	−0.33	−0.05	−0.94	1.15	−0.66	23.29	−7.52
29	14	1.39	8.87	0.00	0.22	−0.36	1.20	−0.75	12.93	−4.58
30	16	1.71	7.60	−0.20	0.06	−0.77	1.32	−0.49	22.02	−4.62
31	5	1.55	9.29	−0.31	0.22	−0.67	1.31	−0.47	13.98	−2.86
32	6	1.50	9.01	−0.20	1.09	−1.19	1.46	−0.61	18.55	−4.40
33	31	1.54	8.71	−0.36	0.07	−0.96	1.48	−0.56	20.25	−4.32
34	43	1.84	6.63	−0.44	−0.10	−1.56	1.10	−0.64	20.93	−6.88
35	105	1.52	7.17	−0.26	0.04	−1.34	1.38	−0.53	35.91	−7.80
36	151	1.44	8.04	−0.25	0.00	−1.43	1.49	−0.29	27.70	−3.03
37	76	1.60	7.66	−0.27	−0.07	−0.51	1.36	−0.66	25.44	−6.94
38	172	1.61	5.85	−0.26	0.05	−1.36	1.07	−0.41	26.85	−5.78
39	13	1.43	7.44	−0.18	0.35	−0.72	1.14	−0.40	16.06	−3.17
40	3	1.57	6.72	0.12	0.67	−0.66	1.02	−0.19	15.18	−1.61
41	1	2.50	16.05	−0.70	−0.60	−0.80	1.05	−0.94	4.29	−1.87
42	24	1.60	6.85	−0.33	0.22	−0.98	0.99	−0.35	14.10	−2.84
44	12	0.82	8.51	−0.17	0.32	−0.79	1.38	−0.41	17.67	−2.99
45	16	1.37	8.82	−0.27	0.26	−1.08	1.20	−0.31	12.56	−1.83
46	5	1.10	7.44	−0.79	0.12	−1.86	0.80	−0.36	8.89	−2.25
47	10	1.35	7.16	−0.83	−0.39	−1.56	1.02	−0.40	13.86	−3.05
48	53	1.51	8.26	−0.64	0.74	−0.89	1.29	−0.64	18.63	−5.17
49	99	0.99	3.89	−0.10	0.03	−0.43	0.61	−0.16	16.88	−2.42
50	43	1.56	6.67	−0.56	−0.21	−1.42	1.22	−0.37	25.61	−4.40
51	33	1.55	5.60	−0.16	0.32	−0.71	0.92	−0.31	19.01	−3.67
52	7	1.99	7.17	−0.04	0.58	−0.69	1.10	−0.17	15.84	−1.38
53	15	1.25	6.86	−0.24	0.01	−0.86	0.99	−0.42	14.58	−3.46
54	13	1.28	6.97	−0.10	0.74	−0.71	0.59	−0.30	6.60	−1.90
55	21	2.11	8.97	−0.29	−0.10	−0.56	1.41	−0.58	17.10	−4.00
56	33	1.61	8.80	−0.17	0.06	−0.62	1.30	−0.71	15.41	−4.79
57	9	1.80	10.33	−0.19	0.39	−1.35	1.38	−0.61	12.93	−3.23
58	35	1.55	6.82	−0.07	1.01	−0.46	0.98	−0.49	14.25	−4.05
59	41	1.84	8.25	−0.32	0.19	−0.69	1.30	−0.95	19.97	−8.26
60	318	1.00	4.75	−0.33	−0.07	−0.59	0.68	−0.29	14.01	−3.39
61	37	1.84	8.15	−0.53	0.00	−0.83	1.23	−0.70	16.06	−5.17
62	64	1.33	6.25	−0.29	−0.08	−0.46	1.21	−0.26	31.98	−3.84
63	78	1.06	5.37	−0.28	−0.09	−0.47	0.93	−0.24	21.45	−3.06
64	13	1.22	5.26	−0.31	0.02	−1.21	0.63	−0.32	10.38	−2.98
65	73	1.22	5.47	−0.20	0.22	−0.60	0.87	−0.43	17.99	−4.99
67	137	1.26	6.03	−0.40	−0.02	−1.00	0.96	−0.44	17.92	−4.62
70	19	1.89	10.73	−0.39	0.05	−1.13	1.62	−0.76	15.70	−4.18
72	8	1.39	6.88	−0.51	−0.13	−0.92	0.99	−0.62	15.55	−5.45
73	337	1.62	6.75	−0.34	0.30	−1.24	1.29	−0.40	32.34	−5.74
75	9	2.38	9.31	−0.36	0.12	−1.00	1.32	−0.68	14.11	−4.10
76	3	1.49	12.07	−0.85	−0.61	−1.31	1.33	−0.57	9.24	−2.22
78	10	1.00	8.07	−0.95	−0.61	−1.66	0.98	−0.39	10.58	−2.40
79	14	1.66	9.30	−0.62	−0.49	−1.22	1.31	−0.84	14.43	−5.21
80	43	1.64	6.62	−0.31	0.06	−0.57	1.00	−0.61	16.15	−5.60
81	1	1.36	10.65	−0.36	−0.17	−0.55	0.72	−0.69	5.22	−2.84
82	18	0.82	8.51	−0.60	−0.34	−0.86	0.79	−0.64	7.58	−3.46
83	2	1.93	8.82	−0.61	−0.46	−0.70	1.01	−0.92	5.62	−3.23
87	269	1.57	7.74	−0.56	−0.21	−1.38	1.11	−0.99	16.36	−8.24
89	2	2.95	28.12	−1.51	−0.64	−3.70	0.83	−2.44	1.30	−2.32

Notes: The table shows the means (μ_j) and standard deviations (sd_j) of the expected returns provided by 69 industry portfolios comprising all publicly traded U.S. companies for which Refinitiv ESG Company Scores and SIC codes are available. These results are expressed in percentages and have been determined using monthly data. The sample covers the period from January 2001 to December 2021. The table also shows the average ESG score g_j for each industry portfolio, as well as its maximum and minimum values. Additionally, the table reports the beta coefficients and t-statistics that result from the time-series regression of the excess returns of industry portfolios on the market portfolio and the ESG factor.



