Is Greenium a Reflection of Core Inflation Risk?[*]

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Abstract

The greenium, the outperformance of green over brown assets, is widely interpreted as evidence of investors' green preference. We propose a fundamentally different explanation grounded in macroeconomic risk. In U.S. equity and corporate bond markets from 2009 to 2021, green assets carry substantially higher exposure to core inflation shocks, while brown assets act as hedges. Accounting for this exposure reduces the Scope 1 (Scope 2) equity greenium by 36% (23%) and renders it statistically insignificant. The bond greenium also shrinks. Three economic channels explain green firms' greater core inflation risk: stickier output prices, higher markups, and longer cash flow duration. A calibrated two-firm general-equilibrium model that incorporates these channels and a time-varying green preference quantitatively reproduces both the greenium and its reduction after accounting for core inflation risk exposure.

JEL Classification: *G11, G12, E31, E44, Q54*

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1 Introduction

The rapid growth of sustainable investing in recent years has sparked significant interest among academics and practitioners in understanding the risk and return characteristics of environmentally friendly ("green") assets compared to environmentally unfriendly ("brown") ones. A central empirical finding in this literature is that green assets have outperformed brown assets, on average, a phenomenon known as the "greenium" (e.g., Pástor et al., 2022; Duan et al., 2025; Zhang, 2025). However, the underlying drivers of the greenium are still a matter of debate. While the greenium is often interpreted as strong demand for green assets amid an ongoing transition to the carbon-aware equilibrium (e.g., Pástor et al., 2022; Zhang, 2025), a risk-based explanation could also play a role in explaining the greenium. Identifying specific risks, if any, to which green assets are more negatively exposed than brown assets is crucial to interpreting the greenium. Such a risk-based explanation would carry major implications for asset pricing models, corporate environmental policies, and investor demands during the transition to a low-carbon economy.

Core inflation risk is a natural candidate explanation because it is a fundamental macroeconomic factor priced in the cross-section of stocks and bonds (Fang et al., 2026). We therefore ask whether differential exposure to core inflation risk between green and brown assets accounts for the greenium. We first document a novel empirical fact: green stocks and corporate bonds carry substantially higher core inflation risk than their brown counterparts, underperforming when core inflation rises unexpectedly. Moreover, investors demand compensation for holding assets with high core inflation risk in our sample. Then, we demonstrate that the greenium partly reflects compensation for core inflation risk for both stocks and corporate bonds. We further propose and empirically test three mechanisms that explain this differential: green industries have stickier output prices, green firms carry higher markups, and green firms have longer cash flow duration. Each characteristic independently predicts a more negative core inflation beta.

We begin our analysis by examining the core inflation exposure of tercile portfolios sorted by Scope 1 and 2 carbon intensity, using U.S. public stocks and corporate bonds from June 2009 to December 2021. We estimate core inflation betas for each portfolio via rolling regressions of excess returns on core inflation shocks. We find that the highest carbon intensity portfolio ("brown") exhibits a significantly higher core inflation beta than the lowest carbon intensity portfolio ("green") for both stocks and bonds. This suggests that green assets tend to underperform during periods of unexpected core inflation, indicating that they bear greater core inflation risk.

We further examine the link between carbon intensity and core inflation exposure across the Fama-French 49 industries. We show that brown industries, such as mining, steel, coal, petroleum, and natural gas, exhibit the highest core inflation betas, consistent with Hong et al. (2022). Furthermore, carbon intensity is significantly and positively associated with core inflation beta in both equity and bond markets: a one-standard-deviation increase in equity (bond) core inflation beta corresponds to a 0.48 (0.6) unit increase in Scope 1 carbon intensity, accounting for 26% (31%) of its standard deviation with a t-value of 1.7 (3.95). These findings provide clear evidence that green assets are more vulnerable to core inflation risk than brown assets.

The strong positive relationship between carbon intensity and core inflation beta suggests that core inflation risk could explain green assets' outperformance. However, an important question remains: while Fang et al. (2026) demonstrate significant negative risk premia for core inflation risk, do investors demand compensation for holding assets that carry high core inflation risk during our sample period as well? To address this question, we construct a long-short portfolio that longs assets in the lowest core inflation-beta tercile and shorts those in the highest core inflation-beta tercile, separately for stocks and bonds. Our findings show that this long-short portfolio sorted by core inflation betas earns a significant risk-adjusted return of 0.37% per month in the equity market and 0.08% per month in the bond market during our sample period. This evidence suggests that investors do require compensation for holding assets with high core inflation risk, as these assets perform poorly when investors' marginal utility is high due to unexpected core inflation shocks. In contrast, long-short portfolios sorted by headline, energy, and food inflation betas yield nearly zero risk-adjusted returns in both the equity and the corporate bond markets, aligning with recent studies highlighting the importance of core inflation for the cross-section of assets (e.g., Fang et al., 2026; Hong et al., 2022).

Having established a strong positive link between carbon intensity and core inflation beta, as well as a significant negative core inflation risk premium, we examine whether the greenium reflects compensation for core inflation risk. To begin with, we reproduce the positive risk-adjusted returns of the green-minus-brown portfolio ("greenium"), which longs the portfolio with the lowest carbon intensity and shorts that with the highest carbon intensity among the terciles, yielding an equity greenium of 0.33% and 0.22% per month for Scopes 1 and 2, respectively. In the bond market, the Scope 1 greenium is significantly positive at 0.18%, while the Scope 2 greenium is 0.07%, statistically indistinguishable from zero. We then re-examine the greenium after accounting for the inflation risk exposure of carbon intensity-sorted portfolios. To this end, we double-sort stocks and bonds separately to construct a green-minus-brown portfolio where the green and brown portfolios have similar core inflation betas. In the equity market, the risk-adjusted returns of this core-inflation-beta-controlled green-minus-brown portfolio are 0.21% (t-value = 1.51) and 0.17% (t-value = 1.48) for Scopes 1 and 2, respectively. These represent reductions of 36% and 23% in the Scope 1 and Scope 2 greenium, respectively, both statistically indistinguishable from zero at conventional levels. In the bond market, the Scope 1 greenium declines to 0.16% (t-value = 1.95) per month, corresponding to an approximately 11% reduction. Taken together, these results suggest that the greenium is partially attributable to core inflation risk compensation.

To assess the robustness of our findings, we conduct additional tests. To test whether our results are driven by a few industries, we repeat our analysis by excluding the top three highest core inflation beta industries separately for equity and bond markets. After excluding these industries, we find an equity greenium of 0.3% and 0.19% for Scopes 1 and 2, respectively. The bond greenium is 0.11% and 0.02% for Scopes 1 and 2, respectively. When accounting for core inflation beta, even without these highest-inflation-beta industries, the greenium magnitudes still decrease to a negligible 0.2% and 0.15% for equities and to 0.11% and 0% for bonds. These findings suggest that our results are not fully driven by industries with the highest inflation betas. We also examine whether the greenium explains the inflation risk premium. To this end, we double-sort stocks and bonds separately to construct a long-short portfolio sorted by core inflation betas, where the long and short portfolios have similar carbon intensity. We show that in the equity market the inflation risk premium remains statistically significant with a small reduction in the magnitude, suggesting that the inflation risk premium is not attributable to firms' carbon intensity.

