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How Do Climate-Related Risks and Opportunities Affect Portfolio Allocation and Asset Pricing?

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ABSTRACT

This paper examines the performance of "clean," "brown," and "dirty" stocks in the S&P 500 from January 2010 to September 2022 using panel random effect estimation and factor models. It also uses cointegration analysis to assess the long-term relationship between risk premiums and two carbon risk factors: "brown minus clean" and "dirty minus clean." Finally, we use random walk tests to examine whether carbon risks are priced, and therefore, the S&P 500 market is weakly efficient. Findings indicate that the brown portfolio outperforms the clean portfolio in factor models, likely due to market trends where energy, driven by rising oil and gas prices, outperforms all other sectors. The results also show that the two carbon risks and the political risk have a negative and significant impact on the risk premium and that the excess return series do not follow random walks and are weak form inefficient.

JEL Classification: C23, G12, G11, G14

1 | Introduction

Sustainability and social responsibility have become central to business and investment decisions as climate change increasingly influences risk and opportunity. The intensifying impact of climate change, coupled with growing societal demands for accountability, has underscored the importance of managing climate-related financial risks. These risks, if not adequately addressed, can jeopardize financial stability, particularly as investors and regulators demand their integration into asset pricing and decision-making processes. Despite this urgency, many financial institutions have yet to incorporate climate risk into interest rate modeling, either due to the perceived insignificance of these risks or the lack of appropriate tools and data. Consequently, there is a critical need for new asset pricing and portfolio allocation approaches to address these challenges.

Climate change has long been recognized as a source of systemic risk, with potentially severe implications for financial markets and institutions (Financial Stability Review, ECB 2022). These risks manifest in physical risks, which can affect companies both directly through damage to assets and indirectly through supply chain disruptions (IIGCC 2019), and transition risks, arising from regulatory changes or shifts toward a low-carbon economy. While these risks pose challenges, they also present opportunities for companies to enhance investment performance and align with sustainability goals. For instance, transitioning to a low-carbon economy creates openings for innovative businesses to capitalize on emerging policies, such as carbon taxation, while achieving sustainability objectives. Managing these risks and opportunities through metrics such as Climate Value-at-Risk (Climate VaR), which provides a forward-looking assessment of the impact of climate-related risks on financial assets (Dietz et al. 2016), has become increasingly important for investment decision-making.

Two primary approaches to managing carbon risks in portfolios are the fundamental analysis approach and the market-based approach. Fundamental analysis involves quantifying emissions at the company level, often verified by third parties, to assess how external factors like carbon taxes influence firm value. By contrast, the market-based approach derives carbon risks from historical stock prices, reflecting market assessments of the transition process. This approach circumvents the inaccuracies often associated with self-reported emissions data and addresses gaps in climate-related information. A widely used framework for this approach is the factor model, which links the expected return of an asset or portfolio to its exposure to various risk factors.

Given the systemic nature of climate risks, factor models are particularly suited for assessing these risks. However, significant challenges persist, including defining specific risk factors that capture physical and transition risks and overcoming the limitations of historical data, which often exclude realizations of extreme climate effects. As these risks are unprecedented, novel, forward-looking modeling techniques are essential to accurately measure them.

This paper seeks to quantify the carbon risks and opportunities associated with financial assets and portfolios in the context of the economy's transition toward a green economy. Using Jensen's alpha, it evaluates the performance of "clean," "brown," and "dirty" stocks within the S&P 500 index. Furthermore, the study employs cointegration analysis, panel random effects estimation, and factor models to investigate the impact of carbon risk on risk premia. Finally, it utilizes random walk tests to assess whether carbon risks are priced, determining the efficiency of the S&P 500 market.

This study advances the literature in three key ways. First, it employs panel regression with random effects, addressing unobserved heterogeneity using time-varying parameters to examine the dynamics of carbon risks. Second, it integrates novel factors such as political risks and the COVID-19 pandemic into a five-factor model for a more comprehensive analysis. Third, it evaluates whether carbon risks are embedded in stock returns using diverse random walk tests, offering unique insights not previously explored in the literature.

Recent developments underscore the urgency of integrating climate risks into financial decision-making. For example, robust stress-testing frameworks (Bank of England 2024) and high-frequency ESG data (MSCI 2023) are enabling more granular analyses, addressing limitations in prior methodologies. This paper contributes to this evolving discourse, offering valuable insights for investors, policymakers, and businesses navigating the complexities of the low-carbon transition.

The remainder of this paper is organized as follows: Section 2 reviews prior studies on climate-related risks; Section 3 outlines the theoretical framework; Section 4 presents the empirical findings; and Section 5 concludes the paper.

2 | Literature Review

The impact of carbon emission on the risk premium and the cost of equity capital have been studied in a rapidly growing climate economy literature. For instance, Görgen, Jacob, and Nerlinger (2021) used more than 50 proxy variables to calculate a "Brown-Minus-Green" (BMG) factor and constructed a portfolio that is long in the stocks of "brown" companies, which are likely to be adversely affected by transition risk, and short in the stocks of "green" companies, which are likely to be positively affected. They used ESG data for 1600 globally listed companies between 2010 and 2017 from four different data sources (Sustainalytics, Carbon Disclosure Project, MSCI ESG Stats, and Thomson Reuters ESG) on the three key company-level characteristics: current emissions, public perception, and adaptability. They found that the average stock returns of green companies exceed those of brown companies over this period, which is contradictory to a carbon risk premium. They provided two explanations for the absence of carbon risk premium: (1) the opposite price movements due to the increased (decreased) demand for green (brown) investing that may have driven up (down) the prices of green and brown stocks, respectively, and (2) carbon risk is coupled with unpriced cash-flow changes rather than priced discount-rate changes. They have extended their analysis to different geographic regions and time periods to confirm the missing risk premium. That is, while carbon risk explains systematic return variation well, they did not find evidence of a carbon risk premium.

Bolton and Kacperczyk (2020) estimated the market-based premium associated with carbon transition risk in a cross-section of 14,400 firms in 77 countries and found evidence of a widespread, significant, rising, carbon premium—higher stock returns for companies with higher carbon emissions. Moreover, stock returns are related not only to firms' direct emissions but also to their indirect emissions through the supply chain, and the carbon premium is associated both with the year-to-year growth in emissions (a short-run carbon transition risk exposure) and the level of emissions (a long-run exposure). The premium is significant with respect to both direct emissions (scope 1), indirect emissions from the consumption of purchased electricity, heat, or steam (scope 2), and other indirect emissions from the production of purchased materials, product use, waste disposal, outsourced activities, and so forth (scope 3). They used firm-level carbon emission and financial data to quantify the carbon premium, that is, the return that compensates investors for taking on the transition risk. If transition risk is excluded, there should be no significant correlation between stock returns and CO_2 emissions (after controlling for all other risk factors and firm characteristics). They found that the premium was insignificant in North America before and after the Paris agreement and has declined in Europe but, astonishingly, has sharply risen in Asia. In effect, Asia is entirely responsible for the rise in the global carbon premium around Paris agreement. Bolton and Kacperczyk (2021) have found that stocks of carbon-intensive firms tend to outperform stocks of firms with lower levels of emissions and that the difference in returns cannot be explained by common risk factors and it has been attributed to carbon risk.

Oestreich and Tsiakas (2015) construct country-specific "dirty-minus-clean" (DMC) portfolios in Europe based on the number of free emission allowances available during the first two phases of the EU Emissions Trading Scheme (ETS) that show positive returns during those time periods. They find that, during the first few years of the scheme, firms that received free carbon emission allowances on average significantly outperformed firms that did not. This indicates the presence of a large and significant carbon premium, explained mainly by the higher cash flows due to the free allocation of carbon emission allowances. Furthermore, they find that the carbon risk factor can explain a portion of the cross-sectional variation in stock return, because firms with high carbon emissions are more vulnerable to carbon risk and have higher expected returns (Pástor, Stambaugh, and Taylor 2022). Fama–French three-factor model examines the pricing of climate risk through the construction of a green-minus-brown portfolio from US stock data from November 2012 through June 2018. They found that green stocks typically outperform brown when climate concerns increase. Their results are similar to the findings by Choi, Gao, and Jiang (2020), Engle et al. (2020), and Ardia et al. (2021).

Recent literature builds upon these findings. Smith, Zhang, and Wilson (2023) employed dynamic factor models integrating real-time climate risk indices, finding that transition risks significantly drive equity volatility. Zhang, Brown, and Li (2023) introduced a machine-learning framework for dynamic portfolio optimization under carbon constraints, demonstrating superior performance compared to traditional models. These advancements underscore the growing sophistication in integrating carbon risk into financial decision-making.

Roncalli et al. (2020) studied the minimum variance portfolio and the enhanced index portfolio and proposed estimating the carbon financial risk of equities by their carbon beta. They used the Trucost and MSCI databases to create a brown-minus-green (or BMG) risk factor, similar to Fama and French (1993), and then estimated the carbon beta using a multi-factor model with time-varying parameters to assess the dynamics of the carbon risk. They differentiate between managing absolute carbon risk, which implies having no exposure to the BMG factor and managing relative carbon risk, which implies having negative exposure to the BMG factor. The immunization-hedging investment strategy against carbon is the goal of managing absolute carbon risk, whereas the goal of managing relative carbon risk is to take an active management bet by overweighting green stocks and underweighting brown stocks.

Furthermore, they investigated whether the BMG factor can be considered a new factor in addition to traditional factors such as size, value, and profitability. They concluded that carbon risk is a risk management issue rather than an investment style such as ESG investing, and that carbon risk is better at defining a minimum variance portfolio rather than improving the diversification of a factor investing portfolio. Investors must be aware that carbon risk is priced in by the stock market and it must be measured and managed, especially when it is too high or when it is inconsistent with their beliefs.