(a) (b)

Fig. 1. Greenness level of the market portfolio and the ESG factor over time.
Notes: Subfigure (a) shows the level of greenness of the market portfolio (g_m) and the ESG factor (g_g), determined by the value-weighed ESG score of the companies in our sample (market portfolio), and the ESG-weighted average ESG score of a zero-cost portfolio formed by a long position in green stocks and a short position in brown stocks (ESG factor). Subfigure (b) shows the behavior over time of the relative greenness of the market portfolio in relation to the greenness of the ESG factor.

as they are directly influenced by the specific characteristics of the corresponding firms. Regarding the ESG score g_j, remarkably, all industry portfolios have negative average ESG scores except those with 2-digit SIC codes 21 (tobacco products), 29 (petroleum refining and related industries) and 40 (railroad transportation), which interestingly are sectors associated with sin-seeking or polluting activities. However, the large spread between the maximum and minimum ESG scores over time across industries suggests that, in general, the ESG performance of the firms under study varies greatly over the period considered, underscoring the convenience of the dynamic methodology that we use in the next section.

Table 1 also reports the portfolio betas that result from Eq. (13), using the entire time period under analysis to run the corresponding time-series regressions. The results show that market betas are generally around 1 for most industries, providing strongly significant estimates in the vast majority of cases. Regarding the ESG factor, the ESG betas $\beta_{g,j}$ are negative for all industry portfolios and statistically significant in most cases. As predicted by the model proposed by Pástor et al. (2021), this fact is consistent with the brown nature ($g_j < 0$) of most industry portfolios based on their average ESG scores. However, the estimation procedure followed to determine these coefficients does not allow us to account for the fact that some brown industries turn green in specific periods of time, and vice versa, as evidenced by the maximum and minimum ESG scores in Table 1. As noted, to overcome this issue, in the next section we use a time rolling window-based CSR methodology that allows us to account for the time-varying nature of betas and risk prices in Eq. (13).

Regarding the level of greenness of both the market portfolio and the ESG factor over time, Fig. 1 shows that while the greenness level of the ESG factor remains approximately constant around its mean value (0.87) throughout the period under study, the greenness level of the market portfolio exhibits an upward trend, consistent with the shifts in investor tastes highlighted by Pástor et al. (2022). Thus, while the greenness level of the market portfolio is -0.1 in December 2004, it rises to 0.15 in December 2021. Furthermore, Subfigure (b) in Fig. 1 shows that the greenness of the market portfolio relative to the ESG factor increases from -12% in December 2004 to 21% in December 2021, with a relative greenness of 100% implying that the market portfolio coincides with the ESG portfolio, as indicated in the previous section. Hence, this pattern is consistent with increased investor engagement with ESG issues driving the market portfolio towards a higher level of greenness. In the next section we study the extent to which this trend leads the market portfolio to subsume the ESG portfolio and consequently allows the classic CAPM to account for ESG concerns.

4.2. *Econometric framework*

In order to dynamically evaluate the behavior of risk loadings and risk prices in Eq. (13) in the context described in the previous subsection, we use a two-pass CSR methodology similar to that developed by Fama and MacBeth (1973), which operates on overlapping returns with a time rolling window of 48 months. There are three main reasons that explain the suitability of this methodology in our research. First, the fact that the model described in the previous section relaxes the restriction introduced by Pástor et al. (2021) of the market portfolio being ESG-neutral explicitly allows for a time-varying greenness of the market portfolio, which can be directly captured by our rolling window-based methodology. Second, the fact that some brown companies can turn green in specific periods of time, and vice versa, implies time-varying ESG betas under the Pástor et al. (2021) setup and, consequently, time-varying risk prices, which again can be easily determined under our econometric framework. Third, as noted in the previous section, the generalization made to the Pástor et al. (2021) model to allow for a non-zero greenness level of the market portfolio implies that the ESG factor may have a non-zero market beta. Consequently, our methodology adopts a two-pass CSR-based approach instead of a time-series regression approach to allow the model to minimize the pricing errors of all assets in our sample, rather than simply forcing both the market portfolio and the ESG factor to be priced with zero error (i.e., the market portfolio to have zero ESG beta and the ESG factor to have zero market beta, see Cochrane (2005, pp. 230-245)).

Accordingly, for each industry portfolio j, we run $T-s+1$ time-series regressions to determine the value of beta coefficients in Eq. (13), where T and s denote the total number of periods and the size of the time rolling window, respectively. In particular, for each time period t from s to T, we run the following time-series regression:

$$\mathbf{r}^{\mathbf{e}}_{\mathbf{j,t}} = \alpha_{j,t} + \mathbf{f}_{\mathbf{m,t}}\beta_{m,j,t} + \mathbf{f}_{\mathbf{g,t}}\beta_{g,j,t} + \boldsymbol{\varepsilon}_{\mathbf{j,t}} \tag{23}$$

where $\mathbf{r}^{\mathbf{e}}_{\mathbf{j,t}}$ is the s-dimensional vector of excess returns from $t-s+1$ to t, the coefficients $\alpha_{j,t}$, $\beta_{m,j,t}$ and $\beta_{g,j,t}$ are model parameters, $\mathbf{f}_{\mathbf{m,t}}$ and $\mathbf{f}_{\mathbf{g,t}}$ are s-dimensional vectors of factors, and $\boldsymbol{\varepsilon}_{\mathbf{j,t}}$ is the s-dimensional vector of errors.