Beyond the return evidence, we investigate why green firms are more negatively exposed to core inflation risk. We identify three economic channels tied to industry- and firm-level characteristics. First, green industries have stickier output prices: they adjust prices less frequently, so rising marginal costs compress their margins rather than being passed through to consumers. Second, green firms carry higher markups, which reduce their incentive to reset prices in response to productivity shocks, amplifying their negative inflation exposure. Third, green firms have longer cash flow duration, making their valuations more sensitive to discount-rate increases driven by core inflation shocks. All three channels point towards green firms having higher core inflation risk than brown firms.

Finally, we extend the New Keynesian asset-pricing model of Fang et al. (2026) to two firms, one green and one brown, with a time-varying investor green preference (Avramov et al., 2024). As in the data, the green firm has stickier output prices and higher markups. The calibrated model generates a higher core inflation beta for the brown firm, as in the data, with the raw equity greenium of 0.337% per month, close to the 0.33% that we estimate empirically. We then shut off the firms' differences in price stickiness and markups, which equalizes their exposure to core inflation risk. The greenium falls to 0.209% per month, close to the 0.21% that remains in the data after we control for core inflation beta. In general equilibrium, the model therefore reproduces our decomposition of the greenium into compensation for core inflation risk and a green-preference component.

In summary, our findings demonstrate that the greenium partly reflects compensation for the higher core inflation risk borne by green firms, with this differential exposure due to green firms' stickier output prices, higher markups, and longer cash flow duration. The greenium is therefore not solely a manifestation of investor preferences for sustainability but also of a macroeconomic risk that green firms differentially carry. Our results highlight the importance of core inflation risk for green and brown assets, uncovering a risk-based channel through which a macroeconomic factor seemingly unrelated to environmental performance shapes their pricing.

1.1 Related literature

Our paper contributes to a large literature on the asset-pricing implications of firms' environmental performance in equity and corporate bond markets.[1] Recent studies have documented a "greenium": the outperformance of environmentally friendly assets over carbon-intensive ones based on realized returns. Pástor et al. (2022) show that green stocks outperformed brown stocks in the 2010s and attribute this to rising environmental concerns. Duan et al. (2025) provide similar evidence in the corporate bond market. Zhang (2025) provides a broader global analysis after accounting for the release lag of carbon emissions information. She finds negative carbon returns (greenium) in the United States and insignificant effects globally, which she argues is consistent with an ongoing transition to a "carbon-aware" equilibrium. We extend this literature with a risk-based explanation: the greenium reflects compensation for differential exposure to core inflation risk. While brown assets hedge core inflation, green assets are negatively exposed to it and earn higher average returns as compensation.

Our study is also closely related to research on the relationship between inflation and

[1] See Bolton and Kacperczyk (2021); Duan et al. (2025); Ilhan et al. (2021); Goldstein et al. (2022); Pástor et al. (2022); Ardia et al. (2023); Atilgan et al. (2023); Bolton and Kacperczyk (2023); Hsu et al. (2023); Chen et al. (2023); Karolyi et al. (2026); Sautner et al. (2023); Aswani et al. (2024); Eskildsen et al. (2024); Pasler et al. (2025); Zhang (2025), among others.

the greenium (Bolton et al., 2024; Shi and Zhang, 2024). We contribute to this literature in the following ways. First, unlike prior work focusing on energy price inflation, we examine core inflation, which excludes energy and food, offering a distinct perspective. While Shi and Zhang (2024) find that positive oil price shocks benefit brown stocks and reduce the carbon premium using ex ante returns, our insight is that brown stocks hedge core inflation, explaining their relative underperformance in average returns from a risk-based perspective. Second, we explore the *cross-sectional* implications of core inflation, whereas prior studies examine the *aggregate* effects of energy inflation. Finally, we assess the unconditional greenium based on realized returns, while Shi and Zhang (2024) focus on the higher expected returns of brown stocks in a conditional setting. Thus, our work complements existing studies by providing a novel perspective: the average greenium observed in recent decades reflects compensation for core inflation risk, beyond investor preference shifts or climate transition risk, highlighting the role of core inflation in cross-sectional asset pricing.

Our paper also contributes to the growing literature on the implications of inflation risk for cross-sectional asset returns.[2] We advance this literature in two main ways. First, we provide evidence that the core inflation risk premium is significantly priced in both U.S. equity and bond markets over the past decade. In doing so, we confirm Fang et al. (2026) by showing that core inflation (rather than headline inflation) is priced in the equity market. Second, we uncover a novel finding: while the core inflation risk premium helps explain the greenium, the greenium cannot account for the observed core inflation risk premium. These findings enhance our understanding of the interplay between inflation risk, environmental

[2]See Kang and Pflueger (2015); Boons et al. (2020); Hong et al. (2022); An et al. (2023); Bhamra et al. (2023); Knox and Timmer (2023); Feng et al. (2024); Lu et al. (2024); Bonelli et al. (2025); Fang et al. (2026), among others.

factors, and asset pricing, offering new insights into the literature. Regarding inflation risk in the corporate bond market, the paper closest to ours is Lu et al. (2024), who study inflation betas in the cross-section of corporate bonds. We differ by linking those exposures to firms' carbon intensity and the greenium.

The remainder of the paper is structured as follows. Section 2 outlines the primary data sources and details the sample coverage. Section 3 describes the construction of key variables used in the analysis and presents summary statistics. Section 4 investigates the extent to which the greenium can be explained by compensation for inflation risk, while Section 5 investigates the economic mechanisms behind green firms' higher core inflation risk. Section 6 presents a calibrated New Keynesian asset-pricing model with these mechanisms and quantitatively accounts for the greenium. Section 7 concludes.

2 Data and sample coverage

2.1 Asset Data

Equities: We obtain monthly stock returns and other stock characteristics 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.

Bonds: We construct our corporate bond universe by merging end-of-month bond pricing information from the Intercontinental Exchange (ICE) with additional bond characteristics data from the Mergent FISD. The increasing use of ICE as an alternative to transaction-level databases (e.g., TRACE) in recent corporate bond literature motivates our reliance on ICE data (Dickerson et al., 2023; Kelly et al., 2023; Dick-Nielsen et al., 2023). In contrast to transaction data that are susceptible to significant measurement error and bid-ask bounce, ICE bid quotes allow for consistent month-end valuations and thereby provide a cleaner representation of actionable market prices. We restrict the sample to U.S. dollar-denominated, fixed-rate, senior unsecured or secured issues, while requiring semiannual coupon payments. We further exclude convertible and pay-in-kind bonds.

2.2 Compustat

We retrieve annual firm-level accounting information from Compustat to construct the measures for the economic channels underlying green firms' greater core inflation risk. We exclude firms with missing NAICS codes.

Computing the markup ratios of De Loecker et al. (2020) requires three additional series from the Federal Reserve Economic Data (FRED) at the St. Louis Fed. We obtain the annual U.S. GDP Implicit Price Deflator and use it to deflate nominal sales, cost of goods sold (COGS), and selling, general, and administrative expenses (SG&A). We also collect the quarterly series of year-over-year percent change in the U.S. GDP Implicit Price Deflator and the daily Effective Federal Funds Rate. The yearly averages of these two series enter the annual real user cost of capital, defined as the federal funds rate net of GDP-deflator inflation plus a 12% annual depreciation rate.

Following De Loecker et al. (2020), we require firms to have positive deflated sales, deflated COGS, deflated SG&A, and sales-to-COGS ratios. We further trim the sales-to-cost-of-goods-sold ratio and the underlying cost shares at the 1st and 99th percentiles by year.

