Is Greenium a Reflection of Inflation Risk?*

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Abstract

We present a novel fact that green stocks carry higher inflation risk than brown stocks, performing poorly during unexpected inflation. Given this observation, can the outperformance of green stocks over brown stocks (the "greenium") be explained as compensation for inflation risk? We find that the magnitude of the greenium decreases by 31% and 54% for Scope 1 and Scope 2, respectively, becoming statistically insignificant after controlling for individual stocks' core inflation risk exposure. These findings are robust to excluding brown industries and are not driven by the post-COVID inflationary period, suggesting that the greenium partially reflects inflation risk compensation.

JEL Classification: *G11, G12, Q54, E31*

Keywords*: Greenium, Inflation risk, Asset pricing, Climate finance*

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1 Introduction

The rapid growth of sustainable investing in recent years has sparked significant academic and practitioner interest in understanding the risk and return characteristics of environmentally friendly ("green") versus environmentally unfriendly ("brown") stocks. A key empirical finding in this literature is that green stocks have outperformed brown stocks on average, based on their realized returns—a phenomenon dubbed the "greenium" (e.g., Pástor et al., 2022; Zhang, 2023). However, the underlying drivers of the greenium are still a matter of debate. Identifying what risks, if any, green stocks are more exposed to compared to brown stocks is crucial for interpreting the greenium. A risk-based explanation for the greenium would have important implications for asset pricing models, corporate environmental policies, and investor demands during the transition to a low-carbon economy.

While the outperformance of green stocks is often interpreted as an ongoing transition to the carbon-aware equilibrium (e.g., Zhang, 2023), is there an alternative risk-based explanation for the greenium? In this paper, we present a novel fact that green stocks exhibit significantly higher inflation risk compared to brown stocks. In other words, green stock prices react negatively to unexpected inflation. Considering this difference in inflation risk exposure between green and brown stocks and the evidence that inflation risk is priced in the cross-section of asset returns (e.g., Fang et al., 2022), we demonstrate that the greenium can be in part interpreted as compensation for bearing higher inflation risk.

We start our analysis by examining the inflation exposure of carbon-sorted portfolios using U.S. public stocks from June 2009 to December 2021. We estimate inflation betas for each of the carbon-sorted tercile portfolios by running a rolling regression of portfolio excess returns on inflation shock with the Dimson (1979) correction to account for the one-month CPI release lag. We find that the portfolio with the highest carbon intensity ("brown portfolio") exhibits a statistically significantly higher inflation beta than the portfolio with the lowest carbon intensity ("green portfolio"). This implies that the brown portfolio relatively outperforms at times of unexpected inflation.

We further analyze the relationship between carbon intensity and inflation exposure at the Fama-French 49 industry level. We find that brown industries such as mining, steel, coal, metals, petroleum, and natural gas exhibit the highest core inflation betas among the industries. Furthermore, carbon intensity is significantly and positively associated with inflation beta: a one-standard-deviation increase in core inflation beta is associated with a 0.89 (0.37) unit increase in Scope 1 (Scope 2) carbon intensity that accounts for 46% (41%) of the standard deviation of carbon intensity with a t-value of 4.23 (3.01). Our firm-level analysis further corroborates a positive relationship between inflation beta and carbon intensity for both Scopes 1 and 2. These findings provide clear evidence that green stocks are more vulnerable to inflation risk compared to brown stocks, as they tend to underperform during periods of unexpected inflation.

The strong positive relationship between carbon intensity and inflation beta suggests that inflation risk could potentially explain the outperformance of green stocks. However, an important question remains: is inflation risk priced in the cross-section of stocks, and do investors demand compensation for holding stocks that carry high inflation risk during our sample period? To address this question, we construct a long-short portfolio that longs stocks in the highest inflation-beta tercile and shorts those in the lowest inflation-beta tercile. We find that the long-short portfolio sorted by core inflation beta earns a significant risk-adjusted return of -0.34% per month (-4.08% per annum) with a t-value of -2.75 during our sample period. This evidence suggests that investors require compensation for holding stocks with low inflation betas (high inflation risk), as these stocks perform poorly when investors' marginal utility is high due to unexpected inflation shocks. While we document a significant negative core-inflation risk premium, risk-adjusted returns based on headline inflation shock or energy inflation shock are virtually zero, albeit negative, consistent with the recent studies that emphasize the importance of core inflation for the cross-section of assets (e.g., Fang et al., 2022; Hong et al., 2022).

Having established a strong positive link between carbon intensity and inflation beta, as well as a significant negative inflation risk premium, we examine whether the greenium can be interpreted as a reflection of inflation risk compensation. To begin with, we reproduce significant negative risk-adjusted returns of the brown-minus-green portfolio (greenium) that longs the portfolio with the highest carbon intensity and shorts that with the lowest carbon intensity among the terciles: -0.39% (t-value = -2.53) and -0.26% (t-value = -2.11) risk-adjusted returns per month for Scopes 1 and 2, respectively. We then re-examine the greenium after controlling for the inflation risk exposure of carbon intensity-sorted portfolios. To this end, we double-sort stocks to construct the brown-minus-green portfolio where the brown and green portfolios have similar levels of core inflation beta. We find that risk-adjusted returns of the core-inflation-beta-controlled brown-minus-green portfolio are -0.27% (t-value = -1.65) and -0.12% (t-value = -0.95) for Scopes 1 and 2, respectively. These magnitudes represent a substantial decrease in the greenium by 31% and 54% for Scopes 1 and 2, respectively, and they are statistically indistinguishable from zero at conventional levels. This suggests that the greenium can be partially explained as a reflection of inflation risk compensation.

To examine the robustness of our findings, we conduct additional tests. Recognizing that industries with the highest carbon intensity tend to have stocks with high inflation betas, we first investigate the extent to which our results are driven by these high carbon intensity industries. After excluding mining, steel, coal, metals, petroleum, and natural gas industries, we find that the greenium is -0.20% and -0.14% for Scopes 1 and 2, respectively. When controlling for core inflation beta, these magnitudes substantially decrease to a negligible -0.13% and -0.03%, suggesting that our results are not driven by brown industries. Furthermore, our sample includes the year 2021, which experienced an inflation rate of 4.7%, the highest since 1990. To address the concern that our results might be strongly influenced by this recent inflation surge, we repeat our tests excluding the year 2021. We find that our results remain consistent, with nearly identical magnitudes as before. Overall, our findings highlight the significance of core inflation risk for the cross-section of equity returns and the greenium. Our evidence suggests that the greenium is in part a reflection of core inflation risk compensation.

This paper first contributes to the literature on the link between corporate environmental performance and risk profiles. Guided by the model of Pástor et al. (2021), Pástor et al. (2022) distinguish between green and brown firms based on environmental ratings and demonstrate that brown firms are more exposed to “climate risk." Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) reach the same conclusion while defining brown firms as those with higher carbon emissions and referring to this climate risk as “carbon transition risk." Focusing on industrial pollution, Hsu et al. (2023) provide evidence that firms with higher toxic releases face greater “regulation regime change risk." Despite differences in the measures of environmental performance, the shared intuition of this paper with the literature is that, as major sources of pollution, brown firms tend to experience a more negative impact on their profits from environmental regulations aimed at reducing emissions. Ilhan et al. (2021) examine the options market and suggest that a firm's carbon intensity increases its downside tail risk, which is reflected in options prices. In contrast to prior studies, Hoepner et al. (2024) adopt a dynamic perspective and investigate ESG shareholder engagements. According to them, improving a firm's ESG performance, especially its environmental performance, can help reduce the firm's downside risk. This paper complements prior work by documenting a new systematic risk factor, inflation risk, which differs significantly between green and brown stocks.

This paper also adds to the literature on the asset-pricing implications of corporate environmental performance. Some studies argue that brown stocks earn higher expected returns because investors demand compensation for the higher policy risk associated with these stocks (e.g., Bolton and Kacperczyk, 2021, 2023; Hsu et al., 2023; Lioui and Misra, 2023). Atilgan et al. (2023) further show that brown stocks have higher earnings surprises, suggesting that both risk and mispricing explain the carbon premium. Aswani et al. (2024) instead attribute the carbon premium documented by Bolton and Kacperczyk (2021) to noise in supplier-estimated emissions and in the choice of carbon risk measures. Zhang (2023) highlights the importance of considering the delay in investors' access to emission data. She observes the outperformance of green stocks in the U.S. stock market, implying that the estimated carbon premium is subject to a look-ahead bias. Separately, Duan et al. (2021) find evidence of underperformance of bonds issued by carbon-intensive firms. Pástor et al. (2021) and Pástor et al. (2022) reconcile the seemingly contradictory findings by claiming that the higher expected returns of brown stocks can coincide with the higher realized returns of green stocks. We extend the existing literature on the greenium by exploring an alternative risk-based explanation for it.