For each industry portfolio, Eq. (23) provides us with $T-s+1$ estimates for β_m and β_g, that is, one estimate for each period from s to T. These estimates allow us to run $T-s+1$ cross-sectional regressions to determine the risk prices in Eq. (13). Thus, for each time period t from s to T, we run the following cross-sectional regression:

$$\boldsymbol{\mu}_{\mathbf{t}} = \alpha_t + \lambda_{m,t}\boldsymbol{\beta}_{\mathbf{m,t}} + \lambda_{g,t}\boldsymbol{\beta}_{\mathbf{g,t}} + \boldsymbol{\varepsilon}_{\mathbf{t}} \tag{24}$$

where $\boldsymbol{\mu}_{\mathbf{t}}$ is the N-dimensional vector comprising the average excess returns from $t-s+1$ to t of N industry portfolios, α_t, $\lambda_{m,t}$ and $\lambda_{g,t}$ are parameters, $\boldsymbol{\beta}_{\mathbf{m,t}}$ and $\boldsymbol{\beta}_{\mathbf{g,t}}$ are N-dimensional vectors of betas, and $\boldsymbol{\varepsilon}_{\mathbf{t}}$ is the N-dimensional vector of errors. Eq. (24) provides us with one estimate for λ_m and λ_g for each time period from s to T. Naturally, the model in Eq. (13) is well-behaved when the prices of risk μ_m and μ_g ($\mu_{m,t}$ and $\mu_{g,t}$ assuming time-varying risk premia) are not significantly different from the coefficients $\lambda_{m,t}$ and $\lambda_{g,t}$ in Eq. (24).

Additionally, the fact that the ESG portfolio is redundant with the market portfolio when α_g in Eq. (17) is zero (that is, when the classic CAPM prices the ESG portfolio with zero error) allows us to study to what extent the market portfolio has subsumed the ESG factor by evaluating the alpha coefficient in the following rolling window time-series regression:

$$\mathbf{f}_{\mathbf{g,t}} = \alpha_{g,t} + \beta_{m,g,t}\mathbf{f}_{\mathbf{m,t}} + \boldsymbol{\varepsilon}_{\mathbf{g,t}} \tag{25}$$

where $\alpha_{g,t}$ and $\beta_{m,g,t}$ are model parameters, $\boldsymbol{\varepsilon}_{\mathbf{g,t}}$ is the s-dimensional vector of errors, and the other terms have been defined in Eq. (23). Eq. (25) provides us with one estimate for $\alpha_{g,t}$ and $\beta_{m,g,t}$ for each period from s to T. Hence, in the case that $\alpha_{g,t}$ is not statistically different from zero, we can conclude that the market portfolio and the ESG factor are redundant. Furthermore, if in addition $\beta_{m,g,t}$ is not statistically different from 1, we can conclude that the market portfolio matches the ESG portfolio.

5. Results and discussion

Based on the data series and the methodology described in the previous section, we use Eq. (23) and a 48-month rolling window to determine all time-varying portfolio betas, for the period from December 2004 to December 2021. We use the ordinary least squares (OLS) method to determine all estimates. Fig. 2 depicts the main regression results, namely the ESG betas of the portfolios, their t-statistics and absolute t-statistics, and the R^2 statistics.

Specifically, Subfigure (a) in Fig. 2 shows the portfolios' time-varying betas for the ESG factor $\mathbf{f}_{\mathbf{g,t}}$, where each line corresponds to an industry portfolio and the green and brown colors represent the green or brown nature of the portfolio in each period, based on the positive or negative value of its greenness level $g_{j,t}$. The gray color represents missing ESG scores for the specific period. The numbers in a box denote the 2-digit SIC codes of the five sectors with the highest ESG beta at some specific period, as well as the five sectors with the lowest ESG beta. Subfigure (b) is identical to Subfigure (a), but plotting t-statistics for ESG betas instead of the ESG betas. Subfigure (c) depicts the absolute value of the t-statistics in Subfigure (b), where the gray dashed lines represent industry portfolios, the solid black line is the cross-sectional median of the absolute t-statistics, and the red lines are the cross-sectional mean of the absolute t-statistics $\pm$ one cross-sectional standard deviation. Subfigure (d) is identical to Subfigure (c), but plotting R^2 statistics instead of absolute t-statistics.

Subfigure (a) in Fig. 2 provides us with several important findings. First, our results show that while brown portfolios are much more likely to have negative rather than positive ESG betas, the opposite is not true for green portfolios. Consequently, these results are only partially in line with those anticipated by the model proposed by Pástor et al. (2021), which predicts that green stocks have positive ESG betas and brown stocks have negative ESG betas. In this regard, although our results may suggest that investors actually behave differently than predicted by Pástor et al. (2021), most likely, deficiencies in the measurement of firms' ESG performance (Erhart, 2022), coupled with the typically poor performance of most asset pricing models to price industry portfolios (Fama & French, 1997), may partly explain our results. Furthermore, the greenness level $g_{j,t}$ of green firms is much closer to zero than that of brown firms (see additionally the maximum and minimum values for g_j in Table 1), which may lead the market to evaluate these borderline scores somewhat erratically.

Importantly, these results are not only robust to proxying for the market portfolio using the value-weighted return of all firms in our sample instead of the market factor provided by Kenneth R. French (see Fig. A1 in the Appendix), but they are also robust to using value-weighted industry portfolios rather than equal-weighted industry portfolios as test assets (see Fig. A4 in the Appendix). In any case, it is worth noting that the number of industries classified as green (brown) using value-weighted portfolios is significantly higher (lower) than that obtained using equal-weighted portfolios, suggesting that, on average, large companies exhibit better ESG performance across industries, consistent with Bissoondoyal-Bheenick, Brooks, and Do (2023).