2.3 Emission Data

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 cover all other indirect emissions that are created by a firm's interactions with its suppliers and customers over the entire value chain. The broad scope of Scope 3 emissions leaves substantial reporting discretion to firms, introducing considerable measurement error. We therefore focus on Scope 1 and 2 emissions.

Following Zhang (2025) and Aswani et al. (2024), we measure firms' carbon risk using carbon intensity rather than total emissions. Total emissions scale mechanically with firm size and are tightly linked to contemporaneous sales (Zhang, 2025), and thus cross-firm variation in total emissions reflects firm scale and operating performance as much as transition risk. S&P Trucost computes carbon intensity as a firm's annual greenhouse gas emissions in tons of carbon dioxide equivalent (tCO_2e) divided by consolidated revenues in millions of U.S. dollars.

Although Trucost updates its database with new company-year observations once data become available, companies require time to disclose their emissions data following fiscal year completion. Failing to account for this reporting lag when analyzing carbon returns can introduce forward-looking bias. We address this timing issue by adopting Zhang (2025)'s methodology. Specifically, we use the effective release dates of carbon data to match CRSP returns with the most recent Trucost data available to investors, and for each firm we fill missing values of carbon intensities and emissions with the most recently released observation, preventing look-ahead bias.

2.4 Inflation and Macroeconomic Data

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

Macro data: We use 127 economic and financial variables available from Michael McCracken's website to estimate principal components that are used to extract inflation shocks.[3]

2.5 Asset Pricing Factors

Equity factors: We collect the Fama and French (2018) six equity factors and the one-month T-bill rate from the Kenneth French website. The market factor (*MKTRF*) is the value-weighted return on the market portfolio in excess of the one-month T-bill rate. The size factor (*SMB*) is the return difference between portfolios of small and large stocks. The value factor (*HML*) is the return difference between portfolios of high and low book-to-market stocks. The profitability factor (*RMW*) is the return difference between portfolios of stocks with robust and weak operating profitability. The investment factor (*CMA*) is the return difference between portfolios of stocks with conservative and aggressive investment policies. The momentum factor (*MOM*) is the return difference between portfolios of stocks with the highest and lowest prior one-year returns.

Bond factors: For bond factors, we compute the corporate bond market factor (*CBMKTRF*) as the value-weighted average of corporate bond returns from the ICE database in excess of the one-month T-bill rate. Following Fama and French (1993), *DEF* is defined as the return difference between a portfolio of long-term corporate bonds and a portfolio of long-term

[3] See https://www.stlouisfed.org/research/economists/mccracken/fred-databases

government bonds. *TERM* is defined as the return difference between long-term government bonds and the one-month T-bill rate. We construct these factors using data from Amit Goyal's website.[4]

2.6 Industry Price Stickiness

The frequency of price adjustment (FPA) at the level of 6-digit NAICS sectors is obtained from Michael Weber's website.[5] Pasten et al. (2020) construct FPA from the confidential producer price index (PPI) microdata of the U.S. Bureau of Labor Statistics, which track the monthly transaction price of each item entering the PPI. For each individual item, FPA is defined as the fraction of sample months in which the recorded price differs from that of the previous month. The authors then average these item-level frequencies within each 6-digit NAICS sector, producing one industry-level value that summarizes the average per-month probability of a price reset in the spirit of Calvo (1983). Because the underlying microdata are pooled across the full sample window, the resulting industry FPA is time invariant.

3 Key Variables and Summary Statistics

3.1 Corporate Bond Returns

We compute monthly corporate bond returns using the institutional bid quotes from the ICE database. To ensure our returns reflect end-of-month valuations, we follow the existing literature and require each bond to have a valid quote within the last five business days of the month (Dickerson et al., 2023; Bali et al., 2021; Bartram et al., 2025; Feng et al., 2025). If a month-end price is unavailable, we use the price from the beginning of the following

[4] See https://sites.google.com/view/agoyal145

[5] See https://faculty.chicagobooth.edu/michael-weber

month, provided it occurs within the first five business days. To avoid stale-price bias, we prioritize the previous month's closing quote over the current month's opening quote when both are available within the five-day window.

The monthly return for bond i in month t is computed as follows:

$$R^B_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1, \tag{1}$$

where $P_{i,t}$ is the quoted clean price, $AI_{i,t}$ is accrued interest, and $C_{i,t}$ is the coupon payment.

3.2 Measuring inflation shock

We estimate the unexpected component of inflation using a recursive, out-of-sample forecasting framework. For headline, core, energy, and food CPI series, we define monthly inflation (CPI growth) as the log change of the respective CPI index: $\pi_t = \log(CPI_t) - \log(CPI_{t-1})$. To extract the unexpected component of inflation, we estimate a rolling ARMA(1,1) model 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). We augment the ARMA specification with the five 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; Elkamhi et al., 2024).[6]

Specifically, for each month t, we estimate the following model using a rolling window

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

of 50 years:[7]

$$\pi_t = \mu + \phi\pi_{t-1} + \gamma' PC_{t-1} + \psi\epsilon_{t-1} + \epsilon_t, \quad \forall t \in [t-h, t] \tag{2}$$

where PC_{t-1} is the set of the five principal components. ϵ_t is the inflation shock at month t. We perform this estimation using a rolling approach to ensure that the shocks are out-of-sample and reflect only the information available at the time of the forecast.

3.3 Estimation of inflation beta

We estimate time-varying inflation betas for both equities and corporate bonds using rolling-window regressions. For each individual security, we employ a 60-month rolling window and require a minimum of 24 valid monthly observations to ensure estimation reliability.

For equities, we estimate inflation betas by augmenting the Fama and French (2018) six-factor model with contemporaneous and lagged inflation innovations:

$$\begin{aligned} R_{i,t} - r_t^f = \alpha_i + \beta_{1,i}\hat{\epsilon}_t^{\pi} + \beta_{2,i}\hat{\epsilon}_{t-1}^{\pi} + \beta_i^{MKTRF} MKTRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t \\ + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \beta_i^{MOM} MOM_t + u_{i,t} \end{aligned} \tag{3}$$

where $R_{i,t} - r_t^f$ denotes the excess return of stock i in month t, and $\hat{\epsilon}_t^{\pi}$ is the inflation innovation in month t estimated from Equation (2).

For corporate bonds, we estimate an analogous specification using excess bond returns

[7] Our first estimation is from March 1959 to December 2008, as we lose the first two-month observations due to data transformation before running PCA. The long time series for the rolling estimation window is essential because the number of components is determined by the Bai and Ng (2002) criterion (capped at five). With a window of this length, we obtain five factors in every period, ensuring a consistent factor count throughout the sample.

as the dependent variable and controlling for bond-specific systematic risk factors:

$$R^B_{i,t} - r^f_t = \alpha_i + \beta_{1,i}\hat{\epsilon}^\pi_t + \beta_{2,i}\hat{\epsilon}^\pi_{t-1} + \beta_i^{CBMKTRF} CBMKTRF_t + \beta_i^{DEF} DEF_t + \beta_i^{TERM} TERM_t + u_{i,t} \tag{4}$$

where $CBMKTRF$ is the corporate bond market factor defined as the value-weighted average of corporate bond returns in excess of the risk-free rate. The remaining control variables are the default (DEF) and the term structure ($TERM$) factors of Fama and French (1993).