Our paper therefore complements the literature on the underlying drivers of the greenium. A large body of literature attributes the higher realized returns on green assets to the positive ESG demand shocks following unexpected increases in climate change concerns (e.g., Pástor et al., 2021, 2022; Ardia et al., 2023; Zhang, 2023). Avramov et al. (2024) provide a structural decomposition of green asset returns. They note that the observed greenium represents not only higher unexpected returns from positive ESG demand shocks, but also higher expected returns from the positive exposure of green assets to such shocks. Goldstein et al. (2022) turn to an information channel and explain the outperformance of green stocks through the higher aggregate information risk associated with a more diversified investor base. Chen et al. (2023) instead link responsible consumption to sustainable investment. By demonstrating that greenium exists only for firms with higher demand elasticity, they propose that higher returns on green assets can be seen as compensation for the higher consumption risk faced by green products. We emphasize the importance of considering differences in macroeconomic risk exposures for understanding the greenium and show that the outperformance of green stocks can be interpreted as compensation for inflation risk.

Our paper relates to two contemporaneous studies by Bolton et al. (2024) and Shi and Zhang (2024), who examine the impact of energy price inflation or oil price levels on the spread between green and brown assets. In contrast, our paper focuses on the differences in core inflation betas between green and brown stocks, which are priced in the cross-section of stock returns and can significantly explain the greenium.

Our paper also contributes to the growing literature that examines the implications of inflation risk on cross-sectional asset returns.[1] We advance this literature in the following ways. First, we provide evidence that the core inflation risk premium is significantly priced in U.S. equity markets over the recent decade. In doing so, we confirm the findings of Fang et al. (2022) by showing that it is core inflation that is priced in the equity market. Second, importantly, our study uncovers a novel finding: while the core inflation risk premium helps explain the greenium to some extent, we show that the greenium cannot account for the observed core inflation risk premium. These findings enhance our understanding of the interplay between inflation risk, environmental factors, and asset pricing, offering new insights into the literature.

2 Data

2.1 CRSP

We obtain the stock returns data from the Center for Research in Security Prices (CRSP). Our sample includes all U.S. common stocks (CRSP share codes 10 or 11) listed on the NYSE, AMEX, and NASDAQ. To be included in our analysis, a stock must have a month-end price greater than $1. We follow the procedure of Shumway (1997) and Shumway and Warther (1999) to adjust stock returns for delisting. We collect the five equity factors of Fama and French (2015): Market factor, SMB, HML, RMW, and CMA, as well as the 30-day T-bill rate from the Kenneth French website.

[1]See Kang and Pflueger (2015); Boons et al. (2020); Fang et al. (2022); Hong et al. (2022); An et al. (2023); Bhamra et al. (2023); Knox and Timmer (2023), among others.

2.2 Trucost

S&P Trucost provides annual information on firm-level environmental performance through a series of greenhouse gas (GHG) emissions-related measures. According to the GHG protocol, emissions from daily business operations can be categorized into three scopes.

Scope 1 GHG emissions are direct emissions from sources owned or controlled by a firm. Scope 2 GHG emissions refer to indirect emissions stemming from the consumption of purchased energy by a firm. Finally, Scope 3 GHG emissions entail all other indirect emissions that are created by a firm's interactions with its suppliers and customers over the entire value chain. The flexibility of the definition of Scope 3 GHG emissions undermines the precision of measurement. Therefore, we focus on Scope 1 and 2 emissions.

We follow Zhang (2023) and use the natural logarithm of a firm's carbon intensity to capture its environmental performance. In contrast to unscaled carbon emissions that are inherently correlated with firm size, carbon intensity excludes sales information and hence better captures a firm's carbon efficiency (Zhang, 2023; Aswani et al., 2024).

S&P Trucost defines carbon intensity as the ratio of a firm's GHG emissions in tons of carbon dioxide equivalent (tCO2e) to its annual consolidated revenues in millions of U.S. dollars. We fill in missing values of carbon intensities with the last available observation for each firm.

2.3 Inflation

We collect monthly headline (CPIAUCSL), core (CPILFESL), and energy (CPIENGSL) Consumer Price Index (CPI) for All Urban Consumers by the U.S. Bureau of Labor Statistics, available from the Federal Reserve Economic Data (FRED).

2.4 Sample

S&P Trucost collects corporate carbon emissions data from various sources, including data shared directly by companies, as well as publicly disclosed information from company financial reports and websites. It also reviews data that companies disclose to third-party datasets such as the Carbon Disclosure Project (CDP). Although Trucost updates its database with new company-year observations once the relevant data is accessible, companies require time to disclose the underlying data after completing their fiscal years. Thus, ignoring the lag in the release of carbon data when examining carbon returns may result in a forward-looking bias (Zhang, 2023). Assuming that carbon data is available within 6 months after each fiscal year-end, we use a 6-month lag from the fiscal year-end when matching Trucost data to CRSP data.

We restrict our analysis to post-2008 carbon data because of the backfiling issue with pre-2008 Trucost data (Zhang, 2023). Given the 6-month lag between Trucost data and CRSP data, the final sample covers the period between June 2009 and December 2021.

3 Methodologies

3.1 Measuring Inflation Shock

For headline, core, and energy CPI, we calculate the inflation (CPI growth) as the log change of the CPI index: $\pi_t = \log(CPI_t) - \log(CPI_{t-1})$. To compute the unexpected component of inflation, we run the ARMA(1,1) for each type of CPI series, as in Fama and Gibbons (1984), Ang et al. (2007), Boons et al. (2020), and Hong et al. (2022). Moreover, to account for the information set that is potentially available to investors, we add the seven principal components of a large set of 127 economic and financial variables as in the literature (e.g., Ludvigson and Ng, 2007, 2009; Jurado et al., 2015; McCracken and Ng, 2016; Elkamhi and Jo, 2023).[2]:

$$\pi_t = \mu + \phi\pi_{t-1} + \gamma' PC_{t-1} + \psi\epsilon_{t-1} + \epsilon_t, \tag{1}$$

where PC_{t-1} is the set of the seven principal components. ϵ_t is the inflation shock at month t.

Table 1 presents summary statistics for our main variables from June 2009 to December 2021.

3.2 Estimation of Inflation Beta

To estimate the inflation beta for each stock, we run a rolling regression for each stock i using a rolling window of 36 months. We require a stock to have at least 24 months available to estimate the inflation beta:

$$\begin{aligned} R_{i,t} - r_t^f = {} & \alpha + \beta_1 \hat{\epsilon}_t^{\pi} + \beta_2 \hat{\epsilon}_{t-1}^{\pi} + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t \\ & + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + u_t, \end{aligned} \tag{2}$$

where $R_{i,t} - r_t^f$ is the excess return of stock i in month t, $\hat{\epsilon}_t^{\pi}$ is the inflation innovation in month t estimated from Equation (1), and the remaining control variables are the five equity factors of Fama and French (2015). The regression includes the lagged inflation innovation (i.e., ϵ_{t-1}^{π}) to account for the one-month CPI release lag.[3] Then, following Dimson (1979), inflation beta β_i^{π} is defined as

$$\beta_i^{\pi} = \beta_1 + \beta_2 \tag{3}$$

[2]These variables are obtained from McCracken's website:
https://research.stlouisfed.org/econ/mccracken/fred-databases/

[3]For example, October (November) 2023 CPI level was released on November 14 (December 12), 2023.

4 Empirical Results

4.1 Carbon Intensity and Inflation Risk

Greenium could in part reflect inflation risk premium if the following two conditions are met. First, green stocks should exhibit higher inflation risk compared to brown stocks. In other words, green stocks should underperform relative to brown stocks during unexpected inflation (low inflation beta). Second, inflation risk should be priced in the cross-section of stock returns, with investors demanding compensation for holding stocks with high inflation risk exposure (negative inflation risk premium).

In this subsection, we focus on the first condition by analyzing the relationship between carbon intensity and inflation risk exposure (stock's sensitivity to inflation shocks). We examine this relationship based on carbon-sorted portfolio-level, industry-level, and firm-level analyses.