Monasterolo and de Angelis (2020) developed an empirical analysis of the low-carbon and carbon-intensive indices for the EU, US, and global stock markets. They examined if financial markets are pricing the Paris Agreement (PA) by decreasing (increasing) the systematic risk and increasing (decreasing) the portfolio weights of low-carbon (carbon-intensive) indices afterward. They find that after the PA the correlation among low-carbon and carbon-intensive indices falls. The general systematic risk for low-carbon indices is consistently decreasing, whereas the stock market reaction for most carbon-intensive indices is mild. Furthermore, after the PA, the weight of low-carbon indices in an optimal portfolio tends to increase. They concluded that, following the PA, stock market investors began to consider low-carbon assets as an appealing investment opportunity, but have not yet penalized carbon-intensive assets.

Chava (2014) analyzes the impact of a firm's environmental profile on its cost of equity and debt capital. He finds that investors demand significantly higher expected returns on stocks excluded by environmental screens (such as hazardous chemicals, large emissions, and climate change concerns) compared to firms without such environmental matters. Lenders also charge a significantly higher interest rate on the bank loans issued to firms with these environmental concerns. These findings suggest that socially responsible investing and environmentally aware lending can have a substantial impact on affected firms' cost of equity and debt capital. Delis, de Greiff, and Ongena (2018) investigate whether banks price the climate policy risk using global data on corporate fossil fuel reserves. They found that before 2015 banks did not price climate policy risk. After 2015, however, the risk is priced, especially for firms holding more fossil fuel reserves, and "green banks" charge marginally higher loan rates to fossil fuel firms.

To study empirically whether temperature shocks are a priced APT factor, Balvers, Du, and Zhao (2016) investigate the effect of temperature shocks on the cost of equity capital. They have tested three hypotheses: (1) The temperature shock factor has a significant and negative risk premium. (2) Industries or firms that are more vulnerable to temperature shocks have higher loadings on the temperature shock factor. (3) The impact of the temperature shock factor on the average cost of equity capital increases over time. They used data from the United States, from April 1953 to May 2015. They obtained the portfolio returns and Fama–French factor data from Kenneth French's website. They merged the CRSP and Compustat to construct a variety of equity portfolios for empirical testing. They have confirmed the hypotheses and found that the uncertainty about temperature changes contributes an annual average of 0.22 percentage points to be the cost of capital (e.g., costs of climate change) which implies a present value loss of 7.92% of the wealth. Furthermore, temperature shocks negatively affect most firms (i.e., the factor loadings), and risk premiums are negative to ensure that riskier assets have higher average returns.

Ehlers, Packer, and de Greiff (2021) combined syndicated loan data with carbon intensity data (CO_2 emissions relative to revenue) of borrowers across different industries and find that a significant carbon premium since the Paris Agreement. The loan risk premium related to CO_2 emission intensity is apparent across industries and broader than that due simply to "stranded assets" in fossil fuel or other carbon-intensive industries. They found that the price of risk appears to be relatively low given the material risks faced by some borrowers. Only carbon emissions that are directly caused by the firm (scope 1) are priced, and not the overall carbon footprint including indirect emissions, and "Green" banks do not appear to price carbon risk differently from other banks.

Several studies have shown that investors are still not fully pricing climate risks and opportunities in their portfolios. Faccini, Matin, and Skiadopoulos (2021), for example, examined four sources of climate risks: natural disasters, global warming, international summits, and US climate-policy news. They found that the transition risks prompted by the US political debate on climate change have only begun to be priced in recent years. In addition, they documented that stocks that are more exposed to climate risks pay higher returns on average than stocks that are less exposed. They conclude that climate risks are mispriced, and policy intervention is required to address the market failure underlying the mispricing. Azlen, Gostlow, and Child (2021) used exchange-traded carbon futures and find that carbon has generated significant positive excess returns combined with a low correlation to other asset classes, making it attractive as a portfolio diversifier. They found that the Carbon Composite has generated an annualized excess return of about 27% over the period 2013–2021 with a Sharpe Ratio of 1.50 and a low correlation to all other asset classes.

Other empirical literature has drawn on the impact of temperature shocks on cash flow and production at both micro and macro levels. For instance, Dell, Jones, and Olken (2012) find that higher temperatures substantially reduce economic growth, agricultural output, industrial output, and political stability, particularly in poor countries. Second, higher temperatures may reduce growth rates, not just the level of output. Third, higher temperatures have wide-ranging effects, reducing agricultural output, industrial output, and political stability. Fisher et al. (2012) found a negative impact of high temperatures on US agriculture. Temperature increases, according to Graff and Neide (2014), reduce labor productivity in weather-sensitive industries such as agriculture, forestry, fishing, and hunting; mining; construction; transportation and utilities; and manufacturing. High temperatures, according to Cachon, Gallino, and Olivares (2012), reduce productivity and automobile production at the plant level.

Another strand of literature considers if the growing popularity of sustainable investment does create additional risks in investing. For instance, Yue et al. (2020) evaluate the performance of both sustainable and traditional funds by comparing samples of 30 sustainable and 30 traditional funds. They used standard statistical measures alongside The Capital Asset Pricing Model (CAPM), Fama–French three-factor model, and Carhart's four-factor model. They found that sustainable funds are less risky than traditional funds, and no clear evidence was found to confirm that sustainable funds can generate higher returns compared to traditional peers or benchmark indexes. They suggested that the Fama–French three-factor model was the most suitable for explaining the traditional and sustainable funds' results. Other empirical papers investigated the impact of climate risks on the financial system. For instance, Barnett, Brock, and Hansen (2020) demonstrate theoretically how emissions and climate uncertainty, including physical risks, can be priced in a dynamic stochastic equilibrium model. Battiston et al. (2017) used a network-based climate stress-test methodology and data for large Euro Area banks in a "green" and a "brown" scenario to investigate how climate policy risk might be transmitted through the financial system. They found that direct and indirect exposures to climate-policy-relevant sectors represent a large portion of investors' equity portfolios, particularly for investment and pension funds. Furthermore, the portion of banks' loan portfolios exposed to these sectors is comparable to banks' capital. They concluded that an early and stable policy framework would allow for smooth asset value adjustments and lead to potential net winners and losers. Dietz et al. (2016) investigated the impact of climate change on asset values. They found that the expected "climate value at risk" (climate VaR) of global financial assets today is 1.8% (or US$2.5 trillion) along a business-as-usual emissions path and that constitutes a substantial write-down in the fundamental value of financial assets. Furthermore, reducing emissions to limit warming to no more than 2°C reduces the climate VaR by an expected 0.6 percentage points, and the 99th percentile reduction is 7.7 percentage points. Involving mitigation costs, the present value of global financial assets is an expected 0.2% higher when warming is limited to no more than 2°C, compared with business as usual. Other studies show that climate policy uncertainty is priced in the options market (Ilhan, Sautner, and Vilkov 2020), and Matsumura, Prakash, and Munoz (2014) used carbon emissions data from 2006 to 2008 that were voluntarily disclosed to the Carbon Disclosure Project by S&P 500 firms, to examine the effects on firm value of carbon emissions and of the act of voluntarily disclosing carbon emissions. They find that, on average, for every additional thousand metric tons of carbon emissions, the firm value decreases by $212,000.

Finally, little empirical literature considers the extent to which stock markets efficiently price climate change risks. Such risks include carbon assets, which might be affected by future carbon prices or taxes (e.g., stranded assets) and have attracted the most discussion in recent years.

Recent studies have highlighted the systemic risks posed by climate change. The European Central Bank (ECB 2024) conducted stress tests showing that carbon-intensive sectors face higher default risks under stringent climate policies. Similarly, Patel and Jones (2024) found that firms adhering to regulatory frameworks, such as the EU Corporate Sustainability Reporting Directive (CSRD), benefit from a reduced cost of capital, illustrating the link between policy compliance and financial performance. The IPCC Sixth Assessment Report (2023) underscores the urgency of mitigating climate change through significant reductions in greenhouse gas emissions and a transition to sustainable energy systems, calling for global cooperation and policy alignment to achieve climate targets. Additionally, the International Sustainability Standards Board (ISSB 2024) highlights the importance of standardized ESG reporting to enhance comparability and transparency, facilitating informed decision-making by investors and stakeholders while aligning global ESG practices with financial reporting standards.

Market inefficiencies in pricing climate risks persist. Hong, Li, and Xu (2019) investigated whether the prices of food stocks efficiently discount the risks of droughts using data from 31 countries with publicly traded food companies. They rank these countries based on their long-term trends toward droughts utilizing the Palmer Drought Severity Index. They found that a poor trend ranking for a country forecasts poor profit growth for food companies in that country and poor food stock returns in that country. The return predictability in their analysis is consistent with food stock prices underreacting to climate change risks. Hino and Burke (2020) examine the effect of information about flood risk on residential property values in the United States using multiple empirical approaches and two decades of sales data covering the universe of homes in the United States. They find little evidence that housing markets fully price information about flood risk in aggregate and that floodplain homes in the United States are currently overvalued by a total of $34B.

Emerging studies (Greenfield, Tran, and Taylor 2024; Lee and Chen 2023) explore behavioral finance dimensions, showing that investor sentiment towards ESG disclosures influences market responses to climate policies. These findings complement traditional asset pricing approaches by accounting for psychological factors in market dynamics.

In terms of portfolio optimization, Azlen, Gostlow, and Child (2021) demonstrated the diversification benefits of carbon as an asset class. Recent contributions (MSCI 2023) have enhanced ESG data granularity, enabling better climate risk quantification and portfolio adjustments.

Despite significant progress, challenges remain. Defining specific risk factors for physical and transition risks and addressing historical data limitations are critical. As De Guindos (2021) and Bank of England (2024) suggest, forward-looking models and robust stress-testing frameworks are essential to bridging these gaps.

This study builds on this evolving literature by incorporating novel methodologies to assess carbon risk's impact on risk premia and portfolio allocation. By employing random walk tests, cointegration analysis, and introducing political risk and COVID-19 into factor models, it advances understanding of how carbon risks influence financial markets.