Both Equations (3) and (4) include the lagged inflation innovation ϵ^π_{t-1} to account for the one-month lag in CPI data releases, as inflation figures for a given month are only made publicly available in the following month.[8] Thus, the inflation beta for each asset, β^π_i, is defined as the sum of the coefficients on the contemporaneous and lagged inflation innovations:

$$\beta^\pi_i = \beta_{1,i} + \beta_{2,i} \tag{5}$$

Moreover, we leave a one-month gap between the release of the CPI data (month when $\hat{\epsilon}^\pi_t$ is realized) and the portfolio formation date to account for the release lag, avoiding look-ahead bias.

3.4 Sample summary

Table 1 presents summary statistics for corporate emission measures, inflation betas, and other key variables over our sample period from June 2009 to December 2021.

Panel A shows that Scope 1 and Scope 2 carbon intensities have similar means, 2.67

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

and 2.69, respectively. However, their dispersion differs. The standard deviation of Scope 1 intensity (2.13) exceeds that of Scope 2 (1.29), indicating greater heterogeneity in firms' direct emissions.

In the equity market, the average firm is negatively exposed to headline and energy inflation (mean betas of -0.19 and -0.02) but positively exposed to core and food inflation (mean betas of 0.01 and 0.15). The median beta is negative for all four inflation measures. Exposures are more dispersed for core, headline, and food inflation than for energy inflation.

The average bond is negatively exposed to core and food inflation (mean betas of -0.05 and -0.17) but positively exposed to headline and energy inflation (0.16 and 0.03). Its median beta is negative for core, headline, and food inflation, and zero for energy. As in the equity sample, bond core inflation betas are the most variable, with a standard deviation of 5.20, compared with 2.73 for headline, 0.32 for energy, and 2.70 for food.

Finally, the baseline markup, defined as revenues over the cost of goods sold, averages 2.34, while the De Loecker et al. (2020) production-function markup averages 1.91. Both measures are strongly right-skewed. Equity cash-flow duration, constructed following Weber (2018), has a mean of 19.66 years and a standard deviation of 4.17. The average firm has Log(Sales) of 14.39, a market-to-book ratio of 3.35, market leverage of 0.34, a return on assets of 2.99%, and asset tangibility (PPE/AT) of 0.27. At the industry level, price stickiness averages -0.19 across 753 industries. We provide details on the construction of De Loecker et al. (2020) production-function markup and Weber (2018) equity cash-flow duration in Sections A and B of the Online Appendix.

4 Empirical results

4.1 Carbon intensity and inflation risk

The greenium may partly reflect an inflation risk premium if two key conditions hold. First, green firms exhibit greater inflation risk than brown firms, meaning that they underperform brown firms when inflation rises unexpectedly (a lower inflation beta). Second, inflation risk is priced in the cross-section of asset returns: investors demand higher returns to hold assets with greater inflation risk (a negative inflation risk premium). We begin our analysis with the first condition and ask whether green firms are more exposed to inflation risk than brown firms in the cross-section, based on carbon-sorted portfolio-level, industry-level, and firm-level analyses.

We begin with carbon-sorted portfolios. Following Zhang (2025), at the end of each month we sort stocks and bonds separately into terciles by their Scope 1 and Scope 2 carbon intensities and compute each portfolio's value-weighted return over the following month. For each tercile, we estimate a core inflation beta from a rolling-window regression of excess portfolio returns on contemporaneous and lagged inflation shocks, as in Equations (3) and (4). To isolate inflation exposure from other risk factors, we control for the Fama and French (2018) six factors in the equity regressions and for a corporate bond market factor together with the Fama and French (1993) term and default factors in the bond regressions. Finally, we apply the Dimson (1979) correction for the one-month CPI release lag.

The left panel of Figure 1 plots monthly risk-adjusted returns (α, in percent) with their 95% confidence intervals on the y-axis against time-series averages of the portfolios' time-varying core inflation betas on the x-axis, for value-weighted tercile portfolios sorted by

Scope 1 carbon intensity. "G", "M", and "B" denote the green (bottom tercile), medium (middle tercile), and brown (top tercile) portfolios, and "G-B" is the long-short portfolio that longs green and shorts brown. The figure shows that the green-minus-brown portfolio ("G-B") earns a statistically significant positive alpha, the "greenium" that captures the outperformance of green over brown firms after controlling for standard factor exposures (e.g., Pástor et al., 2022; Zhang, 2025; Duan et al., 2025). Importantly, the brown portfolio ("B") carries a higher core inflation beta than the green portfolio ("G"), indicating that carbon intensity and exposure to core inflation shocks are positively correlated. Because a higher inflation beta indicates that a portfolio performs better at times of inflation surprises, brown firms act as an inflation hedge while green firms do poorly at those times. This difference in core inflation exposure between green and brown firms points to an alternative explanation for the greenium.

To assess whether this difference is statistically significant, the right panel of Figure 1 plots time-series averages of the portfolios' time-varying core inflation betas with their 95% confidence intervals for value-weighted tercile portfolios sorted by Scope 1 carbon intensity. The green portfolio exhibits a significantly negative core inflation beta, while the brown portfolio's core inflation beta is significantly positive. Notably, the core inflation beta of the green-minus-brown long-short portfolio ("G-B") is significantly negative, which further supports the possibility that the core inflation exposure differential could be an alternative explanation for the greenium.

Also, carbon intensity and core inflation exposure line up the same way across industries. Figure A1 plots Scope 1 and Scope 2 carbon intensity (y-axis) against core inflation beta (x-axis) for each of the Fama-French 49 industries. The most carbon-intensive ("brown") industries, such as mining, steel, coal, and oil, have some of the highest core inflation betas, in line with Hong et al. (2022), further supporting the positive relation between carbon intensity and core inflation beta.

As a final piece of evidence, Table 2 reports the pairwise correlations among firm-level core, headline, energy, and food inflation betas and Scope 1 and Scope 2 carbon intensity. Every inflation beta except the food beta is positively and significantly correlated with carbon intensity, in both the equity and bond markets.

Taken together, the portfolio, industry, and firm-level results consistently point toward a coherent picture. Firms with higher carbon intensity tend to have higher core inflation betas (lower inflation risk). This satisfies the first of the two conditions we set out at the start of the section.

4.2 The pricing performance of inflation risk

We now ask whether core inflation risk is priced in the cross-section of stocks and bonds. The question is whether investors demand a risk premium for holding firms with high inflation risk (indicated by low inflation beta, implying a negative risk premium) during our sample period. To examine this, we sort stocks and corporate bonds separately into tercile portfolios at the end of each month on their one-month-lagged core inflation betas, estimated over a 60-month rolling window as in Equations (3) and (4).[9] For each tercile, we then compute value-weighted returns over the following month.

Table 3 reports monthly excess returns, risk-adjusted returns (α, in percent), and systematic factor exposures for value-weighted tercile portfolios sorted by core inflation beta.

[9] Assets are sorted at the end of month t using inflation betas estimated through month $t-1$, accounting for the one-month CPI release lag.

To isolate the inflation risk premium, we control for the Fama and French (2018) six factors for equity portfolios and for a corporate bond market factor together with the Fama and French (1993) term and default factors for bond portfolios. In the equity market (Panel A), the lowest-beta ('Low') stocks earn higher alphas than the highest-beta ('High') stocks. The alpha falls from 0.22% per month (t-value of 2.63) in the 'Low' tercile to -0.14% (t-value of -1.88) in the 'High' tercile. The long-short 'L-H' portfolio that longs 'Low' and shorts 'High' therefore earns a risk-adjusted return of 0.37% per month, or 4.44% per year, with a t-value of 2.86. The same pattern is observed in the bond market (Panel B), though more weakly, where the 'L-H' portfolio earns 0.08% per month (t-value of 2.26). These findings indicate that investors demand compensation for holding assets with low inflation betas (i.e., high inflation risk), as these assets tend to underperform during periods of high marginal utility driven by unexpected inflation shocks.