To this end, following Zhang (2023), at the end of each month, we first sort stocks into tercile portfolios by their carbon intensity, measured by either Scope 1 or Scope 2 emissions. We then compute their value-weighted monthly returns for the next month. Next, we estimate core inflation beta for each tercile portfolio by running a rolling-window regression of portfolio excess returns on inflation shock as in Equation (2) with the Dimson (1979) correction to account for the one-month CPI release lag, controlling for the five equity factors of Fama and French (2015).

Figure 1 plots monthly risk-adjusted returns (α) in %, relative to the five equity factors of Fama and French (2015), of value-weighted tercile portfolios sorted by carbon intensity (y-axis) along with 95% confidence intervals and these portfolios' average exposure to core inflation risk, measured by core inflation beta (x-axis).

Two key findings emerge from this figure. First, for both Scope 1 and Scope 2 carbon intensity measures, the green (low carbon intensity) portfolio (denoted by "G") generates significantly positive alphas, as indicated by the 95% confidence intervals that are above zero. Furthermore, the figure plots the monthly alpha of a long-short portfolio that buys the brown tercile and shorts the green tercile (denoted by "B-G"). This brown-minus-green portfolio earns a positive alpha that is statistically distinguishable from zero, representing the "greenium" or outperformance of green stocks relative to brown stocks after controlling for factor exposures.

Second, importantly, the brown portfolio (denoted by "B", high carbon intensity stocks) exhibits a higher core inflation beta compared to the green portfolio (denoted by "G"). This finding suggests a positive relationship between carbon intensity and exposure to core inflation shocks. Are these differences in core inflation beta statistically significant?

Figure 2 presents the average core inflation beta along with 95% confidence intervals for each of the carbon intensity-sorted portfolios. For both Scope 1 and Scope 2 carbon emissions, the green portfolio's core inflation beta is significantly negative, while the brown portfolio's core inflation beta is significantly positive, as indicated by their respective confidence intervals. Consequently, the core inflation beta of a long-short portfolio that buys the brown portfolio and sells the green portfolio (denoted by "B-G") is significantly positive. Given that a higher inflation beta implies that a stock performs better at times of unexpected inflation, these results suggest that brown stocks generally provide an inflation hedge, whereas green stocks perform poorly during those times.

To generate more cross-sectional variation, we further analyze the relationship between carbon intensity and inflation exposure at the Fama-French 49 industry level. Figure 3 plots each industry's carbon intensity (y-axis) against its core inflation beta (x-axis) for each of 49 Fama-French industries. The figure shows that carbon-intensive ("brown") industries, such as mining, steel, coal, metals, petroleum, and natural gas, tend to have the highest core inflation betas among the industries.

Moreover, the analysis shows a statistically significant positive association between an industry's carbon intensity and its inflation beta. Specifically, a one standard deviation increase in an industry's core inflation beta is associated with a 0.89 unit increase in the industry's Scope 1 carbon intensity and a 0.37 unit increase in its Scope 2 carbon intensity. These increases in carbon intensity account for a substantial 46% and 41% of the cross-industry standard deviation of Scope 1 and Scope 2 carbon intensity, respectively. The corresponding t-statistics of 4.23 for Scope 1 and 3.01 for Scope 2 highlight the statistical significance of these relationships. These industry-level findings corroborate and strengthen the evidence of a positive relationship between a firm's carbon intensity and its exposure to inflation risk that we documented in the portfolio-level analysis.

As a final piece of evidence, Table 2 reports the pairwise correlation coefficients between firm-level measures of core inflation beta, headline inflation beta, energy inflation beta, Scope 1 carbon intensity, and Scope 2 carbon intensity. The result shows that all types of inflation betas are positively and significantly associated with either Scope 1 or 2 intensity, except for a marginally significant positive relationship between energy inflation beta and Scope 2 intensity.

Collectively, the carbon-sorted portfolio-level, industry-level, and firm-level analyses presented so far point toward a coherent picture: firms with higher carbon intensity tend to have higher inflation betas. In other words, green stocks carry a higher inflation risk than brown stocks. This finding sets the stage for our subsequent analysis, where we examine whether this differential inflation risk exposure can help explain the well-documented "greenium" - the outperformance of green firms relative to their brown counterparts.

4.2 The Pricing Performance of Inflation Risk

In this subsection, we investigate whether inflation risk is a priced risk factor in the stock market and if investors require a risk premium for holding stocks with high inflation risk (that coincides with low inflation beta) during our sample period. To address this question, we sort stocks into tercile portfolios at the end of each month based on their core inflation betas, which are estimated using a rolling window of 36 months. Subsequently, we calculate the value-weighted monthly returns for each tercile portfolio for the following month.

Table 3 reports the monthly raw returns, risk-adjusted returns (α in %), and exposure to the five equity factors of Fama and French (2015) for value-weighted tercile portfolios sorted by core inflation beta. The 'High' portfolio, which contains stocks with the highest inflation betas, generates a risk-adjusted return of –0.25% per month with a *t*-value of -3.17. In contrast, the 'Low' portfolio, consisting of stocks with the lowest inflation betas, earns a risk-adjusted return of 0.09% per month with a *t*-value of 1.24. Importantly, a long-short portfolio that longs the 'High' tercile and shorts the 'Low' tercile earns a significant risk-adjusted return of -0.34% per month (4.08% per annum) with a *t*-value of -2.75 over our sample period. These findings indicate that investors demand compensation for holding stocks with low inflation betas (i.e., high inflation risk exposure), as these stocks tend to underperform when investors' marginal utility is high due to unexpected inflation shocks.

Recent studies in the asset pricing literature that examines the impact of inflation on financial markets emphasize the significance of core inflation relative to headline inflation (e.g., Fang et al., 2022; Hong et al., 2022). Motivated by these findings, we extend our analysis by examining the pricing of headline inflation risk and energy inflation risk in the cross-section of stock returns.

Figure 4 plots monthly risk-adjusted returns (α in %) of value-weighted tercile portfolios sorted by inflation betas, along with their corresponding 95% confidence intervals. The left, middle, and right panels display the results for portfolios sorted by core, headline, and energy inflation betas, respectively. The left panel figure shows a significant negative risk premium for core inflation risk, as evidenced by the negative and statistically significant alpha of the high-minus-low portfolio ('H-L') based on terciles sorted by core inflation betas. In contrast, the alphas of the high-minus-low portfolios for portfolios sorted by headline or energy inflation betas are close to zero, although still negative. These findings align with recent studies that highlight the relative importance of core inflation compared to headline inflation in explaining the cross-sectional variation in asset returns (e.g., Fang et al., 2022; Hong et al., 2022). Our results suggest that investors primarily demand compensation for exposure to core inflation risk rather than headline or energy inflation risk.

Our empirical analyses thus far have uncovered two key findings: (1) green stocks exhibit higher inflation risk (i.e., lower inflation beta) compared to brown stocks, and (2) investors demand compensation for holding stocks with high inflation risk. Taken together, these results suggest that the greenium, or the outperformance of green stocks relative to brown stocks, may be partially explained by the inflation risk premium. In other words, the higher returns of green stocks could be a reflection of the compensation investors require for bearing the higher inflation risk associated with these stocks. In the following subsection, we rigorously investigate this possibility and assess the extent to which the greenium can be attributed to differences in inflation risk exposure between green and brown stocks.

4.3 Re-examining of Greenium

In this subsection, we examine the extent to which the greenium can be explained by differences in inflation risk exposure between green and brown stocks. To test this, we first aim to reproduce the well-documented greenium by constructing a brown-minus-green portfolio (BMG) that longs the tercile portfolio with the highest carbon intensity and shorts the tercile portfolio with the lowest carbon intensity.

Table 4 presents the risk-adjusted returns (alphas) of portfolios sorted by carbon intensity for both Scope 1 and Scope 2 measures. The results confirm the presence of the greenium in our sample, with the brown-minus-green (BMG) portfolios exhibiting significant negative alphas of -0.39% (t-value = -2.53) and -0.26% (t-value = -2.11) per month for Scope 1 and Scope 2, respectively. These magnitudes of alphas are comparable to those reported by Zhang (2023), who finds alphas of -0.40% (t-value = -2.51) and -0.34% (t-value = -2.40) per month for Scope 1 and Scope 2 BMG portfolios, respectively. The similarity of our findings to those of Zhang (2023) reassures the validity of our empirical approach.

Next, we examine whether the greenium survives after controlling for the difference in inflation risk exposure between green and brown stocks. To this end, we use a double-sorting methodology. First, we sort stocks into terciles based on their core inflation betas. Then, within each tercile sorted by core inflation betas, we further sort stocks into terciles based on their carbon intensity. This procedure allows us to create brown-minus-green

(BMG) portfolios in which the brown and green portfolios have similar levels of core inflation betas.