3 | Theoretical Framework (Factor Model Approaches)

Carbon risk, as defined in the corporate finance literature, is the impact of society's transition to a low-carbon economy on firm value as a result of tightening regulations, changing consumer preferences, reputational damage, and so on. Although research on carbon risk is still in its early stages in the corporate finance field, the amount of literature on the subject has grown significantly in the last 2 years.

To assess climate risk, we modify factor models, which are assumed to be the best approach for capturing individual assets' transition risk exposure. The factor model allows us to estimate such exposure using historical data that, for the most part, does not include realizations of extreme climate change impacts or severe transition risk impacts. In what follows, we use the mimicking portfolio for carbon risk developed by Görgen, Jacob, and Nerlinger (2021). We also discuss the different climate change-relevant dimensions to determine which dimensions are priced by the market.

The empirical analysis in this paper stipulates a framework for investigating whether "brown" firms exhibit abnormal excess returns relative to "clean," that is whether there is a carbon risk premium. We address this question by constructing three carbon portfolios "clean," "brown," and "dirty" portfolios. The "clean" portfolio is a portfolio of firms, which have received at least 75 points ESG scores and an A ESG score grade. Of 500 firms in S&P 500, 162 firms are classified as clean. The "brown" portfolio is a portfolio of firms, which have received between 50 and 74 ESG scores and a B ESG score grade. There are 163 firms classified as "brown." The "dirty" portfolio is a portfolio of firms, which have received at least 50 points ESG scores and a C ESG score grade. There are 62 firms in the S&P 500 classified as "dirty." There is no rebalancing in the portfolios as the composition of the three carbon portfolios does not change over time and it is the same firms that each year satisfy the criteria to be part in the portfolios. We also require that the company should be listed for at least 3 years to be included in the portfolio.[1]

The portfolio is constructed to mimic the factors models where alpha (α), measuring the abnormal excess return relative to three standard factor models. The first model is based on the Capital Asset Pricing Model (CAPM), which is described as

$$R_{j,t} - R_{f,t} = \alpha_j + \beta_j \left(R_{m,t} - R_{f,t} \right) + \varepsilon_{j,t} \tag{1}$$

where $R_{j,t}$ is the monthly return of portfolio j at time t for j being one of the clean, brown, and dirty portfolios, $R_{f,t}$ is the monthly riskless rate at time t, $R_{m,t}$ is the monthly return to the market portfolio at time t, and $\varepsilon_{j,t}$ is a normal error term.

The second model is based on the three-factor model by Fama and French (1993):

$$R_{j,t} - R_{j,t} = \alpha_j + \beta_1 \left(R_{M,t} - R_F \right) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{J,t} \tag{2}$$

where SMB_t is size premium (small minus big) and HML_t is value premium (high minus low). If the market efficiency hypothesis holds, the outperformance can be explained by the excess risk that value and small-cap stocks face because of the higher cost of capital and bigger business risk.

The third model is the five-factor model based on Fama and French (2015):

$$\begin{aligned} R_{\mathrm{j},t} - R_{j,t} = \alpha_j + \beta_1 \left(R_{M,t} - R_F \right) + \beta_2 SMB_t \\ + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \varepsilon_{J,t} \end{aligned} \tag{3}$$

where RMW_t is the return spread of the most profitable firms minus the least profitable and CMA is the conservative minus aggressive investment factor, as introduced in the Fama–French five-factor model (2015). Both factors capture distinct aspects of firm characteristics: RMW reflects the profitability premium where highly profitable firms tend to earn higher returns, while CMA measures the return difference between firms with conservative (low asset growth) and aggressive (high asset growth) investment policies. As in Oestreich and Tsiakas (2015), we define the carbon premium as the difference in alphas between clean, brown, and dirty portfolios. Thus, its difference is the abnormal excess return of the dirty portfolio over and above that of brown and clean portfolios. Thus, αj (or Jensen's alpha coefficient) measures the risk-adjusted average return on the portfolio above or below that predicted by the CAPM, three- and five-factor models.

4 | Empirical Findings

4.1 | Data and Variable Descriptions

The data are from Thomson Reuters Eikon ESG, MSCI ESG Score (Refinitiv 2022). Our data comprises all 500 firms in the S&P 500, and the ESG scores for these firms range from 0 to 100. In this paper, a score of more than 70 is regarded as "clean" (C), a score from 50 to 69 is considered "brown" (B), and a score less than 50 is regarded as "dirty" (D). This makes a total of 158 clean firms, 284 brown firms, and 58 dirty firms. We constructed three mimicking stock portfolios: The first portfolio consists of stocks of "clean" firms, the second portfolio consists of stocks of "brown" firms, and the third of stocks of "dirty" firms. A time series of historical portfolios return is calculated for all three portfolios. The difference between the three-time series results in two carbon risk factors. The first is BMC (brown minus clean), which corresponds to a time series of historical returns from an investment in "brown" stocks minus returns from investing in "clean" stocks. The second is DMC (dirty minus clean), which corresponds to a time series of historical returns from an investment in "dirty" stocks minus returns from investing in "clean" stocks. The portfolio returns and Fama–French factor data are from Kenneth French's website. Table A1 shows company names and corresponding ESG scores for the S&P 500 index.[2]

To see the performance of ESG, Figure 1 shows the development of MSCI All Country World Index[3] (ACWI) compared to World

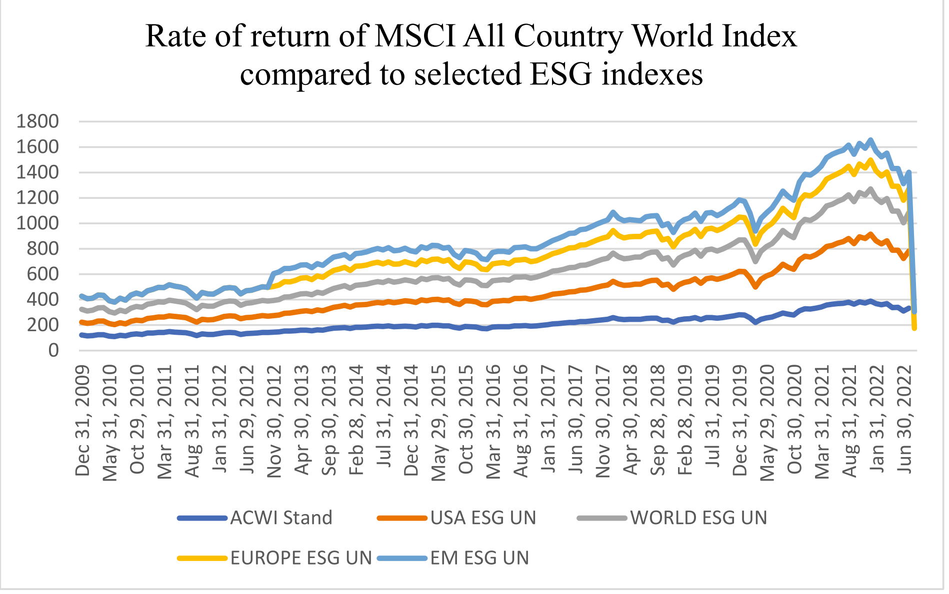

FIGURE 1 | Rate of return of MSCI All Country World Index compared to selected ESG indexes.

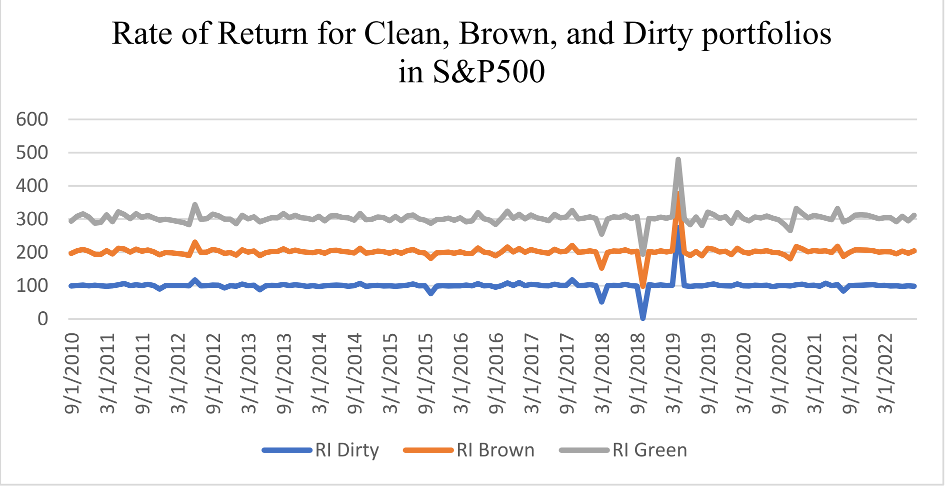

FIGURE 2 | The rate of return for clean, brown, and dirty portfolios in S&P 500 index.

ESG, US ESG, Europe ESG, and Emerging market ESG indexes. It is clear from the figure that all ESG indexes, especially in emerging markets, outperform ACWI index. Figure 2 shows the development of the rate of returns for our three portfolios: clean, brown, and dirty from January 2010 to July 2022. The figure shows the excess return of the clean and brown over the dirty portfolio.

Table 1 presents descriptive statistics for the monthly returns of firms in the S&P 500. The table reveals that the mean return of the dirty-minus-clean (DMC) portfolio is −0.701%, compared to 0.018% for the brown-minus-clean (BMC) portfolio. This suggests the presence of a positive risk premium for BMC and a negative risk premium for DMC. The variables RPC, RPB, and RPD represent the rates of return for "clean," "brown," and "dirty" stocks, respectively. SMB captures the size premium, HML represents the value premium, RMW reflects the profitability premium, and CMA refers to investment premium, as introduced in the Fama–French Five-Factor Model (2015).