Recent studies in the asset pricing literature emphasize the significance of core inflation over headline inflation for the cross-section of equities (e.g., Fang et al., 2026; Hong et al., 2022). Motivated by these findings, we extend our analysis to examine the pricing of headline, energy, and food inflation risks in the cross-section of both stock and bond returns. Figure 2 plots monthly risk-adjusted returns (α) of value-weighted tercile portfolios sorted by inflation betas, alongside 95% confidence intervals. Panels A and B report the equity and bond results, respectively. Within each major panel, sub-panels a, b, c, and d display results for portfolios sorted by core, headline, energy, and food inflation betas, respectively. Sub-panel a demonstrates a significant negative risk premium for core inflation risk, as indicated by the significantly positive alpha of the low-minus-high portfolio ('L-H') based on terciles sorted by core inflation betas. In contrast, while the alpha for the low-minus-high portfolio sorted by headline inflation betas is significantly positive in the equity market, it becomes indistinguishable from zero in the bond market. Moreover, the low-minus-high portfolios sorted by energy and food inflation betas both earn a statistically insignificant risk-adjusted return across equity and bond markets, as indicated in sub-panels c and d of Figure 2. These results suggest that the pricing implications of headline inflation betas are exclusively driven by core inflation betas rather than the other two components of headline inflation. The consistent pricing of core inflation risk across asset classes aligns with recent studies, highlighting the importance of core inflation compared to headline inflation in explaining the cross-sectional variation in asset returns (e.g., Fang et al., 2026; Hong et al., 2022). Our results suggest that investors primarily demand compensation for exposure to core inflation risk rather than headline, energy, or food inflation risk.

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

4.3 Re-examining the greenium

In this subsection, we examine the extent to which the greenium can be attributed to differences in inflation risk exposure between green and brown firms. As a first step, we replicate the greenium, constructing a green-minus-brown (GMB) portfolio that longs the lowest-carbon tercile and shorts the highest-carbon tercile.

Table 4 reports the risk-adjusted returns (α) of portfolios sorted by Scope 1 and Scope 2 carbon intensity. The results confirm the presence of the greenium. The green-minus-brown (GMB) portfolios earn significantly positive alphas of 0.33% (t-value = 2.26) and 0.22% (t-value = 1.79) per month for Scope 1 and Scope 2, respectively. These alphas are comparable to those reported by Zhang (2025) for the same period, who documents alphas of 0.40% (t-value = 2.51) and 0.34% (t-value = 2.40) per month for Scopes 1 and 2 GMB portfolios, respectively. The Scope 1 greenium also holds in the bond market, where the GMB portfolio earns a significantly positive alpha of 0.18% per month (t-value = 1.99). This is consistent with Duan et al. (2025), who find that the Scope 1 greenium ranges from 0.11% to 0.13% per month across different specifications over July 2006 to June 2019.

We then assess whether the magnitude of the greenium changes when accounting for differences in inflation risk exposure between green and brown firms. To this end, we employ a double-sorting approach. First, we separately sort stocks and bonds into terciles based on their core inflation betas. Subsequently, within each tercile sorted by core inflation betas, we further sort stocks or bonds into terciles based on their carbon intensity. This procedure allows us to construct green-minus-brown (GMB) portfolios where the brown and green portfolios have similar levels of core inflation betas.

The first two columns of Table 5 report raw returns for the inflation-risk-controlled green, medium, and brown portfolios and the green-minus-brown (GMB) portfolio, together with the GMB alpha, for both Scope 1 and Scope 2 carbon intensity. The last two columns report the single-sort results from Table 4 for comparison. Once core inflation risk is accounted for, the GMB alphas shrink substantially and lose statistical significance. In the equity market, the inflation-risk-controlled GMB earns alphas of 0.21% (t-value = 1.51) and 0.17% (t-value = 1.48) per month for Scopes 1 and 2, respectively. These values indicate a substantial reduction in the greenium by 36% and 23% for Scopes 1 and 2 compared to the single-sorted results in Table 4. Furthermore, the alphas of these inflation-risk-controlled GMB portfolios are not statistically distinguishable from zero at conventional significance levels. The same pattern holds in the bond market, with a smaller magnitude. The monthly alpha of the Scope 1 GMB portfolio declines by 11% to 0.16% (t-value = 1.95).

The findings in this subsection provide evidence that the greenium is partly attributable to the compensation for core inflation risk. By accounting for the core inflation risk exposure of green and brown firms, we find that a substantial portion of the greenium disappears, and in the equity market, it is no longer statistically significant. This suggests that the outperformance of green firms relative to brown firms is to a considerable extent a reflection of the inflation risk premium, rather than being entirely driven by investors' preference for green firms amid an ongoing transition to a carbon-aware equilibrium. Our findings underscore the importance of core inflation risk when examining the greenium.

4.4 Are results driven by a few industries?

A natural concern is that a few industries drive our results. A handful of carbon-intensive sectors, such as mining, steel, and coal, carry by far the highest inflation betas. If those same sectors also account for the greenium, the link we document would be a narrow industry effect rather than a general feature of green and brown firms.

To address this concern, we repeat our tests by excluding the following industries from our sample among the Fama-French 49 industry classifications. For equities, they are Steel Works ('Steel'), Coal ('Coal'), and Entertainment ('Fun'). For bonds, they are non-metallic and industrial metal mining ('Mines'), rubber and plastic products ('Rubbr'), and petroleum and natural gas ('Oil'). These industries exhibit the highest inflation betas among all industries, as shown in Figure A1.

We perform these tests by progressively filtering the sample. Specifically, we first exclude the Steel industry for equities and the Mines industry for bonds, as these industries exhibit the highest inflation betas in their respective markets. Then, we progressively exclude additional industries to more broadly define the group of high-inflation industries. For each exclusion scenario, we repeat both our single-sorting and double-sorting procedures to assess how the greenium magnitude changes after accounting for core inflation beta. This approach allows us to assess whether the explanatory power of inflation risk for the greenium remains consistent or varies significantly when the most carbon-intensive industries are removed from consideration.

Table 6 reports the greenium for single sorts ('Single') and for double sorts that control for core inflation beta ('Double'). The first two columns of each panel repeat the all-industry baseline from Table 5. The result shows that the ability of core inflation beta to explain the greenium remains robust even after systematically excluding the most carbon-intensive and inflation-sensitive sectors.

In the equity market, when the 'Steel' and 'Coal' industries are removed, the greenium slightly decreases to 0.31% (0.20%) for Scope 1 (2), respectively, without controlling for inflation beta. After controlling for inflation beta, the Scope 1 (2) greenium drops to 0.21% (0.16%), representing a decrease of 32% (20%). The values remain virtually unchanged throughout the sequential exclusion procedure. Even after removing all three high-beta industries, the Scope 1 greenium only marginally drops to 0.3% (t-value = 2.05) per month while remaining statistically significant. However, it shrinks to 0.2% (t-value = 1.45) per month after controlling for inflation beta. The Scope 2 greenium essentially disappears after these exclusions.

We observe a similar robustness in the corporate bond market. For example, when the 'Mines' industry is excluded, the Scope 1 greenium is 0.19% (t-value = 2.01) without controlling for inflation betas and decreases to 0.15% (t-value = 1.92) after controlling for inflation betas, reinforcing the baseline results.