The first two columns of Table 5 present the risk-adjusted returns of the inflation-risk-controlled BMG portfolios for both Scope 1 and Scope 2 carbon intensity measures. The last two columns present the results for single-sorted portfolios presented in Table 4 for comparison. Notably, after controlling for core inflation risk exposure, the alphas of the BMG portfolios decrease considerably in both magnitude and statistical significance. The inflation-risk-controlled BMG portfolios earn alphas of -0.27% (t-value = -1.65) and -0.12% (t-value = -0.95) per month for Scope 1 and Scope 2, respectively. These values represent a substantial 31% and 54% reduction in the greenium compared to the single-sorted results in Table 4. Furthermore, the alphas of the inflation-risk-controlled BMG portfolios are not statistically different from zero at conventional significance levels.

The findings in this subsection provide evidence that the greenium can be in part attributed to the compensation investors require for holding a green stock with a higher inflation risk. By controlling for the inflation risk exposure of green and brown stocks, we show that a significant portion of the greenium disappears. This suggests that the outperformance of green stocks relative to brown stocks is, to a considerable extent, a reflection of the inflation risk premium, rather than being entirely driven by investors' demand for green stocks amid an ongoing transition to the carbon-aware equilibrium. Our findings highlight the importance of inflation risk when examining the greenium.

4.4 Robustness of our Key Findings

In this subsection, we test the robustness of our key findings.

4.4.1 Are Results Driven by a Few Industries?

In the analyses presented thus far, we have provided evidence suggesting that the greenium – the superior performance of green stocks compared to brown stocks – can be partly attributed to the differential exposure of these stocks to core inflation risk. However, a potential issue is that our findings could be mainly driven by a small number of carbon-intensive industries that exhibit the highest levels of inflation betas.

To address this concern and examine the robustness of our findings, we repeat our tests by excluding the following industries from our sample among 49 Fama-French industry classifications: Mines (Non-Metallic and Industrial Metal Mining), Steel (Steel Works Etc), Coal (Coal), Gold (Precious Metals), and Oil (Petroleum and Natural Gas). These industries exhibit the highest inflation betas among all industries, as shown in Figure 3. We perform our analyses by first excluding only the 'Mines' industry (the highest inflation beta industry) and then progressively excluding additional industries to more broadly define the group of high-inflation industries. Furthermore, to assess the incremental change in the magnitude of the greenium after controlling for core inflation beta, in addition to excluding industries, we repeat both single-sorting and double-sorting exercises. This approach allows us to evaluate the sensitivity of our findings to the exclusion of specific industries and to gauge the extent to which the greenium can be explained by differences in core inflation risk exposure, even after accounting for the potential influence of high-inflation-beta and carbon-intensive industries.

Table 6 presents the greenium magnitudes both without (denoted as 'Single') and with (denoted as 'Double') controlling for core inflation beta. For comparison, the first two columns show the results with all industries included, as previously reported in Table 5. Interestingly, the ability of core inflation beta to explain the greenium remains largely unaffected even after excluding a handful of industries. For example, when the 'Mines', 'Steel', 'Coal', and 'Gold' industries are excluded, the greenium magnitudes stand at -0.35% and -0.21% for Scopes 1 and 2, respectively, without controlling for inflation beta. After controlling for inflation beta, these magnitudes decrease to -0.26% and -0.11%, representing a reduction of 26% and 48% in the greenium. Strikingly, when the 'Oil' industry is further excluded, the greenium magnitudes without controlling for inflation beta drop to -0.20% and -0.14% for Scope 1 and 2, respectively. This result suggests that the greenium magnitude is sensitive to the oil industry. More importantly, once core inflation beta is controlled for, these magnitudes shrink to -0.13% and 0.03% for Scopes 1 and 2, respectively, translating to a notable 35% and 79% reduction in the greenium.

The results of this robustness check provide evidence that our main findings are not solely driven by the most inflation-hedging and carbon-intensive industries in our sample. Even after excluding these industries, we still observe a notable decrease in the greenium magnitude once we account for the differential inflation risk exposure of green and brown stocks. Intriguingly, the explanatory power of core inflation beta for the greenium becomes even more pronounced after removing these industries, rather than diminishing. This finding further supports our conclusion that the greenium can be partially attributed to the compensation investors require for bearing the higher inflation risk associated with green stocks.

4.4.2 Exclusion of a High Inflation Environment

This raises the question: do our findings on the inflation risk premium and its role in explaining the greenium depend on this unusual macroeconomic environment? In other words, if we exclude the year 2021 from our analysis, would we still find evidence of inflation risk being priced in the stock market, and would controlling for inflation beta exposure continue to substantially reduce the magnitude of the greenium? To investigate this, we rerun our analyses while leaving out the year 2021. Specifically, we re-estimate the inflation risk premium, the greenium based on single-sorted carbon intensity portfolios without accounting for inflation beta, and the greenium based on double-sorted portfolios that control for inflation beta exposure. This allows us to assess the robustness of our conclusions to the exclusion of the high inflation period of 2021.

We begin by re-estimating the inflation risk premium. Panel A of Table 7 presents the re-estimated inflation risk premium based on the risk-adjusted return of a long-short portfolio that buys the tercile of stocks with the highest core inflation betas and sells the tercile with the lowest betas, excluding the year 2021. We find that the high-minus-low portfolio earns a monthly risk-adjusted return of -0.35% without 2021, which is nearly identical to the -0.34% return obtained using the full sample period. This result indicates that the compensation investors demand for holding stocks with high inflation risk exposure is not primarily driven by the high inflation environment of 2021, but rather persists even in the period preceding this inflationary episode.

We then re-estimate the magnitude of the greenium without accounting for inflation beta exposure by examining the risk-adjusted returns (alphas) of the brown-minus-green

(BMG) portfolios constructed using the sample that excludes 2021. As shown in Panel A, the greenium magnitude is -0.37% for Scope 1 and -0.25% for Scope 2 carbon intensity measures, which closely resemble the alphas obtained using the full sample period (-0.39% and -0.26% for Scopes 1 and 2, respectively). To assess the impact of controlling for inflation risk exposure, we employ the double-sorting approach described in our main analysis to control for the core inflation beta of the BMG portfolios. Even when excluding the year 2021, we find that accounting for the differential inflation risk exposure leads to a substantial reduction in the magnitude of the BMG alphas. Specifically, the alpha decreases to -0.26% per month for Scope 1 and -0.11% per month for Scope 2 carbon intensity measures, representing a notable decline compared to the alphas estimated without controlling for inflation risk exposure.

The results of this robustness check provide strong evidence that our main findings are not mainly driven by the high inflation period experienced in 2021. Even after excluding this specific year from our sample, we continue to observe a significant negative inflation risk premium (high inflation beta – low returns relationship) and a significant reduction in the greenium once we account for the differences in inflation risk exposure between green and brown stocks. These results underscore the robustness of our conclusions, indicating that the role of inflation risk in explaining the outperformance of environmentally friendly stocks is not solely attributable to the unusual macroeconomic conditions experienced in recent years, but rather represents a more fundamental and persistent phenomenon in the stock market.

4.5 Can the Greenium explain Inflation Risk Premium?

Throughout our analyses, we have provided evidence that greenium can be in part interpreted as a reflection of compensation for the higher inflation risk carried by green stocks. An interesting related question is whether the inflation risk premium itself can be explained by the greenium. In other words, can the extra return investors demand for holding stocks with high inflation risk be simply a reflection of those stocks' environmental characteristics? The answer to this question has significant implications for understanding the relative importance of inflation risk and environmental factors in driving cross-sectional differences in stock returns.

To investigate whether the inflation risk premium can be explained by the greenium, we employ a double-sorting approach. First, we sort stocks into terciles based on either their Scope 1 or Scope 2 carbon intensity. Then, within each carbon intensity tercile, we further sort stocks into terciles based on their core inflation beta. Table 8 presents the raw returns of these carbon-intensity-controlled inflation beta portfolios, as well as the raw and risk-adjusted returns of a long-short portfolio that longs the highest inflation beta tercile and shorts the lowest inflation beta tercile. For comparison, the last column of the table shows the results from the single-sorted inflation beta portfolios, without controlling for carbon intensity, as previously reported in Table 3. After controlling for Scope 1 (Scope 2) carbon intensity, the risk-adjusted return of the long-short inflation beta portfolio decreases moderately from -0.34% to -0.28% (-0.32%), representing a reduction of 18% (6%) for Scope 1 (Scope 2). Notably, these reductions are much smaller than the 31% and 54% decreases in the greenium after controlling for core inflation beta. Moreover, the risk-adjusted returns of the long-short inflation beta portfolios remain statistically significant at the 5% level, even after controlling for firms' carbon intensity.