Our findings on the carbon risk premium contradict the results of Görgen, Jacob, and Nerlinger (2021). A possible explanation for the existence of carbon risk premium is opposite price movements due to the decreased (increased) demand for clean (brown) investments in the recent years which may have driven up (down) the prices of brown and clean stocks, respectively.

Modeling excess returns required addressing potential issues of multicollinearity among the variables in Equation (4). To this end, we estimated the contemporaneous (zero lag) coefficients for the variables in the system. Table 2a presents the pairwise correlations between the seven fundamental variables used in the long-run equation (Equation 4), while Table 2b reports the variance inflation factor (VIF) values.

Several key insights emerge from these analyses. First, excess returns have a moderate negative correlation with market returns, with a correlation coefficient of −0.340. Second, excess returns have a moderate positive correlation with carbon risk measure DMC at 0.414, while the correlation with BMC is weak (0.061). The correlations among explanatory variables are generally low, with the highest being between the HML and CMA at 0.615, indicating no significant multicollinearity issues.

The results in Table 2b further confirm this conclusion, as all variables exhibit VIF values below 5, which is the commonly accepted threshold for acceptable multicollinearity. Collectively, the findings from both tables suggest that the regression coefficients for all independent variables are reliable, and no corrective action, such as variable removal or regularization, is necessary.

When modeling panel data, a question is frequently asked about which econometric model to use. Empirical studies have shown that different models can produce significantly different results. To determine whether pooled, fixed effect, or random effect model is the most appropriate we run Chow and Hausman tests. The null hypothesis (H0) is that the preferred model is random effects, and the alternative hypothesis (H1) is that the preferred model is fixed effects, and the results are shown in Table 3. Since the *p*-value is large (greater than 0.05), we cannot reject the null hypothesis that the random effect model is the most appropriate model for our analysis. The presence of large N and small T, as we have in this study, provides additional support to the use of the random effect model since it uses fewer degrees of freedom in estimation and allows for the inclusion of time-invariant covariates. That is, in contrast to fixed effects, the random effect model does not permit the elimination of omitted heterogeneous effects.[4]

Table 4 shows the results for the three standard factor models where the dependent variables are the risk premiums for clean stocks (RP_C), brown stocks (RP_B), and dirty (RP_D). A special focus on the value of α in Equations (1–3), referred to in the literature as "Jensen's alpha," determines if a portfolio is earning the proper return for its level of risk. A positive alpha indicates that the portfolio earned more than enough return to be compensated for the risk it took over the course of the month. A few points are worth noting from the results in Table 4. First, alpha is always positive regardless of the category and factor model used. Second, the brown portfolio slightly outperforms the clean portfolio in the 4-factor model where the values of alphas are

TABLE 1 | Descriptive statistics.

	RI	RF	RPC	RPB	RPD	SMB	HML	CMA	RMW	BMC	DMC
Mean	1.241	0.04	1.426	1.444	0.725	−0.02	−0.19	0.013	0.116	0.018	−0.701
Maximum	59.882	0.21	12.46	13.79	173.72	7.040	8.190	3.690	3.480	1.561	94.89
Minimum	−35.21	0.00	−9.31	−9.57	−98.51	−4.58	−4.76	−3.24	−3.880	−1.81	−170.3
Std. dev.	7.200	0.06	3.580	3.899	19.230	2.296	2.280	1.450	1.486	0.690	18.938
Skewness	3.366	1.38	−0.31	−0.19	4.76	0.194	0.691	0.282	−0.117	−0.22	−4.897
Kurtosis	42.589	3.39	3.843	3.845	60.960	2.817	3.971	2.690	2.819	2.783	60.860
Jarque-Bera	16,932	826	114	91	36,228	19	299	44	9	27	36,158
Probability	0.000	0.00	0.000	0.000	0.000	0.000	0.000	0.000	0.010	0.000	0.000
Sum	3128	108	3593	3639	1827	−67	−495	32	291	−46	1319
Sum sq. dev.	13,057	11	3228	3828	931,500	13,281	13,097	5294	5566	1199	90,344
Observations	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520

TABLE 2 | Contemporaneous cross-correlations and variance inflation factor (VIF) for the dependent variables.

a. Contemporaneous cross-correlations for the variables

	Ri	Rm	HML	CMA	RMW	SMB	DMC	BMC
Ri	1.000							
Rm	−0.340	1.000						
HML	−0.002	0.100	1.000					
CMA	0.057	−0.109	0.615	1.000				
RMW	0.090	−0.115	0.058	0.062	1.000			
SMB	−0.158	0.293	0.252	0.004	−0.380	1.000		
DMC	0.414	0.147	0.102	0.033	−0.007	0.062	1.000	
BMC	0.061	−0.399	−0.384	−0.052	0.204	−0.472	−0.203	1.000

b. Variance inflation factor (VIF)

Variable	Coefficient variance	Uncentered
Rm	0.002	1.293
HML	0.006	2.092
CMA	0.013	1.757
SMB	0.007	1.577
RMW	0.011	1.216
DMC	0.000	1.051
BMC	0.087	1.651

Note: The table reports the contemporaneous cross-correlations for the variables. Ri-Rf refers to the excess return over the risk-free rate, Rm is the monthly return on the market, SMB refers to the size premium, HML refers to the value premium, RMW refers to the profitability premium, CMA refers to conservative minus aggressive, which is based on Fama–French Five-Factor, DMC refers to "Dirty Minus Clean," and BMC refers to "Brown Minus Clean." Two different alternative measures are used as a proxy for Rm including the return of the S&P 500 and MCSI All Country World Index, and both provided equivalent results.

TABLE 3 | Correlated effects—Hausman test.

Test summary	Chi-sq. statistic	Chi-sq. df.	Prob.
Cross-section random	0.000	6.000	1.000

0.63 and 0.65 for the clean and brown portfolios, respectively. This result is consistent with a mean risk premium of 0.018 for BMC reported in Table 1. Third, the values of the Durbin-Watson statistic are above 2 in all regressions indicating zero autocorrelation. Finally, the 4-factor model implies higher explanatory power (0.92) compared to the CAPM (0.90) and the 3-factor model (0.91) and is the one that will be used in the rest of this study.

As sustainable investing evolved from an ethical approach to an investment opportunity, investors began to reallocate from brown firms such as energy companies that rely on fossil fuels to their clean energy counterparts.[5] Yet market trends in recent years have trended in the opposite direction with energy outperforming all sectors in the S&P 500 due to rising oil and gas prices. Table 5 shows the performance of the energy sector versus the other sectors in the S&P 500. The figures show that over the past 3 years, the energy sector's return has increased by 49.55% compared to only 26.85% for the S&P 500 index.[6] This difference could have led many investors to believe that there is a profit to be made in the brown stocks rather than exclusion and avoidance. The discrepancy may also suggest that the path to a low-carbon economy is not linear and requires more research. For the past 10 years, investors thought the "brown" stocks were dead. Price pressures from supply constraints in 2021, the covid-19 pandemic, inflationary pressures, and the current energy crises made the transition to a greener economy more complex. Brown stocks showed strong performance and traditional energy made a comeback as increased demand drove oil prices to multi-year highs and renewables lacked the bandwidth to meet surges in demand.

4.2 | Long-Run Relationship and Robustness Testing

Critics of Jensen's alpha measure generally believe in Fama's efficient market hypothesis (EMH), which asserts that each portfolio's excess returns are due to random chance. If so, the market is said to be "efficient" and correctly priced because it has already priced in all available information, thus preventing any active portfolio manager from bringing anything new to the table.

As mentioned above, there are several ways to measure carbon risk at the company level. Two commonly used approaches are the fundamental and the market-based approaches. The

TABLE 4 | Generalized least square (GLS) panel random effect estimation of factor model for the stocks in S&P 500 sample: 2010M01–2022M09.

	Dependent variable: RP_C					Dependent variable: RP_B					Dependent variable: RP_D				
Model	Variable	Coefficient	Std. error	*t*-statistic	Prob.	Variable	Coefficient	Std. error	*t*-statistic	Prob.	Variable	Coefficient	Std, error	*t*-statistic	Prob.
CAPM	A	0.637	0.027	23.609	0.000	α	0.637	0.027	23.609	0.000	α	0.301	0.307	0.983	0.326
	Rm	1.034	0.006	163.744	0.000	Rm	1.034	0.006	163.744	0.000	Rm	0.304	0.072	4.239	0.000
	Adjusted *R*-squared = 0.901, Durbin-Watson sta. = 2.15					Adjusted *R*-squared = 0.89, Durbin-Watson sta. = 2.15					Adjusted *R*-squared = 0.09, Durbin-Watson sta. = 2.01				
3-factor	A	0.681	0.023	30.241	0.000	α	0.683	0.023	29.839	0.000	α	0.245	0.307	0.798	0.425
	Rm	0.926	0.006	168.204	0.000	Rm	0.977	0.006	174.761	0.000	Rm	0.300	0.075	3.998	0.000
	SMB	0.181	0.009	19.342	0.000	SMB	0.273	0.010	28.745	0.000	SMB	0.197	0.127	1.550	0.121
	HML	0.033	0.007	4.562	0.000	HML	0.100	0.007	13.634	0.000	HML	−0.392	0.098	−4.004	0.000
	Adjusted *R*-squared = 0.91, Durbin-Watson sta. = 2.06					Adjusted *R*-squared = 0.003, Durbin-Watson sta. = 2.11					Adjusted *R*-squared = 0.91, Durbin-Watson sta. = 2.04				
5-factor	A	0.63	0.02	28.04	0.00	α	0.65	0.02	28.21	0.00	α	0.20	0.31	0.64	0.52
	Rm	0.93	0.01	170.48	0.00	Rm	0.98	0.01	174.73	0.00	Rm	0.31	0.08	4.05	0.00
	SMB	0.23	0.01	23.29	0.00	SMB	0.31	0.01	30.11	0.00	SMB	0.24	0.14	1.69	0.09
	HML	0.01	0.01	1.25	0.21	HML	0.10	0.01	10.70	0.00	HML	−0.45	0.13	−3.49	0.00
	RMW	0.17	0.01	13.23	0.00	RMW	0.13	0.01	9.97	0.00	RMW	0.09	0.18	0.50	0.62
	CMA	0.01	0.01	0.89	0.38	CMA	−0.03	0.01	−2.39	0.02	CMA	0.12	0.20	0.62	0.54
	Adjusted *R*-squared = 0.92, Durbin-Watson sta. = 2.09					Adjusted *R*-squared = 0.925, Durbin-Watson sta. = 2.07					Adjusted *R*-squared = 0.003, Durbin-Watson sta. = 2.07				

Note: Durbin-Watson sta. refers to The Durbin-Watson statistic.