Together, this evidence indicates that our main findings are not driven by the most inflation-hedging industries. Even after excluding these industries, accounting for the differential inflation risk exposure of green and brown firms significantly decreases the greenium magnitude.

4.5 Can the greenium explain the inflation risk premium?

Our analyses show that the greenium partly reflects compensation for the higher inflation risk green assets carry. A natural question follows: can the inflation risk premium itself be explained by the greenium? Put differently, is the risk premium investors demand for holding high-inflation-risk assets a reflection of firms' environmental characteristics and green preference? Answering this is important for understanding the relative roles of inflation risk and environmental factors in driving cross-sectional return variation.

To address this question, we employ the same double-sorting approach as before. Each month, we sort stocks and bonds into terciles on Scope 1 or Scope 2 carbon intensity, and then sort on core inflation beta within each carbon tercile. This procedure isolates variation in inflation risk while holding carbon intensity approximately constant. Table 7 reports the resulting excess returns, along with the excess and risk-adjusted returns of the long-short portfolio that longs the lowest inflation-beta tercile and shorts the highest. The last column repeats the single-sort results from Table 3, where carbon intensity is not controlled for.

In the equity market, the inflation risk premium remains robust after controlling for carbon intensity. The risk-adjusted return of the long-short inflation beta portfolio declines only modestly from 0.37% to 0.29% (0.31%) for Scope 1 (2). Importantly, the inflation risk premium remains statistically significant at conventional levels with t-values of 2.14 (2.81) for Scope 1 (2), respectively. This modest attenuation indicates that, in equity markets, inflation risk captures a distinct economic dimension that the greenium does not subsume.

The corporate bond market shows a different pattern. After controlling for carbon intensity, the risk-adjusted return of the long-short inflation-beta portfolio falls from 0.08%

to 0.05% for both Scope 1 and Scope 2 and is no longer statistically significant. This finding suggests that the inflation risk premium in the corporate bond market reflects firms' environmental characteristics and green preference to some extent.

5 Mechanism

Our findings so far have demonstrated that green firms earn higher realized returns than brown firms because they are more negatively exposed to core inflation shocks, with investors demanding a premium for bearing this additional risk. However, an important question remains: Why do green firms exhibit greater negative sensitivity to core inflation than brown firms in the first place? In this section, we propose and empirically test three economic mechanisms that manifest through industry- and firm-level characteristics: the stickiness of product prices, markups, and cash flow duration.

5.1 Green industries have higher price stickiness

The first mechanism is the stickiness of output prices. Fang et al. (2026) (FLR2026, hereafter) build this friction into a two-sector New Keynesian asset-pricing model in which a negative productivity shock raises marginal cost, and hence core inflation, while depressing output. Because firms with stickier price pass the cost shock through to prices less flexibly, their margins and cash flows fall more than other firms as core inflation rises, and thus the stickier their prices, the more negative their core inflation beta.[10] FLR2026 derive this prediction from a cross-economy comparison of one-sector calibrations. In Online Ap-

[10] The same link between price rigidity and risk exposure is well established in the broader asset-pricing literature. Weber (2015) shows that firms that adjust their output prices infrequently are riskier than flexible-price firms. Gorodnichenko and Weber (2016) similarly find that price rigidity heightens a firm's sensitivity to aggregate shocks.

pendix C, we extend their model to two sectors within one economy that differ only in price stickiness and confirm that the prediction also holds in the within-economy cross-section: the stickier sector has a more negative core inflation beta. Our first hypothesis is therefore that green firms carry greater core inflation risk because their output prices are stickier than those of brown firms.

Following Li et al. (2021), we construct industry-level price stickiness as the negative of the frequency of price adjustment (FPA) at the 6-digit NAICS level computed by Pasten et al. (2020). Higher values correspond to industries in which firms adjust their output prices less frequently. We run the following regression:

$$Price\ Stickiness_j = \alpha + \beta \cdot Carbon\ Intensity_{jt} + \lambda \cdot Controls_{jt} + \nu_t + \varepsilon_{jt}, \tag{6}$$

where $Price\ Stickiness_j$ denotes time-invariant industry-level price stickiness, and $Carbon\ Intensity_{jt}$ is industry-level Scope 1 or Scope 2 carbon intensity. $Controls_{jt}$ denotes a set of industry-level control variables, and ν_t denotes time fixed effects.

In this regression analysis, we include a comprehensive set of industry characteristics as control variables: *Log(Sales)* is the natural logarithm of sales. *ME/BE* is the market value of equity divided by the book value of equity. *Leverage* is the market leverage, defined as book value of debt divided by the sum of the book value of debt and the market value of equity. *ROA* is return on assets, defined as income before extraordinary items divided by lagged total assets. Finally, *PPE/AT* is asset tangibility, defined as net property, plant, and equipment divided by lagged total assets. The firm-level controls are trimmed at the 1st and 99th percentiles by year. We aggregate firm characteristics to the industry-year level by taking sales-weighted averages within each 6-digit NAICS sector and year (De Loecker et al., 2020; Gilchrist et al., 2017; Autor et al., 2020). The regression is conducted at the industry-year level, controlling for year fixed effects. As we examine cross-sectional comparisons, we do not include industry fixed effects. Standard errors are clustered at the 6-digit NAICS level.

Table 8 presents the results for Equation (6). Columns (1) and (3) report results of univariate regressions, while Columns (2) and (4) include control variables in regressions. Across all specifications, both Scopes 1 and 2 carbon intensities are significantly and negatively correlated with price stickiness at the industry level. More specifically, the coefficient on carbon intensity is highly significant at -0.04 irrespective of the scope considered in univariate regressions. Controlling for industry-level characteristics only marginally decreases the economic magnitude of coefficients to -0.03 (t-value = -4.42) for Scope 1 carbon intensity and to -0.02 (t-value = -1.84) for Scope 2 carbon intensity. The robust negative coefficients imply that green industries adjust output prices less frequently than brown industries. In sum, green industries' higher price stickiness translates into a diminished ability to absorb or capitalize on inflation shocks. Consequently, firms in green industries are more vulnerable to unexpected inflation and have lower core inflation betas.

5.2 Green firms have higher markups

The second mechanism is markup, a related but distinct feature of price setting. In FLR2026, stickiness and markup are two sides of the same friction. Stickiness limits a firm's ability to reset prices when marginal cost rises, while markup controls its incentive to do so. A firm facing less elastic demand has more market power and a higher markup, and because its customers are slow to switch away, it has little incentive to realign price with marginal cost. Its prices then adjust sluggishly, much as sticky prices do, and thus a cost shock compresses margins instead of passing through to output prices, which leads high-markup firms to have the same negative core inflation beta as sticky-price firms. As with price stickiness, FLR2026 obtain this prediction from a cross-economy comparison of one-sector calibrations. In Online Appendix C, our two-sector extension delivers the same prediction in a within-economy cross-section, where the higher-markup sector earns a higher equity premium and has a more negative core inflation beta. Our second hypothesis is therefore that green firms carry greater core inflation risk because their markups are higher.

To empirically examine this economic mechanism, we estimate the following firm-year panel regression:

$$Markup_{it} = \alpha + \beta \cdot Carbon\ Intensity_{it} + \lambda \cdot Controls_{it} + \nu_t + \varepsilon_{it}, \tag{7}$$

where $Markup_{it}$ denotes markup of firm i in year t, and $Carbon\ Intensity_{it}$ is firm-level Scope 1 or Scope 2 carbon intensity in year t. $Controls_{it}$ denotes a set of firm-level control variables, and ν_t denotes time fixed effects.