Second, the five industry portfolios with the highest positive ESG betas have predominantly positive ESG scores for most periods under analysis. That is especially the case for portfolios with 2-digit SIC codes 21 (tobacco products) and 40 (railroad transportation), while portfolios with codes 2 (agricultural production - livestock and animal specialties) and 57 (home furniture, furnishings and equipment stores) represent typically brown sectors that have turned green in recent years. The case of the portfolio with the 2-digit SIC code 41 (local & suburban transit & interurban highway transportation) deserves special mention as it is one of the portfolios with the highest ESG beta in some time periods (its maximum value is reached at the end of 2008) and, simultaneously, one the portfolios with the lowest ESG beta in other periods (the minimum value is reached in 2011). However, it should be noted that this portfolio comprises a single stock and, furthermore, its ESG score is only available since February 2016. Remarkably, the fact that this ESG score is negative from that date to the end of our sample is consistent with the portfolio's negative ESG beta for that period.

Third, the five industry portfolios with the lowest ESG betas also have negative ESG scores across the entire sample, with the exception of the portfolio with 2-digit SIC code 70 (hotels, rooming houses, camps, and other lodging places), which turns green starting in 2020. Moreover, the fact that brown portfolios most often have negative ESG betas is also supported by the t-statistics shown in Subfigures (b) and (c), where the five portfolios with the highest absolute t-statistics (see Subfigure (c)) are brown most of the time (see Subfigure (b)). Across sectors, portfolios with 2-digit SIC codes 70 and 89 (services, not elsewhere classified) are the assets with the lowest ESG betas among those considered. However, the fact that the portfolio with 2-digit SIC code 89 only includes two firms (see Table 1) leads us to take its results with caution. Moreover, as shown in Fig. A4 in the Appendix, the lack of market value data series for these two firms until the end of 2019 prevents determining the value-weighted return of this portfolio —and consequently its ESG beta—

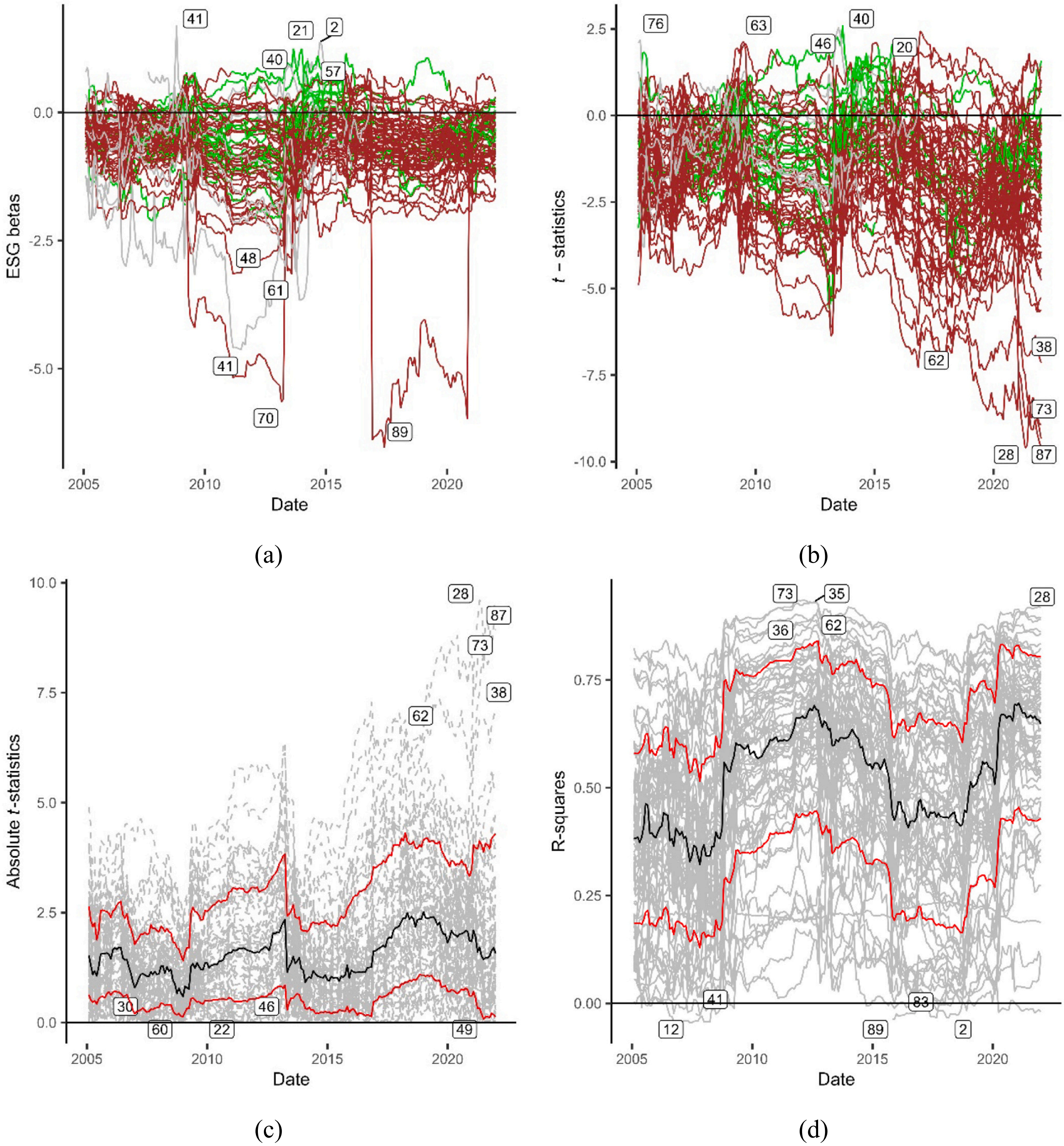


Fig. 2. ESG betas and main results from the time-series regressions.