Overall, our analysis shows that while the greenium can be interpreted as a reflection of inflation risk premium in part, not the other way around. We observe a significant inflation risk premium after controlling for carbon intensity. This result underscores the importance of inflation risk for the cross-section of stock returns.

In summary, our analysis suggests that while the greenium can be partially explained as compensation for the inflation risk differential between green and brown stocks, the inflation risk premium itself cannot be fully attributed to firms' carbon intensity. Even after controlling for carbon intensity, we still observe a statistically and economically significant premium for stocks with low inflation betas relative to stocks with high inflation betas (i.e., high inflation beta – low returns relationship). This finding highlights the distinct role of inflation risk in driving cross-sectional variation in stock returns, above and beyond the impact of carbon intensity.

5 Conclusion

In this paper, we present a novel fact that green stocks exhibit significantly higher inflation risk compared to brown stocks. Considering this difference in inflation risk exposure and the evidence that inflation risk is priced in the cross-section of asset returns (e.g., Fang et al., 2022), we demonstrate that the greenium—the outperformance of green stocks over brown stocks—can be partially explained as a reflection of inflation risk compensation. After controlling for the inflation risk exposure of carbon intensity-sorted portfolios, we find that the magnitude of the greenium decreases substantially, by 31% and 54% for Scope

1 and Scope 2 emissions, respectively. The greenium becomes statistically insignificant at conventional levels after accounting for inflation risk. These findings are robust to excluding brown industries and are not driven by the post-COVID inflationary period.

Our results contribute to the rapidly growing climate finance literature by documenting that green stocks carry significantly higher core inflation risk than brown stocks. Moreover, our analysis provides a novel risk-based explanation for the greenium, offering an alternative perspective on the ongoing transition to the carbon-aware equilibrium (e.g., Zhang, 2023).

More broadly, our findings highlight the importance of accounting for differences in macroeconomic risk exposures when comparing the pricing of green and brown assets. As the transition to a low-carbon economy progresses, understanding the underlying drivers of the greenium and the risk characteristics of green and brown assets will be crucial for asset pricing models, corporate environmental policies, and investor demands. Future research could further explore the dynamics of inflation risk exposure in a conditional asset pricing setting and its implications for the pricing of green and brown assets over time, as well as the potential impact of climate-related policies on these relationships.

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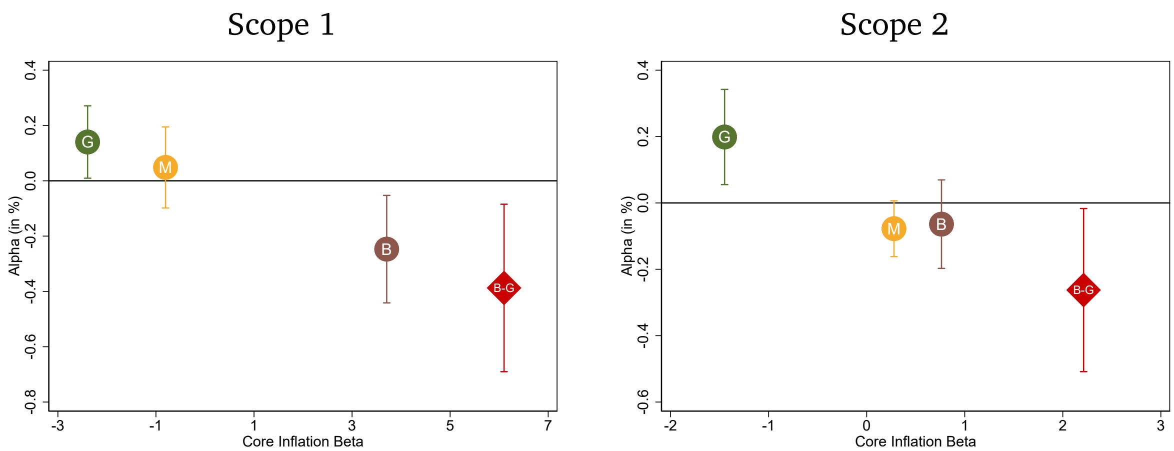

Figure 1. **Risk-adjusted Returns (alpha) of Carbon Intensity-sorted Equity portfolios and their Core Inflation Exposures**

This figure plots monthly risk-adjusted returns (α in %) of value-weighted tercile portfolios sorted by carbon intensity (*y*-axis) along with their corresponding 95% confidence intervals and their exposure to core inflation risk (*x*-axis). 'G' denotes the 'G'reen portfolio which is the bottom tercile portfolio (low carbon intensity). 'M' denotes the 'M'edium portfolio which is the middle tercile portfolio (medium carbon intensity). 'B' denotes the 'B'rown portfolio which is the top tercile portfolio (top carbon intensity). 'B-G' is a long-short portfolio that longs the Brown portfolio and shorts the Green portfolio. Every month, we sort stocks into tercile portfolios based on their either Scope 1 or Scope 2 carbon intensities. Once we obtain these portfolios, we compute their value-weighted monthly returns for the next month for each portfolio. Fama and French (2015) five equity factors are used for risk adjustment. Inflation betas are estimated at the carbon-sorted portfolio level using a 36-month rolling regression of excess returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Newey and West (1987)-corrected standard errors, where the lag is optimally selected according to Newey and West (1994), are used to compute confidence intervals. The sample period is from June 2009 to December 2021.

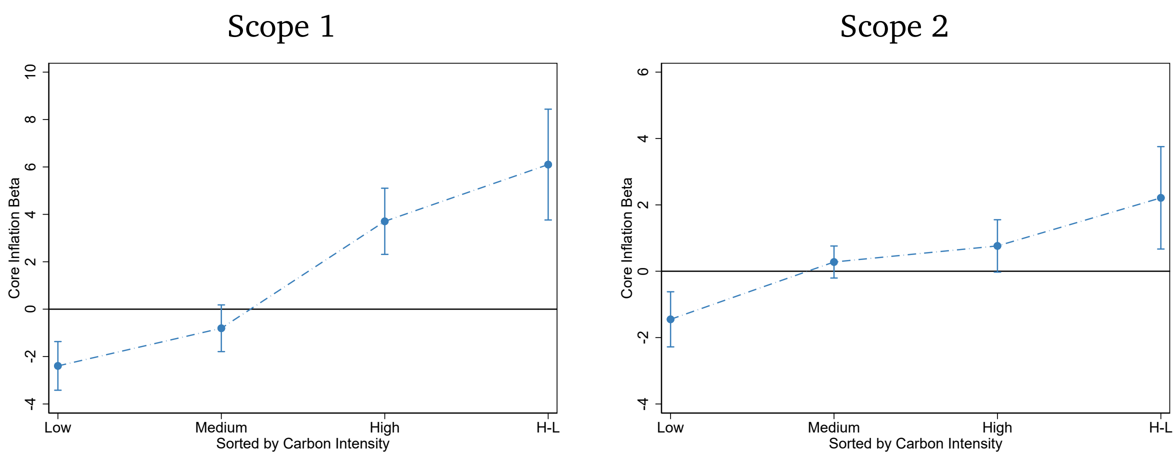

Figure 2. **Core Inflation Exposures of Carbon Intensity-sorted Equity portfolios**

This figure plots the average exposure to core inflation (*y*-axis) along with 95% confidence intervals for each of carbon intensity-sorted equity portfolios (*x*-axis). 'Low' denotes the Green portfolio which is the bottom tercile portfolio (low carbon intensity). 'Medium' denotes the medium portfolio which is the middle tercile portfolio (medium carbon intensity). 'High' denotes the Brown portfolio which is the top tercile portfolio (top carbon intensity). 'H-L' is a long-short portfolio that longs the Brown portfolio and shorts the Green portfolio. Every month, we sort stocks into tercile portfolios based on their either Scope 1 or Scope 2 carbon intensities. Once we obtain these portfolios, we compute their value-weighted monthly returns for the next month for each portfolio. Fama and French (2015) five equity factors are used for risk adjustment. Inflation betas are estimated at the carbon-sorted portfolio level using a 36-month rolling regression of excess returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Newey and West (1987)-corrected standard errors, where the lag is optimally selected according to Newey and West (1994), are used to compute confidence intervals. The sample period is from June 2009 to December 2021.