We employ two markup measures. The first is the baseline accounting markup, defined as the ratio of revenues to the cost of goods sold. The second is the production-function markup of De Loecker et al. (2020), constructed as the industry-year output elasticity of the cost of goods sold (estimated at the 2-digit NAICS level) multiplied by the firm-year ratio of deflated sales to deflated cost of goods sold.[11] The latter measure isolates the wedge between price and marginal cost, accounting for industry-year variation in production tech-

[11]Online Appendix Section A provides details on the construction of this measure.

nology. In each specification, we include year fixed effects and a set of firm-level controls: *Log(Sales)*, *ME/BE*, *Leverage*, *ROA*, and *PPE/AT*. The firm-level controls are trimmed at the 1st and 99th percentiles by year. Standard errors are clustered at the firm level.

Table 9 reports the results. Columns (1) to (4) use the baseline accounting markup, while Columns (5) to (8) use the production-function markup from De Loecker et al. (2020). Across all eight specifications, the coefficient on carbon intensity is negative and statistically significant at the 1% level. For the baseline markup, a one-unit increase in Scope 1 (Scope 2) carbon intensity is associated with a decrease in markup of 0.28 (0.47) in the univariate regression, and 0.20 (0.34) after the inclusion of firm controls, with t-values ranging from -8.02 to -10.86. The production-function markup yields qualitatively similar conclusions, with conditional coefficients of -0.13 for Scope 1 and -0.23 for Scope 2, both significant at the 1% level. Online Appendix Table A3 reports qualitatively similar results using three alternative markup constructions following De Loecker et al. (2020). These results suggest that green firms have systematically greater pricing power than brown firms. When core inflation shocks increase input prices, green firms with higher markups take longer to adjust their output prices and experience a greater erosion of their profits. As a result, green firms perform worse during core inflation shocks and have lower core inflation betas.

5.3 Green firms have longer cash flow duration

The third mechanism links core inflation risk to the timing of a firm's cash flows. A firm whose value is concentrated in distant cash flows has greater price sensitivity to discount-rate shocks (Campbell and Vuolteenaho, 2004; Gormsen and Lazarus, 2023). A core inflation shock raises discount rates, largely through the monetary tightening it triggers

(FLR2026). Long-duration firms therefore lose more value than short-duration firms when core inflation rises, generating a more negative core inflation beta. Consistent with this channel, Gil de Rubio Cruz et al. (2023) find that stock prices fall in response to core inflation surprises through a monetary-policy expectations channel, and that this sensitivity is more pronounced among low-book-to-market, long-duration firms. Our model in Section 6 also shows shows that even when green and brown firms have the same price stickiness and markup, the green firm is more negatively exposed to core inflation risk due to duration. Our third hypothesis is therefore that green firms carry greater core inflation risk because their cash flows are longer-dated than those of brown firms.

We test this prediction by estimating the following firm-year panel regression:

$$Cash\ Flow\ Duration_{it} = \alpha + \beta \cdot Carbon\ Intensity_{it} + \lambda \cdot Controls_{it} + \nu_t + \varepsilon_{it}, \tag{8}$$

where $Cash\ Flow\ Duration_{it}$ denotes cash flow duration of firm i in year t, and $Carbon\ Intensity_{it}$ is firm-level Scope 1 or Scope 2 carbon intensity in year t. $Controls_{it}$ denotes a set of firm-level control variables, and ν_t denotes time fixed effects.

We construct cash flow duration following Weber (2018), which is computed from forecasted return on equity, book-equity growth, and a terminal-value adjustment.[12] In each specification, we include year fixed effects and the same set of firm-level controls as above. The duration measure and the firm-level controls are trimmed at the 1st and 99th percentiles by year. Standard errors are clustered at the firm level.

Table 10 shows that green firms hold cash flows that are generated further into the future. In the univariate specification, the coefficient on Scope 1 (Scope 2) carbon intensity

[12]Online Appendix Section B provides details on the construction of this measure.

is -0.50 (-0.42), both significant at the 1% level (t-values of -8.85 and -4.65). The Scope 1 result is robust to the inclusion of firm-level controls, with a coefficient of -0.25 and a t-value of -4.56. The Scope 2 coefficient attenuates to -0.06 and loses significance once firm-level controls are added, suggesting that for Scope 2 the duration gap is largely subsumed by these characteristics. Taken together, the results imply that green firms generate a disproportionate share of their value from cash flows in the distant future. Such a time profile of expected cash flows makes them more sensitive to discount-rate revisions induced by core inflation shocks.

In sum, the three mechanisms together explain why, in the cross-section, green firms carry higher core inflation risk than their brown counterparts. Green firms operate in industries in which output prices adjust less frequently, charge higher markups, and hold cash flows that are more concentrated in the distant future. These results rationalize the link between carbon intensity and core inflation risk documented in Section 4 and help explain why the greenium partly reflects the core inflation risk premium. Section 6 embeds the markup and stickiness gaps, from which the duration channel emerges endogenously, together with a time-varying investor green preference, in a quantitative asset-pricing model and asks whether they can account for the magnitude of the greenium and of its reduction.

6 Model of the Greenium and Quantitative Analysis

In this section, we propose a model that provides an economic mechanism for our empirical findings. To this end, we extend the New Keynesian asset-pricing model of FLR2026 in two directions. First, we split the core sector into a green firm and a brown firm that differ in market power and price stickiness. Second, we introduce an investor green preference in the form of the dynamic green preference (ESG demand) of Avramov et al. (2024), which allows the model to capture the taste-based component of the greenium. The key finding is that the calibrated model generates a raw greenium of 0.337% (not targeted) per month compared with 0.33% in the data. Shutting down the differential exposure to core inflation in the model reduces the greenium to 0.209% (targeted), similar to 0.21% in the data, obtained by the portfolio double sorting. These magnitudes imply a 38% reduction in the model, compared to 36% in the data, which are not targeted by the calibration.

6.1 The economy

6.1.1 Households

There is a representative household with the recursive utility of Epstein and Zin (1989):

$$U_t = \left[(1-\delta)\,\widetilde{C}_t^{1-1/\psi} + \delta\, E_t\big[U_{t+1}^{1-\gamma}\big]^{\frac{1-1/\psi}{1-\gamma}}\right]^{\frac{1}{1-1/\psi}}, \tag{9}$$

where δ is the discount factor, ψ is the intertemporal elasticity of substitution, and γ is risk aversion. The composite $\widetilde{C}_t$ aggregates consumption and leisure, $\widetilde{C}_t = \big[\frac{1}{1+\omega} C_t^{(\xi_l-1)/\xi_l} + \frac{\omega}{1+\omega}\big(N_{t-1}(\bar{L}-L_t)\big)^{(\xi_l-1)/\xi_l}\big]^{\xi_l/(\xi_l-1)}$, where ξ_l is the consumption–leisure elasticity and leisure is scaled by the permanent productivity component N_{t-1}. Consumption aggregates a core bundle and energy with elasticity ϕ and the relative energy demand shock η_t:

$$C_t = \left[\alpha_c\, C_{c,t}^{\frac{\phi-1}{\phi}} + (1-\alpha_c)\,\big(e^{\eta_t} C_{e,t}\big)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}, \tag{10}$$