Notes: Using monthly excess returns for 69 industry portfolios comprising all publicly traded U.S. companies for which Refinitiv ESG Company Scores and SIC codes are available, for each portfolio *j*, we run all monthly time-series regressions of excess returns on $\mathbf{f}_{\mathbf{m},\mathbf{t}}$ and $\mathbf{f}_{\mathbf{g},\mathbf{t}}$ that result from a time rolling window of 48 months and a time interval ranging from January 2001 to December 2021. Subfigure (a) shows the portfolios' time-varying betas for the ESG factor $\mathbf{f}_{\mathbf{g},\mathbf{t}}$, where each line corresponds to an industry portfolio and the green and brown colors represent the green or brown nature of the portfolio in each period, based on the positive or negative value of its greenness level $g_{j,t}$. The gray color represents missing ESG scores for the specific period. The numbers in a box denote the 2-digit SIC codes of the five sectors with the highest ESG beta at some specific period, as well as the five sectors with the lowest ESG beta. Subfigure (b) is identical to Subfigure (a), but plotting *t*-statistics for ESG betas instead of the ESG betas. Subfigure (c) depicts the absolute value of the *t*-statistics in Subfigure (b), where the gray dashed lines represent industry portfolios, the solid black line is the cross-sectional median of the absolute *t*-statistics, and the red lines are the cross-sectional mean of the absolute *t*-statistics ± one cross-sectional standard deviation. Subfigure (d) is identical to Subfigure (c), but plotting R^2 statistics instead of absolute *t*-statistics.

until that date.

Regarding the explanatory power of the time-series regressions of excess returns on factors $\mathbf{f}_{\mathbf{m},\mathbf{t}}$ and $\mathbf{f}_{\mathbf{g},\mathbf{t}}$, Subfigure (d) in Fig. 2 shows that the R^2 statistics of these regressions are widely dispersed both over time and across assets, reaching the highest cross-sectional median (around 65%) in the period from 2012 to 2013 and in 2021. As shown, the sectors with the highest R^2 statistics are those with 2-digit SIC codes 28 (chemicals and allied products), 35 (industrial and commercial machinery and computer equipment), 36 (electronic & other electrical equipment & components), 62 (security & commodity brokers, dealers, exchanges & services) and 73 (business services).

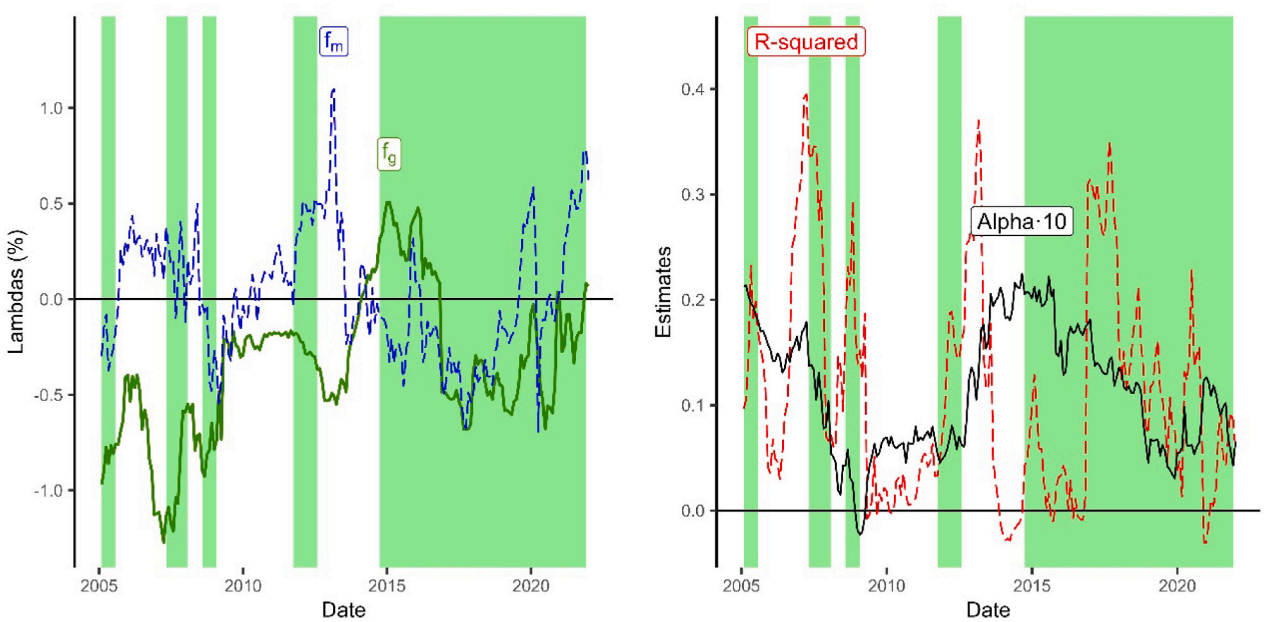
In order to evaluate the cross-sectional implications of the increased level of greenness of the market portfolio on risk prices, we use the beta coefficients estimated above and the average excess returns resulting from a 48-month rolling window to determine the lambdas in Eq. (24). Fig. 3 shows the resulting prices of risk for the factors $\mathbf{f}_{\mathbf{m},\mathbf{t}}$ and $\mathbf{f}_{\mathbf{g},\mathbf{t}}$ (Subfigure (a)), as well as the cross-sectional R^2 statistic and the alpha coefficient in Eq. (24) (Subfigure (b)). The green shaded regions in Fig. 3 represent the periods in which the market portfolio turns green (i.e., the periods in which $g_m > 0$).