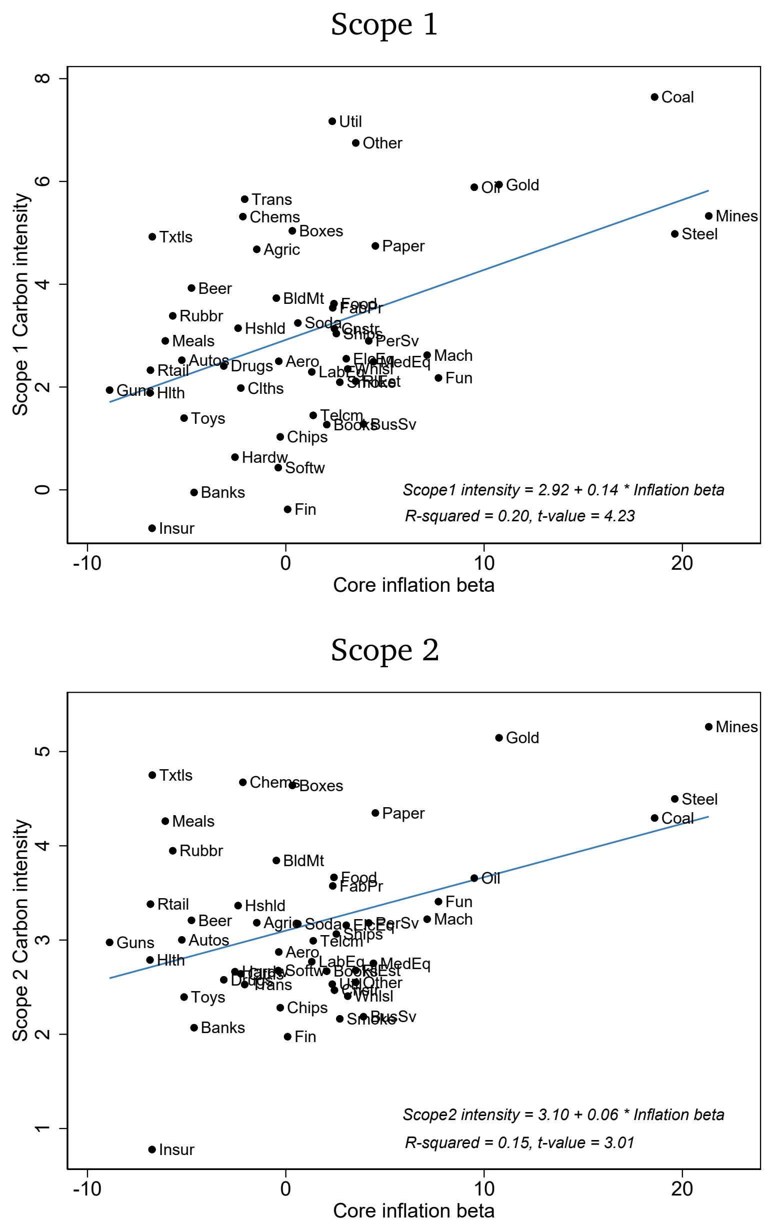

Figure 3. **Carbon Intensity and Core Inflation Exposure of FF49 Industry portfolios**

This figure plots carbon intensity (y-axis) and core inflation beta (x-axis) for each of 49 Fama-French industries. Inflation betas are estimated at the industry portfolio level using a 36-month rolling regression of excess returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. The list of 49 Fama-French industries is presented in Online Appendix Table A2.

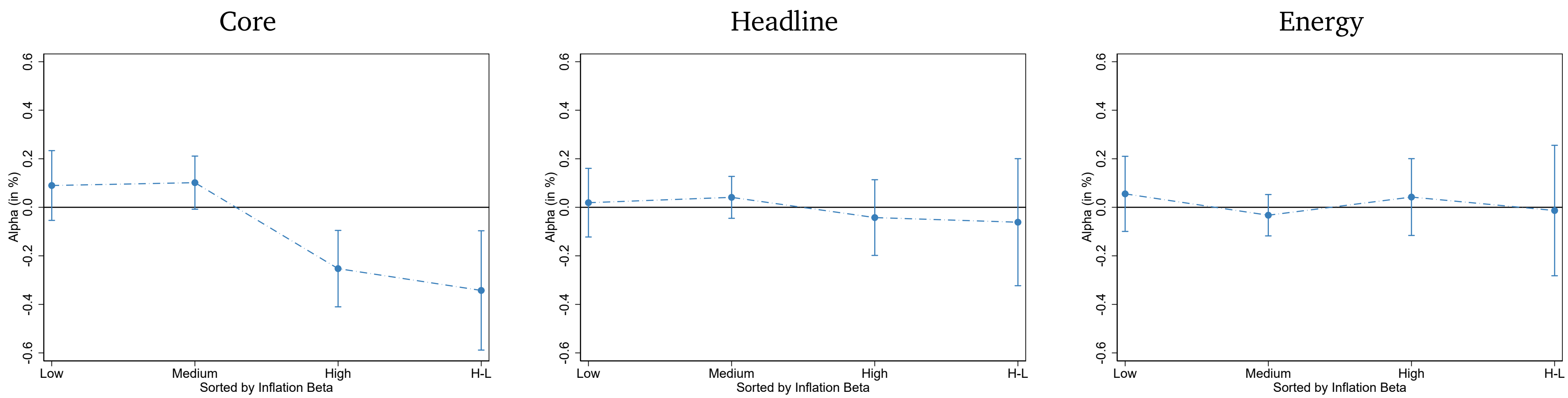

Figure 4. **Risk-adjusted Returns of Inflation-sorted Equity portfolios**

This figure plots monthly risk-adjusted returns (α in %) of value-weighted tercile portfolios sorted by inflation beta (y-axis) along with 95% confidence intervals for each of inflation beta-sorted portfolios (x-axis). For the left, middle, and right panel figures, core, headline, and energy inflation betas are used as a sorting variable, respectively. 'Low' denotes the low-inflation beta portfolio. 'Medium' denotes the medium inflation beta portfolio. 'High' denotes the high-inflation beta portfolio. 'H-L' is a long-short portfolio that longs the high-inflation beta portfolio and shorts the low-inflation beta portfolio. Every month, we sort stocks into tercile portfolios based on their core inflation betas. Once we obtain these portfolios, we compute their value-weighted monthly returns for the next month for each portfolio. Fama and French (2015) five equity factors are used for risk adjustment. Inflation betas are estimated at the stock level using a 36-month rolling regression of excess stock returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Newey and West (1987)-corrected standard errors, where the lag is optimally selected according to Newey and West (1994), are used to compute confidence intervals. The sample period is from June 2009 to December 2021.

Table 1. **Summary Statistics**

Variable	Observations	Mean	St. Dev.	P1	P10	Median	P90	P99
Panel A: Stock-Level Variables								
Scope 1 Intensity	217,661	2.59	2.13	-1.30	-0.23	2.61	5.56	8.42
Scope 2 Intensity	217,661	2.69	1.30	-0.21	0.69	2.79	4.16	5.54
RET	217,396	1.56	14.35	-31.08	-11.34	1.15	13.90	41.65
Panel B: Time-Series Variables (in %)								
Headline Inflation	151	0.18	0.25	-0.64	-0.08	0.20	0.47	0.85
Core Inflation	151	0.18	0.15	-0.13	0.07	0.16	0.26	0.76
Energy Inflation	151	0.26	2.49	-8.90	-2.51	0.34	3.23	5.45
Headline Inflation Shocks	151	0.00	0.20	-0.59	-0.25	0.00	0.23	0.57
Core Inflation Shocks	151	0.00	0.12	-0.34	-0.10	-0.01	0.09	0.43
Energy Inflation Shocks	151	0.10	2.20	-5.22	-2.62	0.12	2.74	5.65
MKT	151	1.32	4.14	-9.57	-3.63	1.55	5.77	12.47
SMB	151	0.05	2.64	-4.93	-3.20	0.16	3.31	7.07
HML	151	-0.20	2.96	-7.87	-3.16	-0.42	3.40	7.63
RMW	151	0.24	1.86	-3.78	-1.96	0.14	2.45	6.36
CMA	151	0.05	1.63	-3.25	-1.83	-0.02	2.02	4.40

This table reports summary statistics of variables in %. Panel A reports the stock-level variables. The Carbon Intensity is computed as the log ratio of a firm's carbon emissions (in tonnes of CO2e) to its revenues (in millions of U.S. dollars). Panel B reports the time-series variables. MKT is the monthly market premium defined as the excess market return over the risk-free rate. SMB is the size factor that captures the monthly return on the portfolio by buying small-cap stocks and selling large-cap stocks. HML is the value factor that captures the monthly return on the portfolio buying value stocks and selling growth stocks. RMW is the profitability factor that captures the difference in monthly returns between firms with robust and weak profitability. CMA is the investment factor that captures the difference in monthly returns between firms with conservative and aggressive investment strategies. The sample period is from June 2009 to December 2021.