TABLE 5 | The performance of the energy sector versus the other sectors in the S&P 500 in percent.

Sector name	1-day %	5-D %	1-M %	3-M %	YTD %	1-Y %	3-Y %	5-Y %	10-Y %
Information technology	−0.85	3.96	−5.08	−2.26	−27.83	−16.36	55.91	113.99	346.80
Energy	1.82	13.65	4.14	19.15	49.91	51.61	49.55	24.76	14.61
Health care	−1.30	2.04	0.46	−2.85	−11.15	−0.73	39.99	52.12	205.99
Materials	−1.02	4.45	−3.85	−1.88	−21.29	−11.57	27.04	23.29	90.65
Consumer discretionary	−0.71	0.63	−5.80	2.35	−28.58	−19.58	22.75	57.76	205.33
Financials	−1.45	3.13	−3.54	−0.45	−19.09	−17.95	15.42	20.34	143.01
Industrials	−1.09	3.51	−5.39	0.14	−17.90	−12.86	15.18	19.93	126.41
Consumer staples	−1.46	−0.64	−6.61	−6.94	−12.51	−1.86	11.75	25.91	86.85
Communication services	−0.65	2.70	−7.50	−12.00	−36.74	−37.63	1.33	3.25	6.54
Utilities	−3.30	−2.51	−12.3	−6.26	−9.08	0.72	0.49	22.00	77.12
Real estate	−3.20	−0.73	−13.9	−14.3	−31.61	−20.35	−9.02	10.72	—
S&P 500 index	−1.02	2.86	−4.58	−2.27	−21.44	−13.83	26.85	46.72	156.31

Source: Fidelity, 10/6/2022.

fundamental approach entails defining a carbon risk score for each stock in an investment portfolio using a set of objective measures, whereas the market approach entails constructing a brown minus clean, or BMG, carbon risk factor and computing the risk sensitivity of stock prices in relation to this BMG factor (Roncalli et al. 2020). As a result, the carbon factor is derived from climate change-related data for a variety of companies.

Görgen, Jacob, and Nerlinger (2021) identified three distinct components that may impact a firm's stock value in the event of unexpected shifts toward a low-carbon economy: (1) value chain, (2) public perception, and (3) adaptability. The value chain focuses on current emissions, public perception focuses on the relationship between companies' value and their ability to support the climate, while the adaptability aspect considers potential future emissions. In this section, we follow the market-based approach in line with Görgen, Jacob, and Nerlinger (2021) with two modifications. First, we introduce two carbon risk factors described above: BMC and DMC. Second, we use a time-varying panel with Random effect estimation to assess the dynamics of the carbon risk. Let $R_i(t)$ denotes the monthly excess return of stock *i* at time *t*. We assume that

$$R_i(t) = \alpha_i(t) + \beta_{i,t}(Mkt) + \gamma 1_{i,t}(SMB) + \gamma 2_{i,t}(HML)\gamma 3_{i,t}(RMW) + \gamma 4_{i,t}(CMA) + \delta 1_{i,t}(BMC) + \delta 2_{i,t}(DMC) + Dummy1 + Dummy2 + \in_{i,t} \quad (4)$$

where *Mkt* refers total market portfolio return at time *t*, *SMB* is the return spread of small minus large stocks (i.e., the size effect), *HML* is the return spread of cheap minus expensive stocks (i.e. the value effect), *RMW* is the return spread of the most profitable firms minus the least profitable, *CMA* measures the return difference between firms with conservative and aggressive investment policies. *BMC* refers to the first carbon risk (Brown Minus Clean), and *DMC* refers to the carbon risk (dirty minus clean). We used the stocks that were present in the S&P 500 index. We use the time series provided by Kenneth French on his website. We estimate the parameters for the stocks belong to the S&P 500 index between January 2010 and September 2022.

The long-run analysis is conducted in three phases: (1) We evaluated the variables for stationarity through a unit root test, (2) testing for cointegration to determine the presence of the long-run relationship for the variables in Equation (4) and (3) estimate the long-term relationships of excess return. We have also included two dummies. The first dummy (Dummy1) refers to the political risk of the US withdrawing from the Paris Climate Agreement announced by President Trump on June 1, 2017. Not until President Biden signed the instrument to bring the United States back into the Paris Agreement in January 2020. Dummy1 takes the value 1 for the period June 2017 to December 2019 and the value zero otherwise. The second dummy (Dummy 2) for the Covid pandemic started when the World Health Organization (WHO) announced on March 11, 2020, that the new coronavirus (COVID-19) is breaking out into a global pandemic. Not until the Biden administration lifted travel restrictions for fully vaccinated international visitors in October 2021. Dummy 2 has the value 1 for the period between March 2020 and September 2021 and the value zero otherwise.

Table 6 shows the results of different panel unit root tests. The first is the Levin, Lin, and Chu statistics, which assume a common unit root process. The second is Im, Pesaran, and Shin and ADF-Fisher and PP-Fisher statistics, which assume an individual unit root process. In both tests, the null hypothesis is H0: The series has a unit root. The alternative hypothesis H1: The series has no unit root. In all tests, the *p*-values are 0 and therefore we reject the null hypothesis that the series have a unit root (e.g., stationary). For variables Ri, RM, SMB, and RMW, all test statistics strongly reject the null hypothesis of a unit root with *p*-values of 0.000, indicating stationarity. For BMC, DMC, HML, and CMA, we observe divergent results: While the Levin, Lin, and Chu t test yields *p*-values of 1.0000, suggesting non-stationarity under the common unit root assumption, all other tests—particularly the ADF test which is most reliable for

TABLE 6 | Return: panel unit root test for S&P 500 stocks return.

Variable	Method	Statistic	Prob	Obs
Ri	Null: unit root (assumes common unit root)			
	Levin, Lin, and Chu	−6.458	0.000	3108
	Null: unit root (assumes individual unit root)			
	Im, Pesaran, and Shin W-stat	−21.808	0.000	3108
	ADF-Fisher chi-square	543.788	0.000	3108
	PP-Fisher chi-square	2044.570	0.000	3192
RM	Null: unit root (assumes common unit root)			
	Levin, Lin, and Chu	−11.460	0.000	3108
	Null: unit root (assumes individual unit root process)			
	Im, Pesaran, and Shin W-stat	−21.974	0.000	3108
	ADF-Fisher chi-square	549.704	0.000	3108
	PP-Fisher chi-square	1973.460	0.000	3192
SMB	Null: unit root (assumes common unit root)			
	Levin, Lin, and Chu	−13.112	0.000	3108
	Null: unit root (assumes individual unit root process)			
	Im, Pesaran, and Shin W-stat	−19.817	0.000	3108
	ADF-Fisher chi-square	474.071	0.000	3108
	PP-Fisher chi-square	1764.180	0.000	3192

(Continues)

TABLE 6 | (Continued)

Variable	Method	Statistic	Prob	Obs
RMW	Null: unit root (assumes common unit root)			
	Levin, Lin, and Chu	−12.862	0.000	3108
	Null: unit root (assumes individual unit root)			
	Im, Pesaran, and Shin W-stat	−21.485	0.000	3108
	ADF-Fisher chi-square	532.274	0.000	3108
	PP-Fisher chi-square	1349.800	0.000	3192
BMC	Null: unit root (assumes common unit root process)			
	Levin, Lin, and Chu	23.648	1.000	3108
	Null: unit root (assumes individual unit root)			
	Im, Pesaran, and Shin W-stat	−20.601	0.000	3108
	ADF-Fisher chi-square	501.186	0.000	3108
	PP-Fisher chi-square	1283.230	0.000	3192
DMC	Null: unit root (assumes common unit root)			
	Levin, Lin, and Chu	14.632	1.000	3108
	Null: unit root (assumes individual unit root)			
	Im, Pesaran, and Shin W-stat	−22.900	0.000	3108
	ADF-Fisher chi-square	583.162	0.000	3108
	PP-Fisher chi-square	1754.610	0.000	3192

(Continues)

TABLE 6 | (Continued)

Variable	Method	Statistic	Prob	Obs
HML	Null: unit root (assumes common unit root process)			
	Levin, Lin, and Chu	5.470	1.000	3108.000
	Null: unit root (assumes individual unit root process)			
	Im, Pesaran, and Shin W-stat	−17.032	0.000	3108.000
	ADF-Fisher chi-square	386.834	0.000	3108.000
	PP-Fisher chi-square	1476.150	0.000	3192.000
CMA	Null: unit root (assumes common unit root process)			
	Levin, Lin, and Chu	23.6479	1.0000	3108
	Null: unit root (assumes individual unit root process)			
	Im, Pesaran, and Shin W-stat	−20.6011	0.0000	3108
	ADF-Fisher chi-square	501.186	0.0000	3108
	PP-Fisher chi-square	1283.23	0.0000	3192

Note: Sample period: 2010M01–2022M09. Probabilities for Fisher tests are computed using an asymptotic chi-square distribution. All other tests assume asymptotic normality. MacKinnon, Haug, and Michelis (1999) *p*-value. Series: RI, ACWILCARL_RETURN, SMB, HML, RMW, CMA, DMC, and BMC.

unbalanced data—strongly indicate stationarity with *p*-values of 0.0000. The consistent results across Im, Pesaran, and Shin W-stat, ADF-Fisher, and PP-Fisher tests ultimately provide robust evidence for the stationarity of all series when allowing for individual unit root processes.