Subfigure (a) in Fig. 3 shows that for almost all the periods under analysis the lambda coefficient for f_g is negative, consistent with the model proposed by Pástor et al. (2021), which predicts a negative price of risk for the new ESG factor. However, the green line in Subfigure (a) shows that the lambda coefficient for f_g increases progressively towards zero throughout the period considered, which suggests that the ESG factor is progressively less explanatory for the expected returns of test assets. Thus, while $\lambda_{g,t}$ amounts to -0.97% in January 2005 and reaches its minimum value (-1.27%) in the first quarter of 2007, it takes values close to zero in different subsequent periods, specifically in 2014, 2016 and several periods from December 2019. Importantly, to a large extent, this trend tracks the pattern followed by the greenness level of the market portfolio depicted in Fig. 1, as represented synthetically in Fig. 3 by the green shaded vertical regions. Therefore, our results are consistent with investors' greater commitment to ESG principles leading the market portfolio to partially capture investors' ESG preferences, with the consequent decrease in the explanatory power of the ESG factor.

Additionally, Subfigure (a) in Fig. 3 shows that the lambda coefficient for the ESG factor turns positive in the period from January 2014 to November 2016, as well as at the end of 2021. Although the model proposed by Pástor et al. (2021) predicts a negative price of risk for the ESG factor, this result may be a side effect of the high returns provided by green stocks in those years as a consequence of shifts in green tastes, as noted by Pástor et al. (2022). On the other hand, Subfigure (a) also shows that the lambda coefficient for the ESG factor falls sharply from February 2020 to November 2020, consistent with the lower level of greenness of the market portfolio for that period (see Fig. 1). The fact that this time period coincides with the emergence of the COVID-19 pandemic suggests temporary effects of the health crisis on investors' ESG preferences, leading the market portfolio to overweight brown sectors and the ESG factor to recover some of its explanatory power.

Importantly, these results are not only robust to using the value-weighted return of the firms in our sample as a proxy for the market portfolio (see Fig. A2 in the Appendix) or value-weighted industry portfolios as test assets (see Fig. A5 in the Appendix), but also to using different anomaly portfolios as test assets instead of industry portfolios. In this regard, using data series provided by Kenneth R. French on his website, Figs. A6 and A7 in the Appendix depict the risk prices resulting from 10 value-weighted size portfolios and 40 portfolios combining univariate sorts on size, book-to-market equity, investment and operating profitability, respectively. As shown, in all cases, the lambda coefficient for the ESG factor progressively increases towards zero until 2020, decreases throughout that year, and finally increases again in 2021, which is proof of the robustness of the results shown in Fig. 3.

Regarding the market factor f_m, Subfigure (a) in Fig. 3 shows that the



(a) (b)

Fig. 3. Risk prices and cross-sectional model performance.
Notes: Using monthly excess returns for 69 industry portfolios comprising all publicly traded U.S. companies for which Refinitiv ESG Company Scores and SIC codes are available, for each portfolio, we estimate all market and ESG betas that result from a time rolling window of 48 months and a time interval ranging from January 2001 to December 2021. We use these betas and the average returns resulting from a 48-month rolling window to determine the prices of risk for both the market factor and the ESG factor. Subfigure (a) shows the time-varying estimates for these prices of risk, while Subfigure (b) depicts the R^2 statistics and the alpha coefficients for the rolling window cross-sectional regressions. The green shaded regions represent the periods in which the market portfolio turns green (i.e., the periods in which $g_m > 0$).

risk premium is highly variable over time, consistent with the main results of the literature on stock return predictability (Baker & Wurgler, 2000; Campbell, 1987; Cochrane, 2011; Fama & French, 1988; Lamont & Stein, 2004; Lettau & Ludvigson, 2001; Novy-Marx, 2014). In this regard, Subfigure (b) in Fig. 3 shows that, in general, the two-factor model proposed by Pástor et al. (2021) performs poorly in pricing industry portfolios, which suggests that factors other than f_m and f_g are required to capture the cross-sectional variation of stock returns, consistent with the vast majority of the literature on the topic.

In order to explicitly study the level of redundancy between the ESG factor f_g and the market portfolio over time, we use Eq. (25) to determine the time-varying estimates for $\alpha_{g,t}$ and $\beta_{m,g,t}$, using a 48-month rolling window for that purpose. Fig. 4 shows the coefficient estimates for these regressions and their t-statistics, where the green shaded regions represent the periods in which the market portfolio turns green.

Importantly, Subfigure (a) in Fig. 4 shows that the alpha coefficient $\alpha_{g,t}$ that results from the classic CAPM for the ESG factor is negative for the entire period under analysis, which is consistent with the model proposed by Pástor et al. (2021), who explain that the fact that green assets have negative CAPM alphas does not imply lower utility for agents with stronger ESG preferences, since they derive utility from these holdings.

Additionally, the results in Fig. 3, Subfigure (a), show that the coefficient $\alpha_{g,t}$ and, especially, its t-statistic exhibit a clear upward trend from 2005 to 2018, in line with the pattern followed by both the greenness level of the market portfolio (g_m) in Fig. 1 and the price of risk for the ESG factor ($\lambda_{g,t}$) in Fig. 3, Subfigure (a). This result indicates that, for that period, the ESG factor becomes progressively more redundant with the market portfolio and, consequently, the classic CAPM better captures the ESG characteristics of traded firms, consistent with Eqs. (15), (17) and (18). However, in the years after 2018, and especially from November 2019, the coefficient $\alpha_{g,t}$ experiences a trend reversal in this pattern, which is shared by the greenness level of the market portfolio in Fig. 1 and the price of risk for the ESG factor in Fig. 3. Remarkably, at the end of 2021 the market portfolio recovers its explanatory power on the ESG factor, with Eq. (25) providing a near-zero alpha coefficient (−0.1%). As noted above, this recent trend in the explanatory power of the market portfolio to account for ESG characteristics may have been influenced by the effects of the COVID-19 pandemic on investors' ESG tastes.