Table 2. **Correlation between Inflation Betas and Carbon Intensity**

Variables	Core beta	Headline beta	Energy beta	Scope 1 Intensity	Scope 2 Intensity
Core beta	1.00				
Headline beta	0.49	1.00			
	(0.00)				
Energy beta	0.17	0.86	1.00		
	(0.00)	(0.00)			
Scope 1 Intensity	0.02	0.03	0.03	1.00	
	(0.00)	(0.00)	(0.00)		
Scope 2 Intensity	0.03	0.03	0.00	0.55	1.00
	(0.00)	(0.00)	(0.05)	(0.00)	

This table presents the correlation coefficients between each pair of core inflation betas, headline inflation betas, energy inflation betas, Scope 1 intensity, and Scope 2 intensity. Inflation betas are estimated using a 36-month rolling regression of excess stock returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. *p*-values that indicate the statistical significance of the correlations are reported in parentheses. The sample period is from June 2009 to December 2021.

Table 3. **Core Inflation Beta-Sorted Equity Portfolio Returns**

	Low	2	High	H-L
Raw Return	1.31***	1.32***	1.16***	-0.15
	(4.82)	(5.09)	(3.63)	(-1.11)
α	0.09	0.10*	-0.25***	-0.34***
	(1.24)	(1.83)	(-3.17)	(-2.75)
MKT	0.96***	0.94***	1.11***	0.15***
	(41.73)	(64.78)	(50.94)	(4.38)
SMB	-0.04	-0.11***	0.05	0.09
	(-1.10)	(-4.90)	(1.35)	(1.52)
HML	-0.06**	0.06***	0.02	0.08
	(-2.32)	(2.77)	(0.41)	(1.53)
RMW	-0.08*	0.15***	-0.00	0.08
	(-1.94)	(4.62)	(-0.10)	(1.35)
CMA	0.10*	-0.05	-0.02	-0.12
	(1.75)	(-1.31)	(-0.23)	(-1.09)
R^2	0.95	0.98	0.96	0.20
Obs.	151	151	151	151

This table presents monthly raw returns, risk-adjusted returns (α in %), and exposure to Fama and French (2015) five equity factors for value-weighted tercile portfolios sorted by inflation beta. Every month, we sort stocks into tercile portfolios based on their core inflation betas. Then, we construct a high-minus-low long-short portfolio (H-L) by taking a long position in the High portfolio and a short position in the Low portfolio. Once we obtain these portfolios, we compute their value-weighted monthly returns for the next month for each portfolio for each portfolio. Fama and French (2015) five equity factors are used for risk adjustment. Inflation betas are estimated at the stock level using a 36-month rolling regression of excess stock returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Newey and West (1987)-corrected t-statistics, where the lag is optimally selected according to Newey and West (1994), are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is from June 2009 to December 2021.

Table 4. **Carbon Intensity-Sorted Equity Portfolio Returns**

	Scope 1				Scope 2			
	Low	2	High	H-L	Low	2	High	H-L
Raw Return	1.42***	1.32***	1.00***	-0.42***	1.47***	1.23***	1.17***	-0.30**
	(4.90)	(4.90)	(3.52)	(-2.66)	(5.20)	(4.21)	(4.53)	(-2.36)
α	0.14**	0.05	-0.25**	-0.39**	0.20***	-0.08*	-0.06	-0.26**
	(2.12)	(0.65)	(-2.51)	(-2.53)	(2.74)	(-1.82)	(-0.95)	(-2.11)
MKT	1.05***	0.95***	0.94***	-0.11***	1.01***	1.05***	0.92***	-0.09**
	(62.06)	(55.94)	(33.65)	(-2.68)	(53.39)	(68.01)	(40.17)	(-2.42)
SMB	-0.16***	0.07*	0.02	0.18***	-0.02	-0.12***	0.02	0.04
	(-6.12)	(1.73)	(0.56)	(3.31)	(-0.77)	(-4.65)	(0.57)	(0.80)
HML	0.10***	-0.21***	0.07**	-0.03	0.02	0.00	0.00	-0.02
	(3.70)	(-5.37)	(2.05)	(-0.56)	(0.60)	(0.07)	(0.01)	(-0.29)
RMW	-0.08*	0.06	0.18***	0.26**	0.05	-0.13***	0.22***	0.18**
	(-1.82)	(1.31)	(2.77)	(2.53)	(1.32)	(-4.78)	(5.33)	(2.56)
CMA	-0.20***	0.21***	0.14**	0.34***	-0.17***	0.04	0.13**	0.30***
	(-3.96)	(3.69)	(2.19)	(3.17)	(-3.53)	(0.82)	(2.49)	(3.35)
R^2	0.97	0.96	0.93	0.18	0.96	0.98	0.96	0.18
Obs.	151	151	151	151	151	151	151	151

This table presents monthly raw returns, risk-adjusted returns (α in %), and exposure to Fama and French (2015) five equity factors for value-weighted tercile portfolios sorted by carbon intensity. Every month, we sort stocks into tercile portfolios based on their either Scope 1 or Scope 2 carbon intensities. Then, we construct a high-minus-low long-short portfolio (H-L) by taking a long position in the High portfolio and a short position in the Low portfolio. Once we obtain these portfolios, we compute their value-weighted monthly returns for the next month for each portfolio for each portfolio. Fama and French (2015) five equity factors are used for risk adjustment. Newey and West (1987)-corrected *t*-statistics, where the lag is optimally selected according to Newey and West (1994), are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is from June 2009 to December 2021.

Table 5. **Carbon Intensity-Sorted Equity Portfolio Returns after controlling for Inflation Betas**

	Double sorted (Control: Inflation beta)		Single sorted (Table 4)	
	Scope 1	Scope 2	Scope 1	Scope 2
Low Carbon	1.38***	1.40***	1.42***	1.47***
	(4.75)	(4.83)	(4.90)	(5.20)
2	1.27***	1.20***	1.32***	1.23***
	(4.52)	(4.02)	(4.90)	(4.21)
High Carbon	1.07***	1.26***	1.00***	1.17***
	(3.59)	(4.60)	(3.52)	(4.53)
H-L Return	-0.31*	-0.14	-0.42***	-0.30**
Difference	(-1.86)	(-1.02)	(-2.66)	(-2.36)
H-L α	-0.27	-0.12	-0.39**	-0.26**
Difference	(-1.65)	(-0.95)	(-2.53)	(-2.11)

This table presents monthly raw returns and risk-adjusted returns (α in %) for value-weighted tercile portfolios sorted by carbon intensity after controlling for core inflation betas. Every month, we first sort stocks into tercile portfolios using core inflation beta, then within each tercile portfolio, we sort stocks into tercile portfolios based on their either Scope 1 or Scope 2 carbon intensities. We compute average returns across the tercile inflation beta-sorted portfolios for each carbon intensity-sorted portfolio to produce tercile portfolios with dispersion in carbon intensity but with similar levels of inflation betas. The first two columns report returns for these double-sorted portfolios. The last two columns report those for single-sorted portfolios reported in Table 4 for comparison. Fama and French (2015) five equity factors are used for risk adjustment. Inflation betas are estimated at the stock level using a 36-month rolling regression of excess stock returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Newey and West (1987)-corrected *t*-statistics, where the lag is optimally selected according to Newey and West (1994), are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is from June 2009 to December 2021.