Next, we tested for cointegration of the variables in Equation (4) using the Johansen test, which is powerful even when the sample size is small. The Johansen procedure involves the use of two test statistics for cointegration: the trace test, which tests the hypothesis that there are at most r cointegrating vectors, and the maximum eigenvalue test, which tests the hypothesis stating that there are cointegrating vectors. The corresponding test results are presented in Table 7. The null hypothesis of no cointegration is rejected because statistics > critical values. Both tests indicate 7 cointegrating equations at the 0.05 level for the seven variables in the system, showing that excess returns are determined by market risk premium, SMB, HML, RMW, CMA, DMC, and BMC. Given that there are at least two cointegrating relationships between these variables, we proceed to estimate the long-run relationship of risk premium determinants in Equation (4).

Table 8 presents the estimation results of the long-run determinants of the risk premium using generalized least squares (GLS) panel estimation with the random effect for the firms in the S&P 500 from January 2010 to September 2022. A few general striking results emerge from our analysis. First, the coefficients for market β (0.918), SMB (0.254), HML (0.052), and RMW (0.151) are positive and statistically significant at the 1% level. Second, the coefficients for DMC (−0.341) and BMC (−0.098) are negative and statistically significant at 5% level. The CMA factor, while negative (−0.011), is not statistically significant ($p=0.472$). Third, the coefficient for Dummies are negative but insignificant, though DUMMY2 is marginally significant at the 10% level ($p=0.051$).

Finally, we use the Wald chi-squared test to examine the explanatory power of the parameters δ1 and δ2 of the two carbon risk factors in Equation (4). The null hypothesis is that $\delta1=\delta2=0$, and the results are shown in Table 9. As shown in the table, the *p*-values for *F*-statistics and chi-square are zero and rejecting the null hypothesis that both carbon risks are zero and suggesting that the two variables are significant to the model fit.

4.3 | Are Carbon Risks Priced?

Carbon pricing is a tool that depicts the costs of emissions, such as health-care costs associated with heat waves, and ties them to their sources via a price, usually in the form of a price on the carbon dioxide (CO_2) emitted. As a result, a carbon price sends an economic signal to emitters and contributes to the mobilization of investments needed to stimulate clean technology and market innovation in the pursuit of low-carbon economic growth.

Carbon pricing thus plays a crucial role for governments, companies, and investors in the transition to a low-carbon economy. For governments, it is an instrument in their climate policy package to reduce emissions. For companies, it is used to identify potential climate risks and opportunities in their operations. For investors, it helps assess the potential impact of climate change policies on their investment portfolios, enabling them to rethink investment schemes and reallocate capital to low-carbon or climate-resilient activities. It also helps mobilize the investment needed to stimulate clean technology and innovation, thereby encouraging new low-carbon economic drivers. Given that carbon dioxide pricing is essential to achieving society's overall environmental goals, it is natural to ask whether and to what extent the carbon risk is priced by the market.

Our results above have strong implications for carbon pricing, predictability, and market efficiency. It can be argued that if a market is fully efficient and any new information is quickly and correctly incorporated into financial markets, it would be impossible for any individual to persistently outperform the market. In this section, we combine statistical performance analysis with predictability capabilities to test for market efficiency based on random walk tests. If the market efficiency hypothesis holds, the outperformance of

TABLE 7 | Cointegration test—Johansen method: null H0: no cointegration.

Hypothesized		Trace	0.05		Hypothesized		Max-eigen	0.05
No. of CE(s)	Eigenvalue	Statistic	Critical value	Prob.	No. of CE(s)	Eigenvalue	Statistic	Critical value
None*	0.405	5969.99	125.62	1.00	None*	0.40	1494.10	46.23
At most 1*	0.287	4475.89	95.75	1.00	At most 1*	0.29	973.97	40.08
At most 2*	0.279	3501.92	69.82	1.00	At most 2*	0.28	943.39	33.88
At most 3*	0.248	2558.53	47.86	1.00	At most 3*	0.25	819.96	27.58
At most 4*	0.226	1738.57	29.80	1.00	At most 4*	0.23	736.79	21.13
At most 5*	0.190	1001.77	15.49	0.00	At most 5*	0.19	605.53	14.26
At most 6*	0.129	396.24	3.84	0.00	At most 6*	0.13	396.24	3.84

Note: The table shows the results of the Johansen test for cointegration using two test statistics: the trace test and the maximum eigenvalue test. Both tests confirm 7 cointegrating eqn(s) at the 0.05 level.
*Rejection of the hypothesis at the 0.05 level.

TABLE 8 | Long-run determinants of the risk premium for S&P 500 companies using S&P 500 companies, panel EGLS with random effects.

Variable	Coefficient	Std. error	*t*-statistic	Prob.
C (alpha)	0.683	0.029	23.405	0.000
B (beta)	0.918	0.006	146.532	0.000
HML	0.052	0.011	4.780	0.000
CMA	−0.011	0.016	−0.720	0.472
RMW	0.151	0.014	10.562	0.000
SMB	0.254	0.012	22.055	0.000
DMC	−0.340	0.001	−239.732	0.000
BMC	−0.098	0.040	−2.421	0.016
DUMMY1	−0.077	0.060	−1.281	0.200
DUMMY2	−0.145	0.074	−1.950	0.051
Effects specification	S.D.	Rho		
Cross-section random	0.000	0.000		
Idiosyncratic random	1.334808	1.000		
Adjusted *R*-squared	0.960640	Mean dependent var	1.123817	
S.E. of regression	1.330634	S.D. dependent var	6.707002	
F-statistic	8711.297	Sum squared resid	5671.192	
Prob(*F*-statistic)	0.000000	Durbin-Watson stat	2.167826	
Sum squared resid	5671.192			

Note: Sample period: January 2010 to September 2022. Two different measures for the market portfolio have been used, the S&P 500 index and the MSCI All Country World Index (ACWI), and the results are similar.

brown stocks can be explained by the excess risk that stocks face because of the higher cost of capital and bigger business risk. We use three tests to avoid a spurious result from relying on only one test, namely, unit root, serial correlation, and variance ratio tests.

In this section we examine whether the excess return Ri follows a random walk or is weak form efficient. Accordingly, the null hypothesis (H0) is that the excess return follows a random walk and is a weak-form efficient and alternative hypothesis (H1) is that the excess return does not follow the random walk.

4.3.1 | Unit Root Tests

Our first test of the random walk property is for the presence of a unit root in the excess return series. A random walk can be

TABLE 9 | Wald test for the restrictions that both carbon risks are equal to zero.

Null hypothesis: DMC = 0				Null hypothesis: BMC = 0			
Test statistic	**Value**	**df**	**Prob.**	**Test statistic**	**Value**	**df**	**Prob.**
t-statistic	−224.269	3206.0	0.000	*t*-statistic	−8.32	3206.0	0.000
F-statistic	0296.76	(1.320)	0.000	*F*-statistic	69.33	(1.32)	0.000
Chi-square	50296.7	1.000	0.000	Chi-square	69.33	1.000	0.000
Null H summary:				Null H summary:			
Normalized restriction (= 0)		Value	Std. err.	Normalized restriction (= 0)		Value	Std. err.
DMC		−0.341	0.002	BMC		−0.347	0.042
Restrictions are linear in coefficients.				Restrictions are linear in coefficients.			

expressed as an AR(1) where the value of excess return at time "t," r_t, is equal to the last period value plus a stochastic component assumed to be white noise that is, the error term is independent and identically distributed with mean "0" and variance σ^2. In addition, the variance in a random walk model changes over time and goes to infinity as time goes to infinity; therefore, a random walk cannot be predicted. The *p*-values of 0.00 implies that there is 0% chance that stationarity of a process cannot be rejected which implies 0% chance that non-stationarity is possible. So, there is a 100% chance that the process is stationary. This indicates that the excess return series do not follow random walks and are weak from inefficient.

4.3.2 | Serial Correlation Test

One of the commonly used tests of market efficiency is the test for serial correlation of returns. If the return for a specific stock in period t is correlated with its return in period $t-1$, then the unbiased minimum mean square error prediction for the return in period t should equal the prior return multiplied by the correlation coefficient (Rosenberg and Rudd 1982). As a result, an investor who is only concerned with the mean and variance of portfolio return would take a long position in stocks expected to have high returns and a short position in stocks expected to have low returns. This violates the weak form of market efficiency (Fama 1970). In other words, if the excess returns exhibit a random walk, it should be uncorrelated at all leads and lags. The Durbin-Watson statistic, which tests whether the residuals from linear regression are independent, is commonly used to test for serial correlation. The Durbin-Watson test assumes that the error in Equation (4) is generated by a first-order autoregressive process observed at equally spaced time periods. As shown in Table 8, the values of the Durbin-Watson statistic are above 2; therefore, we reject the null hypothesis of zero autocorrelation (stationary). The existence of zero autocorrelation forms the null hypothesis in an efficient market.

4.3.3 | Variance Ratio Test

Our final test of the random walk property is examined using the variance ratio test. Lo and MacKinlay (1989) used the variance ratio test to examine the predictability of returns data by comparing the variance in the differences of the returns calculated over diverse intervals. If the returns follow a random walk, the variance of a q-period difference should be q times the variance of the one-period difference. They argue that under a heteroscedastic random walk null, the variance ratio test is more reliable than either the Dickey-Fuller or Box-Pierce tests. We use two groups of tests, the "joint" variance ratio test applied to stocks in the S&P 500 and the "individual" variance ratio test applied to individual stock from 1 to 500 (not shown to save space). In all these tests, the null hypothesis is H0: The excess return series is a random walk. Its alternative hypothesis is H1: The excess return series does not follow a random walk. Table 10 presents the results of the "joint" variance ratio test applied to all firms in the S&P 500 index using the Fisher combined test statistics and the common procedure of selecting lags 2, 4, 8, and 16 for homoscedastic and heteroscedastic random walks with asymptotic normal distribution. As shown in

TABLE 10 | Variance ratio test.