Regarding the beta coefficient in Eq. (25), although Subfigure (b) in Fig. 4 provides negative results for $\beta_{m,g,t}$ throughout the entire sample —well far from the value of 1 theorized at the end of Section 3—, from June 2015 its value is not statistically different from zero at a significance level of 5%. This fact is an evident consequence of the progressive increase in the greenness level of the market portfolio over time, which shifts from brown to green in the period under study (see Fig. 1). Interestingly, this result is consistent with the zero ESG portfolio's market beta anticipated by Pástor et al. (2021), under the assumption that the market portfolio is ESG-neutral.

Remarkably, the results depicted in Fig. 4 are fully consistent with those shown in Fig. A3 in the Appendix, which uses the value-weighted return of the firms in our sample instead of the market factor from Kenneth R. French's website as a proxy for the market portfolio, thus supporting the robustness of our results.

All of the above results suggest that predominantly negative ESG betas for brown assets, coupled with a negative price of ESG risk in most periods, imply higher expected returns and, consequently, higher discount rates for these firms across sectors. Therefore, our results are consistent with a large body of prior research analyzing the implications of ESG performance on the cost of capital, which mostly concludes that worse ESG performance generally results in higher discount rates (Baker et al., 2018; Heinkel et al., 2001; Larcker & Watts, 2020; Pedersen et al., 2021; Zerbib, 2019). Furthermore, most of our results are largely in line with the predictions derived from the Pástor et al. (2021) model and the subsequent analysis developed by Pástor et al. (2022). However, as a novelty, in our research we find strong evidence that this set of relationships is not quantitatively constant over time, but varies strongly with changes in corporate ESG performance, both at the firm level and at the aggregate level. Thus, while shifts in corporate ESG performance at the firm level give rise to variations in ESG betas and, consequently, in companies' exposure to ESG risk, shifts in corporate ESG performance at

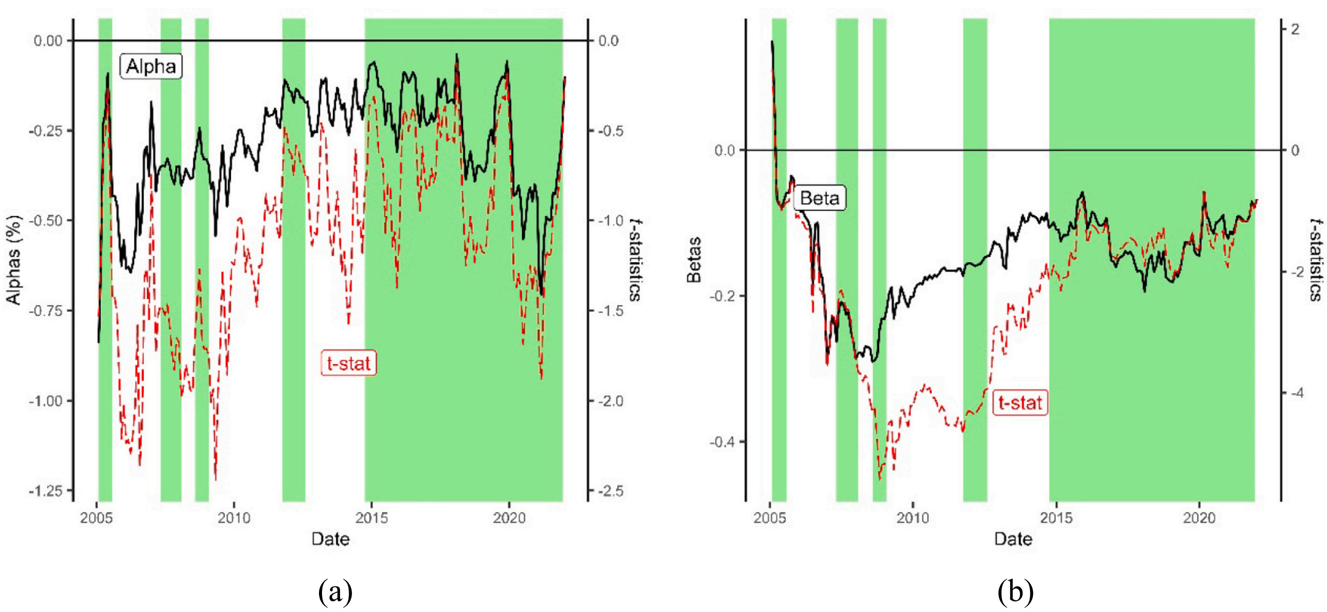


Fig. 4. Estimates from the regression of the ESG factor on the market portfolio.
Notes: Using the monthly excess returns of all publicly traded U.S. companies and their Refinitiv ESG Company Scores, we follow Pástor et al. (2021) to estimate the ESG factor as the difference between returns on green-stock and brown-stock portfolios, based on their ESG scores. Additionally, we use the excess return on the U.S. equity market, as provided by Kenneth R. French on his website, to proxy for the pricing factor that corresponds to the excess return on the market portfolio. The figure shows the alpha and beta coefficients that result from the time-series regression of the ESG factor on the market factor, using a time rolling window of 48-months. The green shaded regions represent the periods in which the market portfolio turns green (i.e., the periods in which $g_m > 0$).

the aggregate level imply widespread variations in the price of ESG risk, which may lead the market to overweight or underweight this source of uncertainty depending on the direction of those shifts.

In this regard, and most importantly, our results suggest that high increases in overall corporate ESG performance can lead market risk to partially subsume ESG risk and, consequently, restore the explanatory power of the classic CAPM to account for ESG issues. Naturally, this does not mean that the CAPM performs well in pricing industry portfolios or that it has recovered its past explanatory power. In fact, the persistence of a large number of market anomalies that predict stock returns in ways that the CAPM cannot account for explains the poor performance of the model in most empirical research on the topic. However, our results show how the fraction of realized CAPM alphas that results from investors' ESG tastes is progressively captured by the market portfolio as the greenness level of the stock market increases.