Table 6. **Robustness: Carbon Intensity-Sorted Equity Portfolio Returns after Excluding Brown Industries**

	All industries (Table 5)		Ex: Mines		Ex: Mines + Steel	
	Single	Double	Single	Double	Single	Double
Scope 1 Intensity	-0.39**	-0.27	-0.38**	-0.25	-0.36**	-0.27*
	(-2.53)	(-1.65)	(-2.50)	(-1.57)	(-2.30)	(-1.69)
Scope 2 Intensity	-0.26**	-0.12	-0.24*	-0.13	-0.22*	-0.12
	(-2.11)	(-0.95)	(-1.95)	(-1.02)	(-1.82)	(-1.02)

	Ex: Mines + Steel + Coal		Ex: Mines + Steel + Coal + Gold		Ex: Mines + Steel + Coal + Gold + Oil	
	Single	Double	Single	Double	Single	Double
Scope 1 Intensity	-0.35**	-0.27*	-0.35**	-0.26*	-0.20	-0.13
	(-2.25)	(-1.71)	(-2.27)	(-1.69)	(-1.35)	(-0.93)
Scope 2 Intensity	-0.21*	-0.11	-0.21*	-0.11	-0.14	-0.03
	(-1.73)	(-0.96)	(-1.74)	(-0.93)	(-1.13)	(-0.26)

This table presents monthly risk-adjusted returns (α in %) of the long-short (Brown-minus-Green) portfolios that long the Brown portfolio and short the Green portfolio from the value-weighted tercile portfolios sorted by carbon intensity either without (denoted by 'Single') or with controlling for core inflation betas (denoted by 'Double'). Fama and French (2015) five equity factors are used for risk adjustment. Inflation betas are estimated at the stock level using a 36-month rolling regression of excess stock returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Newey and West (1987)-corrected *t*-statistics, where the lag is optimally selected according to Newey and West (1994), are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is from June 2009 to December 2021.

Table 7. **Robustness: Main Results Without the Year 2021**

Panel A: HML Portfolio of Single Sorted Portfolios			
	Inflation beta	Scope 1 Intensity	Scope 2 Intensity
Raw Return	-0.20	-0.42**	-0.33**
	(-1.46)	(-2.52)	(-2.43)
α	-0.35***	-0.37**	-0.25*
	(-2.76)	(-2.19)	(-1.78)

Panel B: Brown-minus-Green Portfolio of Double Sorted Portfolios (Control: Inflation beta)		
	Scope 1	Scope 2
Raw Return	-0.34**	-0.15
	(-2.01)	(-1.11)
α	-0.28	-0.12
	(-1.59)	(-0.86)

This table presents our main results without the recent high inflation period in the year 2021. Panel A presents monthly raw returns and risk-adjusted returns (α in %) of the High-minus-Low portfolios from value-weighted terciles where stocks are sorted based on either core inflation beta (First column), Scope 1 carbon intensity (Second column), and Scope 2 carbon intensity (Third column). Panel B presents monthly raw returns and risk-adjusted returns (α in %) of the long-short (Brown-minus-Green) portfolios that long the Brown portfolio and short the Green portfolio from the value-weighted tercile portfolios sorted by carbon intensity. Fama and French (2015) five equity factors are used for risk adjustment. Inflation betas are estimated at the stock level using a 36-month rolling regression of excess stock returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Newey and West (1987)-corrected *t*-statistics, where the lag is optimally selected according to Newey and West (1994), are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is from June 2009 to December 2020.

Table 8. **Core Inflation Beta-Sorted Equity Portfolio Returns after controlling for Carbon Intensity**

	Double Sorted (Control: Carbon intensity)		Single Sorted (Table 3)
	Scope 1	Scope 2	
Low Inflation Beta	1.26***	1.32***	1.31***
	(4.59)	(4.89)	(4.82)
2	1.28***	1.34***	1.32***
	(5.10)	(5.17)	(5.09)
High Inflation Beta	1.14***	1.18***	1.16***
	(3.45)	(3.62)	(3.63)
Return	-0.11	-0.14	-0.15
Difference	(-0.82)	(-1.02)	(-1.11)
α	-0.28**	-0.32**	-0.34***
Difference	(-2.07)	(-2.46)	(-2.75)

This table presents monthly raw returns and risk-adjusted returns (α in %) for value-weighted tercile portfolios sorted by core inflation beta after controlling for carbon intensities. Every month, we first sort stocks into tercile portfolios using either Scope 1 or Scope 2 carbon intensities, then within each tercile portfolio, we sort stocks into tercile portfolios based on their core inflation betas. We compute average returns across the tercile carbon intensity-sorted portfolios for each inflation beta-sorted portfolio to produce tercile portfolios with dispersion in inflation beta but with similar levels of carbon intensities. The first two columns report returns for these double-sorted portfolios. The last column reports those for single-sorted portfolios reported in Table 3 for comparison. Fama and French (2015) five equity factors are used for risk adjustment. Inflation betas are estimated at the stock level using a 36-month rolling regression of excess stock returns on contemporaneous inflation shock, one-month-lagged inflation shock, and Fama and French (2015) five equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Newey and West (1987)-corrected *t*-statistics, where the lag is optimally selected according to Newey and West (1994), are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is from June 2009 to December 2021.

Online Appendix to "Is Greenium a Reflection of Inflation Risk?"

September 21, 2024

Table A1. **Variable Definitions**

Variables	Description	Source	Level
Headline Inflation	Monthly log change in headline price index	Federal Reserve Economic Data	Month
Core Inflation	Monthly log change in core price index	Federal Reserve Economic Data	Month
Energy Inflation	Monthly log change in energy price index	Federal Reserve Economic Data	Month
Headline Inflation Shocks	Residuals of headline inflation from ARMA(1,1) plus 7 principal components of 127 economic variables	Federal Reserve Economic Data	Month
Core Inflation Shocks	Residuals of core inflation from ARMA(1,1) plus 7 principal components of 127 economic variables	Federal Reserve Economic Data	Month
Energy Inflation Shocks	Residuals of energy inflation from ARMA(1,1) plus 7 principal components of 127 economic variables	Federal Reserve Economic Data	Month
MKT	Market factor defined as CRSP-valued weighted returns minus 30-day T-bill rate	Kenneth French website	Month
SMB	Size factor defined as small-cap stocks minus large-cap stocks	Kenneth French website	Month
HML	Value factor defined as high book-to-market ratio stocks minus low book-to-market stocks	Kenneth French website	Month
RMW	Profitability factor defined as stocks of companies with robust operating profitability minus those with weak operating profitability	Kenneth French website	Month
CMA	Investment factor defined as stocks of companies with conservative investment strategies minus those with aggressive investment strategies	Kenneth French website	Month
Principal components	Seven principal components from 127 economic and financial variables	Michael McCracken website	Month
RET	Excess returns of stocks	CRSP	Firm-month
Core beta	Core inflation beta	Authors	Firm-month
Headline beta	Headline inflation beta	Authors	Firm-month
Energy beta	Energy inflation beta	Authors	Firm-month
Scope 1 Intensity	Log ratio of scope 1 total carbon emissions to annual consolidated revenues (tCO2e per million US dollar)	Trucost	Firm-year
Scope 2 Intensity	Log ratio of scope 2 total carbon emissions to annual consolidated revenues (tCO2e per million US dollar)	Trucost	Firm-year

Table A2. **Fama-French 49 Industry Classifications**

Order	Acronym	Industry	Order	Acronym	Industry
1	Agric	Agriculture	26	Guns	Defense
2	Food	Food Products	27	Gold	Precious Metals
3	Soda	Candy & Soda	28	Mines	Non-Metallic and Industrial Metal Mining
4	Beer	Beer & Liquor	29	Coal	Coal
5	Smoke	Tobacco Products	30	Oil	Petroleum and Natural Gas
6	Toys	Recreation	31	Util	Utilities
7	Fun	Entertainment	32	Telcm	Communication
8	Books	Printing and Publishing	33	PerSv	Personal Services
9	Hshld	Consumer Goods	34	BusSv	Business Services
10	Clths	Apparel	35	Hardw	Computers
11	Hlth	Healthcare	36	Softw	Computer Software
12	MedEq	Medical Equipment	37	Chips	Electronic Equipment
13	Drugs	Pharmaceutical Products	38	LabEq	Measuring and Control Equipment
14	Chems	Chemicals	39	Paper	Business Supplies
15	Rubbr	Rubber and Plastic Products	40	Boxes	Shipping Containers
16	Txtls	Textiles	41	Trans	Transportation
17	BldMt	Construction Materials	42	Whlsl	Wholesale
18	Cnstr	Construction	43	Rtail	Retail
19	Steel	Steel Works Etc	44	Meals	Restaurants, Hotels, Motels
20	FabPr	Fabricated Products	45	Banks	Banking
21	Mach	Machinery	46	Insur	Insurance
22	ElcEq	Electrical Equipment	47	RlEst	Real Estate
23	Autos	Automobiles and Trucks	48	Fin	Trading
24	Aero	Aircraft	49	Other	Almost Nothing
25	Ships	Shipbuilding, Railroad Equipment			