Variable	Max |z| stocks	Prob.	df
Ri-RF	267.29	0.0000	42

Note: Sample period: 2010M01–2022M09. Null hypothesis: Ri-RF is a martingale. Heteroskedasticity robust standard error estimates. User-specified lags: 2, 4, 8, and 16.

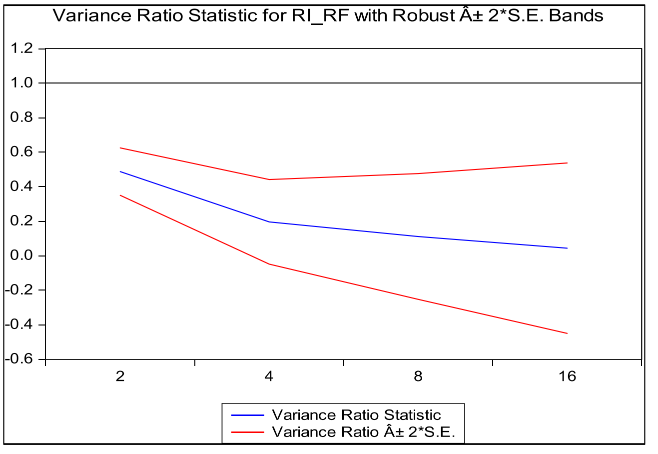

FIGURE 3 | Variance ratio test with Robust 2 S.E. band of excess return in the S&P 500 index.

the table, the Chow-Denning maximum |z| statistic of 267.29 is associated with a p-value of 0.000—obtained using the studentized maximum modulus with infinite degrees of freedom—which strongly rejects the null of a random walk. Figure 3 shows the variance ratio statistics for excess return plus or minus two asymptotic standard error bands, along with a horizontal reference line at 1 representing the null hypothesis. The figure shows that the null reference line lies outside the bands which again strongly rejects the null of a random walk.

The fact that the random walk model is rejected for the excess returns of the stocks in the S&P 500 index means that stock prices neither reflect all available information related to carbon risk nor accurately reflect its true value, which prove market inefficiency and the possibility of predictability and a market failure. As a result, the different classes of assets, clean, brown, and dirty may be over- or undervalued in the market, creating opportunities for predictability and excess profits. Our findings are in line with Rosenbloom et al. (2020) and suggest that carbon pricing may be insufficient to reduce emissions and should not be the primary policy strategy to do so. Instead, carbon pricing can be used as part of a policy mix that encourages innovation and considers the different dynamics that exist across sectors and over time.

5 | Conclusion

In recent years, the world has experienced high inflation, geopolitical instability, rising interest rates, and slowing economic growth, creating levels of uncertainty not seen since the late 1970s. Meanwhile, the global energy crisis is causing reflective and long-lasting changes that have the potential to accelerate the transition to a more sustainable and secure energy system (IEA's World Energy Outlook 2022). At the same time, Egypt's COP27 climate summit is taking place to translate the ambition of keeping the 1.5°C targets into action. In the wake of all this, many investors have begun to reassess their equity investments as they consider dealing with climate change to be one of the ultimate challenges of our time.

This paper aims to quantify the existing carbon risks and opportunities of financial assets and portfolios as a result of increasing carbon emission restrictions in the economy's transition to a green economy. The main findings of this paper are that the brown portfolio outperforms the clean portfolio in the S&P 500 index, which can be explained by market trends over the past few years with energy outperforming all sectors due to rising oil and gas prices. The results also show that the two carbon risks and the political risk have a negative and significant impact on the risk premium and that the excess return series do not follow random walks and are weak from inefficient.

Given these findings, the implications for investors, policymakers, and companies are profound. First, the evidence suggests that carbon risks are not fully reflected in current market prices, indicating potential inefficiencies in how markets are pricing these risks. This gap presents both a challenge and an opportunity for investors to identify undervalued assets that may benefit from the transition to a low-carbon economy. For policymakers, the findings highlight the importance of implementing and enforcing policies that accurately price carbon emissions, which could help drive capital towards more sustainable investments. Additionally, companies that proactively manage their carbon footprint and transition risks are likely to be more resilient in the face of increasing regulatory pressures and shifts in consumer preferences towards greener alternatives.

Moreover, the study underscores the necessity for enhanced disclosure and transparency around carbon risks. Improved reporting standards would allow investors to make more informed decisions regarding the carbon risk exposure of their portfolios, thus contributing to a more efficient allocation of resources in the market. Finally, as the global economy continues to grapple with the dual challenges of climate change and energy security, the findings of this paper serve as a reminder that the path to a sustainable future requires coordinated efforts across all sectors of society. By acknowledging and addressing the financial implications of carbon risks and opportunities, we can pave the way for further research and studies aimed at achieving a more resilient and sustainable economy.

Disclosure

All authors have seen and approved the final version of the manuscript being submitted.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from Thomson Reuters Eikon. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of Thomson Reuters Eikon .

Endnotes

[1] The mimicking stock portfolios are equal-weighted, ensuring all firms within an ESG category contribute equally to portfolio performance, regardless of market capitalization. Weights are approximately 0.633% for clean (158 firms), 0.352% for brown (284 firms), and 1.724% for dirty (58 firms) portfolios

[2] The study uses static portfolios to assess the long-term impact of initial ESG scores, avoiding rebalancing to prevent bias and reflect score stability. Future research could explore dynamic rebalancing to assess evolving ESG impacts.

[3] Our analysis relies on the most complete and reliable dataset available at the time, but we acknowledge that incorporating more recent data could refine or extend the conclusions. Future research should explore data beyond 2022 to assess the persistence or evolution of the observed trends and relationships.

[4] In the case with time variation random effect model, a time-specific error term is included as such:

$$R_{j,t} - R_{j,t} = \alpha_j + \beta_1 \left(R_{M,t} - R_F \right) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \omega_{i,t}$$

where $\omega_{i,t} = \varepsilon_t + \mu_{i,t}$.

[5] The energy (electricity, heat, and transport) accounts for 73.2% of emissions in 2020.

[6] In 2018, the fossil fuels fed about 80% of energy demand as solar and wind power sources accounted for less than 4% of all the energy used in the United States (DeSilver 2020).

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Appendix A

TABLE A1 | List of the clean, brown, and dirty companies in S&P 500 based on ESG scores and grades.

Clean companies			Brown companies						Dirty companies		
Company name	Score	Gr.	Company name	Score	Gr.	Company name	Score	Gr.	Company name	Score	Gr.
Microsoft Corp	92.59	A+	Henry Schein Inc	74.87	B+	DaVita Inc	64.06	B	Jack Henry & Associates Inc	49.90	C+
Baker Hughes Co	91.50	A	Newell Brands Inc	74.86	B+	FirstEnergy Corp	63.89	B	United Airlines Holdings Inc	49.84	C+
Colgate-Palmolive Co	90.25	A	Analog Devices Inc	74.84	B+	Assurant Inc	63.88	B	Fleetcor Technologies Inc	49.79	C+
PepsiCo Inc	89.86	A	Sempra Energy	74.80	B+	Willis Towers Watson PLC	63.75	B	CME Group Inc	49.70	C+
3 M Co	89.84	A	Wynn Resorts Ltd	74.78	B+	Equinix Inc	63.73	B	Signature Bank	49.69	C+
Healthpeak Properties Inc	88.94	A	Northern Trust Corp	74.76	B+	Capital One Financial Corp	63.68	B	Alaska Air Group Inc	49.45	C+
Walgreens Boots Alliance Inc	88.79	A	Alphabet Inc	74.54	B+	APA Corp (US)	63.63	B	ServiceNow Inc	49.43	C+
Agilent Technologies Inc	88.74	A	Alphabet Inc	74.54	B+	Synchrony Financial	63.62	B	Darden Restaurants Inc	49.41	C+
Humana Inc	88.47	A	Waters Corp	74.52	B+	Pinnacle West Capital Corp	63.55	B	Pool Corp	48.99	C+
Hershey Co	88.38	A	Westrock Co	74.50	B+	Cooper Companies Inc	63.44	B	Equifax Inc	48.34	C+
Target Corp	88.34	A	AT&T Inc	74.44	B+	Rockwell Automation Inc	63.44	B	AMETEK Inc	47.71	C+
Johnson & Johnson	88.31	A	ResMed Inc	74.19	B+	Arista Networks Inc	63.42	B	CH Robinson Worldwide Inc	47.42	C+
CVS Health Corp	87.85	A	Charles River Laboratories	74.12	B+	General Dynamics Corp	63.13	B	PENN Entertainment Inc	47.35	C+
Waste Management Inc	87.83	A	Packaging Corp of Ameri	74.11	B+	Garmin Ltd	63.06	B	Dexcom Inc	47.12	C+
Cisco Systems Inc	87.81	A	VF Corp	74.09	B+	Dupont De Nemours Inc	63.06	B	Citrix Systems Inc	46.83	C+
S&P Global Inc	87.43	A	Mondelez International I	74.06	B+	Ralph Lauren Corp	63.02	B	Live Nation Entertainment Inc	46.57	C+
Linde PLC	87.13	A	Alexandria Real Estate Eq	74.04	B+	Corteva Inc	62.98	B	SVB Financial Group	46.50	C+
Altria Group Inc	87.05	A	NRG Energy Inc	74.02	B+	Laboratory Corporation of Amer	62.92	B	Incyte Corp	46.32	C+
Baxter International Inc	87.05	A	Yum! Brands Inc	73.82	B+	Tyson Foods Inc	62.62	B	Charles Schwab Corp	46.32	C+
Newmont Corporation	86.89	A	Bank of America Corp	73.76	B+	ANSYS Inc	62.57	B	Martin Marietta Materials Inc	46.28	C+
Amazon.com Inc	86.86	A	UnitedHealth Group Inc	73.70	B+	IDEXX Laboratories Inc	62.52	B	Teradyne Inc	46.24	C+
Intel Corp	86.17	A	Ball Corp	73.17	B+	Morgan Stanley	62.28	B	Genuine Parts Co	46.05	C+
Edison International	86.13	A	Procter & Gamble Co	73.10	B+	Centene Corp	62.14	B	Twitter Inc	45.66	C+
Elevance Health Inc	86.06	A	BlackRock Inc	73.09	B+	Mettler-Toledo International Inc	62.11	B	Dollar General Corp	44.13	C+
Walmart Inc	86.00	A	American Electric Power	72.96	B+	Discover Financial Services	62.09	B	Match Group Inc	43.42	C+