Nevertheless, the sharp drop in the greenness of the market portfolio in the period from February 2020 to November 2020, coinciding with the emergence of the COVID-19 pandemic, together with the consequent resurgence of the explanatory power of the ESG factor in that period, raises questions about the implications of rare events on corporate ESG performance and climate risk. These concerns are shared by other research in the area that emphasizes the importance of ESG issues in the presence of rare events (Chai et al., 2022; Dhifaoui et al., 2022; Dhifaoui et al., 2023; Khalfaoui et al., 2022).

In this framework, our results point to some general guidelines aimed at reducing firms' risk exposure and preserving corporate value. Specifically, at the firm level, companies with poorer ESG performance should make efforts to improve their greenness level in order to increase exposure to the ESG factor —i.e., increase ESG betas—, especially in the presence of rare events (e.g., wars, pandemics, etc.). In this context, higher ESG betas, coupled with decreasing negative prices of ESG risk, should translate into lower required rates of return and, consequently, smaller price declines. Naturally, this guideline implies that, in a context of overall decline in corporate ESG performance, firms that maintain policies committed to ESG principles are rewarded with lower discount rates, emphasizing the importance of heterogeneity in corporate ESG performance across companies in contrast to heterogeneity in ESG tastes across investors. On the other hand, at the government level, public authorities should make efforts to promote increases in overall corporate ESG performance, which should translate into relatively low absolute prices of ESG risk and, consequently, a lower overall ESG risk.

6. Conclusion

The effect of corporate ESG performance on asset prices and stock returns is currently the subject of a lively debate in academic research, given growing concern about ESG issues in a wide range of areas and the extraordinary boom in investments labeled as green in financial markets. Although previous research in the area provides mixed —or even contradictory— results on the implications of corporate commitment to ESG principles on asset prices, Pástor et al. (2021) propose a robust equilibrium framework in which expected returns can be determined according to a two-factor asset pricing model. Although model factors are given by the return on the market portfolio and an ESG factor proxied by a position in the stock portfolio that maximizes the level of greenness attainable in the market, the authors show that, in the case that there is no dispersion in ESG tastes across market participants, the new ESG factor has not explanatory power on asset prices and the Pástor et al. (2021) model converges to the classic CAPM.

On this basis, in this paper we implement a generalization of the model proposed by Pástor et al. (2021), which shows that when the market portfolio is not ESG-neutral and its greenness level increases, the market factor and the ESG factor become progressively redundant, allowing the classic CAPM to account for ESG characteristics. Our findings provide us with the following main conclusions. First, although the model proposed by Pástor et al. (2021) predicts that green stocks have positive ESG betas and brown stocks have negative ESG betas, our results show that while brown portfolios are much more likely to have negative rather than positive ESG betas, the opposite is not true for green portfolios. In any case, the fact that the absolute value of the greenness level of green firms is much lower than that of brown firms, together with deficiencies in the measurement of the ESG performance of companies, may explain these results.

Second, the time-varying price of risk of the new ESG factor is not only negative, as predicted by the model proposed by Pástor et al. (2021), but also progressively increases towards zero over time, tracking the pattern followed by the greenness level of the market portfolio, which turns from negative to positive throughout the period under study. This result suggests that the ESG factor is progressively less explanatory of stock returns as the equity market becomes greener.

Third, the time rolling window regression of the ESG factor on the market portfolio provides alpha coefficients and *t*-statistics that progressively decrease over time in absolute value, suggesting that, for the period under study, the ESG factor and the market portfolio become progressively more redundant and consequently the classic CAPM better accounts for the ESG characteristics of firms. In any case, the period from February 2020 to November 2020 implies a reversal in this trend, with both the explanatory power of the market portfolio on the ESG factor and the greenness level of the market factor falling sharply, and the price of risk of the ESG factor increasing in absolute value. The fact that this period coincides with the emergence of the COVID-19 pandemic raises questions about the effects of rare events on the mechanics of the model proposed by Pástor et al. (2021).

These findings have some important implications for public policies aimed at promoting the green transition and enhancing corporate value creation. In this regard, the fact that corporate ESG performance appears to be negatively related to required rates of return across industries, together with decreases in corporate ESG performance resulting from different situations, such as rare events (e.g., the COVID-19 pandemic, the conflict in Ukraine, etc.), makes it desirable for public authorities to promote initiatives aimed at improving overall corporate ESG performance, for example, enhancing energy use and efficiency, waste management, reducing carbon emissions, pollution, community impact, etc. Across sectors, special efforts should be made for industries that exhibit poor ESG performance and have high exposure to rare event risk.

On the other hand, our findings have also important implications for stakeholders, and particularly for shareholders and financial managers. Thus, ignoring interests other than purely financial ones, both parties share common ground to improve the ESG performance of companies in order to reduce the cost of capital and enhance corporate value creation, especially in extreme market scenarios that lead to declines in overall corporate ESG performance. Furthermore, from a methodological perspective, our results show that financial managers should carefully consider the effects of ESG risk on discount rates in corporate decision making, particularly in contexts where the absolute price of ESG risk is relatively high or may increase significantly.

In any case, our results show that the Pástor et al. (2021) model continues to have the same problems as the CAPM in explaining the cross-sectional behavior of stock returns, even when the ESG factor exhibits explanatory power on asset prices. This fact brings back into focus the effect of market anomalies on the performance of the classic CAPM. Consequently, future research should study how factors other than the market portfolio, such that those proposed by Fama and French (1993), Fama and French (2015) or Hou, Xue, and Zhang (2014), among others, affect our results. Furthermore, while our empirical analysis focuses on the U.S. equity market, future research should study the extent to which our findings are applicable to other countries which offer different support for ESG practices (Fuente, Ortiz, & Velasco, 2022).

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2023.103019.

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