(Continues)

TABLE A1 | (Continued)

Clean companies			Brown companies						Dirty companies		
Company name	**Score**	**Gr.**	**Company name**	**Score**	**Gr.**	**Company name**	**Score**	**Gr.**	**Company name**	**Score**	**Gr.**
Cadence Design Systems Inc	85.58	A	Micron Technology Inc	72.74	B+	Westinghouse Air Brake Technol	62.08	B	D R Horton Inc	43.27	C+
Realty Income Corp	85.48	A	Lam Research Corp	72.69	B+	Chipotle Mexican Grill Inc	62.07	B	TransDigm Group Inc	43.26	C+
Ventas Inc	85.03	A	Allstate Corp	72.67	B+	HCA Healthcare Inc	62.01	B	First Republic Bank	43.21	C+
Jacobs Solutions Inc	85.01	A	Costco Wholesale Corp	72.61	B+	Brown-Forman Corp	61.93	B	Paycom Software Inc	43.18	C+
Kinder Morgan Inc	84.91	A	TJX Companies Inc	72.53	B+	Ross Stores Inc	61.90	B	Zebra Technologies Corp	42.99	C+
CBRE Group Inc	84.82	A	Wells Fargo & Co	72.50	B+	Seagate Technology Holdings PL	61.79	B	Constellation Brands Inc	42.50	C+
Philip Morris International In	84.67	A	TE Connectivity Ltd	72.49	B+	Fidelity National Information Ser	61.78	B	Huntington Ingalls Industries I	42.41	C+
Motorola Solutions Inc	84.59	A	International Business M	72.46	B+	Fortinet Inc	61.61	B	Expedia Group Inc	42.36	C+
JPMorgan Chase & Co	84.55	A	ON Semiconductor Corp	72.43	B+	Carmax Inc	61.55	B	LKQ Corp	42.07	C+
Juniper Networks Inc	84.52	A	FedEx Corp	72.17	B+	Aon PLC	61.53	B	Snap-On Inc	41.67	C+
Lowe's Companies Inc	84.43	A	Bank of New York Mello	72.05	B+	WEC Energy Group Inc	61.44	B	Global Payments Inc	41.35	C
Best Buy Co Inc	84.42	A	Williams Companies Inc	72.02	B+	Vornado Realty Trust	61.35	B	Teledyne Technologies Inc	41.30	C
Xylem Inc	84.04	A	International Paper Co	71.96	B+	Celanese Corp	61.32	B	Quanta Services Inc	41.15	C
Chevron Corp	83.96	A	Comerica Inc	71.90	B+	SBA Communications Corp	61.31	B	O'Reilly Automotive Inc	40.69	C
Leidos Holdings Inc	83.96	A	Raymond James Financial	71.74	B+	Equity Residential	61.21	B	Duke Realty Corp	40.46	C
Gilead Sciences Inc	83.91	A	Deere & Co	71.66	B+	Invesco Ltd	61.00	B	Ingersoll Rand Inc	40.26	C
Halliburton Co	83.76	A	Masco Corp	71.61	B+	Molson Coors Beverage Co	60.81	B	Ameren Corp	39.76	C
Freeport-McMoRan Inc	83.41	A	Union Pacific Corp	71.54	B+	Sealed Air Corp	60.77	B	Monster Beverage Corp	39.42	C
Marriott International Inc	83.37	A	Federal Realty Investment	71.43	B+	Aptiv PLC	60.70	B	Fastenal Co	39.04	C
Archer-Daniels-Midland Co	83.17	A–	AES Corp	71.36	B+	Tapestry Inc	60.68	B	Copart Inc	38.04	C
Citigroup Inc	83.10	A–	SolarEdge Technologies I	71.27	B+	Chubb Ltd	60.48	B	DISH Network Corp	37.30	C
PVH Corp	82.92	A–	Lockheed Martin Corp	71.25	B+	Tyler Technologies Inc	60.46	B	Atmos Energy Corp	36.54	C
DTE Energy Co	82.73	A–	KeyCorp	71.21	B+	STERIS plc	60.27	B	Charter Communications Inc	35.73	C
Phillips 66	82.72	A–	Textron Inc	71.14	B+	Lincoln National Corp	60.20	B	Universal Health Services Inc	35.02	C
Regency Centers Corp	82.71	A–	Medtronic PLC	71.08	B+	Ulta Beauty Inc	60.12	B	Brown & Brown Inc	34.98	C
Stanley Black & Decker Inc	82.68	A–	Fortune Brands Home &	71.06	B+	Devon Energy Corp	60.11	B	Monolithic Power Systems Inc	34.89	C
United Rentals Inc	82.64	A–	Home Depot Inc	70.97	B+	CDW Corp	60.08	B	Loews Corp	34.34	C

(Continues)

TABLE A1 | (Continued)

Clean companies			Brown companies						Dirty companies		
Company name	Score	Gr.	Company name	Score	Gr.	Company name	Score	Gr.	Company name	Score	Gr.
Texas Instruments Inc	82.58	A−	Raytheon Technologies C	70.82	B+	Consolidated Edison Inc	60.03	B	Netflix Inc	32.98	C−
Goldman Sachs Group Inc	82.48	A−	Mid-America Apartment	70.81	B+	Fiserv Inc	59.79	B	Extra Space Storage Inc	32.88	C−
AbbVie Inc	82.33	A−	Dollar Tree Inc	70.76	B+	Akamai Technologies Inc	59.05	B	NVR Inc	32.57	C−
Abbott Laboratories	82.30	A−	Royal Caribbean Cruises	70.62	B+	MSCI Inc	59.00	B	CenterPoint Energy Inc	32.21	C−
Eastman Chemical Co	82.21	A−	McCormick & Company	70.59	B+	Parker-Hannifin Corp	58.67	B	Coterra Energy Inc	32.17	C−
Merck & Co Inc	82.06	A−	Eaton Corporation PLC	70.49	B+	VICI Properties Inc	58.61	B	Old Dominion Freight Line Inc	31.33	C−
Accenture PLC	81.94	A−	AutoZone Inc	70.43	B+	Dover Corp	58.60	B	Lennar Corp	31.01	C−
PayPal Holdings Inc	81.75	A−	JM Smucker Co	70.41	B+	Truist Financial Corp	58.58	B	Generac Holdings Inc	30.81	C−
Xcel Energy Inc	81.72	A−	Vertex Pharmaceuticals I	70.32	B+	Microchip Technology Inc	58.46	B	Berkshire Hathaway Inc	28.57	C−
American Water Works Com	81.62	A−	Evergy Inc	70.31	B+	Domino's Pizza Inc	58.45	B	ABIOMED Inc	25.35	C−
Trane Technologies PLC	81.61	A−	Avery Dennison Corp	70.28	B+	Electronic Arts Inc	58.32	B−	Rollins Inc	13.80	D
Honeywell International Inc	81.58	A−	United Parcel Service Inc	70.06	B+	W R Berkley Corp	58.26	B−			
Host Hotels & Resorts Inc	81.56	A−	J B Hunt Transport Services	70.01	B+	Moderna Inc	58.21	B−			
Air Products and Chemicals I	81.51	A−	Occidental Petroleum Co	70.01	B+	Intercontinental Exchange Inc	58.20	B−			
Ameriprise Financial Inc	81.51	A−	Southern Co	69.95	B+	Nordson Corp	58.15	B−			
Danaher Corp	81.49	A−	Viatris Inc	69.84	B+	CSX Corp	58.06	B−			
DXC Technology Co	81.41	A−	Norwegian Cruise Line H	69.67	B+	Roper Technologies Inc	58.03	B−			
Kimco Realty Corp	81.34	A−	Cardinal Health Inc	69.66	B+	Ceridian HCM Holding Inc	57.90	B−			
Bristol-Myers Squibb Co	81.24	A−	Delta Air Lines Inc	69.65	B+	Nucor Corp	57.71	B−			
Stryker Corp	81.23	A−	American Airlines Group	69.54	B+	Booking Holdings Inc	57.69	B−			
Northrop Grumman Corp	81.20	A−	Church & Dwight Co Inc	69.53	B+	Bio-Techne Corp	57.56	B−			
Quest Diagnostics Inc	81.17	A−	Comcast Corp	69.51	B+	Intuitive Surgical Inc	57.50	B−			
Dow Inc	81.15	A−	eBay Inc	69.50	B+	Diamondback Energy Inc	57.33	B−			
West Pharmaceutical Service	81.13	A−	Thermo Fisher Scientific	69.40	B+	IQVIA Holdings Inc	57.08	B−			
Hilton Worldwide Holdings In	80.88	A−	ONEOK Inc	69.36	B+	Paychex Inc	56.92	B−			

Note: Sample period: 2010-01-01 to 2022-09-15.