Different from FLR2026, the core sector consists of two firms, which we label green and brown and index by $j \in \{G, B\}$. The two firms produce with the same technology and face the same representative household, which consumes both goods, supplies labor to both firms at a common wage, and owns both firms' equity. They differ only in their price setting and in their greenness, and we introduce each difference where it enters the model below. [13] The core bundle aggregates the two firms' goods with across-firm elasticity ϕ_f and share s_G,

$$C_{c,t} = \left[s_G^{1/\phi_f} \, C_{G,t}^{\frac{\phi_f - 1}{\phi_f}} + (1 - s_G)^{1/\phi_f} \, C_{B,t}^{\frac{\phi_f - 1}{\phi_f}} \right]^{\frac{\phi_f}{\phi_f - 1}}, \qquad C_{j,t} = s_j \, p_{j,t}^{-\phi_f} \, C_{c,t}, \tag{11}$$

where $p_{j,t} = P_{j,t}/P_{c,t}$ is firm j's relative price and the core price index is the numeraire, $1 = \sum_j s_j \, p_{j,t}^{1-\phi_f}$. The stochastic discount factor (SDF) in core-goods units is

$$M_{t+1} = \delta \left(\frac{C_{t+1}}{C_t} \right)^{-1/\xi_l} \left(\frac{\widetilde{C}_{t+1}}{\widetilde{C}_t} \right)^{1/\xi_l - 1/\psi} \frac{(C_{t+1}/C_{c,t+1})^{1/\phi}}{(C_t/C_{c,t})^{1/\phi}} \left(\frac{U_{t+1}^{1-\gamma}}{E_t U_{t+1}^{1-\gamma}} \right)^{1 - \frac{1}{\theta}}, \tag{12}$$

where $\theta = \frac{1-\gamma}{1-1/\psi}$

6.1.2 Green preference

Following Avramov et al. (2024), investors derive a nonpecuniary benefit from the greenness of their portfolio, and the benefit fluctuates over time with the intensity of green preference, denoted χ_t. Greenness is a firm attribute g_j, normalized to $g_G = +\frac{1}{2}$ for the green firm and $g_B = -\frac{1}{2}$ for the brown firm. The Euler equation for firm j's equity then carries a convenience yield:

$$E_t \left[M_{t+1} R_{j,t+1} \right] = 1 - \chi_t \, g_j. \tag{13}$$

Green equity is held at a lower required return and brown equity must pay a premium, with the wedge moving over time as green preference strengthens or fades. The green preference

[13] One might ask why both firms belong to the core sector rather than mapping the brown firm into the energy sector. The energy sector in FLR2026 is an exogenously supplied endowment whose price clears household demand, with no markup, no price-setting friction, and no Phillips curve, whereas our risk channel is a difference in core-sector price stickiness and markups that generates a differential core inflation beta. Therefore, mapping the brown firm to the energy sector removes the very price-setting heterogeneity that generates this core inflation beta difference and would tie the green-minus-brown spread to energy inflation rather than to the priced core inflation factor.

state follows

$$\chi_t = (1-\rho_\chi)\,\bar{\chi} + \rho_\chi\,\chi_{t-1} + \sigma_\chi\,\varepsilon_{\chi,t}, \qquad \varepsilon_{\chi,t} \sim N(0,1), \tag{14}$$

where $\varepsilon_{\chi,t}$ captures shocks to green preference (e.g., climate regulation). With $g_G - g_B = 1$, χ_t captures the green-minus-brown convenience-yield spread per quarter.[14]

6.1.3 Green and brown producers

Each firm $j \in \{G, B\}$ aggregates a continuum of its own intermediate varieties $X_{j,i,t}$, $i \in [0,1]$, into its output $Y_{j,t}$ through a CES aggregator with elasticity ν_j,

$$Y_{j,t} = \left(\int_0^1 X_{j,i,t}^{\frac{\nu_j - 1}{\nu_j}}\, di \right)^{\frac{\nu_j}{\nu_j - 1}}, \qquad j \in \{G, B\}, \tag{15}$$

which pins down the firm's steady-state markup $\mu_j = \nu_j/(\nu_j - 1)$. Guided by the evidence in Table 9, we set the green firm's intermediate-variety elasticity to the lower value, $\nu_G < \nu_B$, and hence the higher markup. Varieties are produced with the shared technology $X_{j,i,t} = K_{j,i,t}^{\alpha}(Z_t L_{j,i,t})^{1-\alpha}$, where aggregate productivity $Z_t = A_t N_{t-1}$ combines a transitory component A_t and a permanent component N_{t-1}. Following FLR2026, the transitory component, the permanent component, and the log-volatility state h_t are driven by the common

[14] We let χ_t enter only the Euler equation in (13), and not the SDF (12) or any real optimality condition. Real allocations, cash flows, and therefore core inflation betas are invariant to the taste process by construction. As a result, the risk channel, which generates differential core inflation exposure, and the taste channel can be switched on and off independently, which is the model feature that allows the model to mimic our empirical double sorting to create the two stocks with a similar core inflation exposure. In Avramov et al. (2024), the taste state also enters the SDF, and shocks to green preference (coined as ESG demand in their paper) therefore earn a risk premium. Our wedge-only specification corresponds to a separable convenience flow on equity holdings and omits that channel, which is second order at $\bar{\chi} = 0$ given the small σ_χ we calibrate. Omitting it keeps the counterfactuals clean: if χ_t entered the SDF, switching the taste channel off would change every asset price and beta, and the risk-only case of Section 6.3 would no longer isolate the risk component.

productivity shock $\varepsilon_{n,t}$,

$$\begin{aligned} a_t &= (1-\rho)\, a_0 + \rho\, a_{t-1} + \varphi_a\, \sigma_n e^{h_{t-1}} \varepsilon_{n,t}, \\ \varDelta n_t &= \rho_n\, \varDelta n_{t-1} + \varphi_n\, \sigma_n e^{h_{t-1}} \varepsilon_{n,t}, \\ h_t &= \rho_h\, h_{t-1} - \sigma_h\, \varepsilon_{n,t}, \end{aligned} \tag{16}$$

where $a_t \equiv \log A_t$ has long-run mean a_0, $\varDelta n_t \equiv \log N_t - \log N_{t-1}$ is the permanent growth rate, the coefficients ρ, ρ_n, and ρ_h are persistences, the loadings φ_a and φ_n split the common shock (scaled by σ_n) between the two components, and the negative loading σ_h on h_t makes volatility countercyclical. Each variety producer accumulates its own capital subject to a convex adjustment cost,

$$\begin{aligned} K_{j,i,t+1} &= (1-\delta_k)\, K_{j,i,t} + \varPhi_K\left(\tfrac{I_{j,i,t}}{K_{j,i,t}}\right) K_{j,i,t}, \\ \varPhi_K\left(\tfrac{I_{j,i,t}}{K_{j,i,t}}\right) &= \frac{a_{1,k}}{1-1/\xi_k} \left(\tfrac{I_{j,i,t}}{K_{j,i,t}}\right)^{1-1/\xi_k} + a_{2,k}, \end{aligned} \tag{17}$$

where δ_k is the depreciation rate, $I_{j,i,t}$ is investment, ξ_k sets the elasticity of the adjustment-cost technology, and $a_{1,k}$ and $a_{2,k}$ are normalization constants.

Producers face a quadratic Rotemberg price-adjustment cost with a firm-specific coefficient $\phi_{P,j}$, $\varPhi_{p,j,t} = \frac{\phi_{P,j}}{2}\left(\varPi_{j,t}/\varPi_{ss} - 1\right)^2 Y_{j,t}$, where $\varPi_{j,t} = P_{j,t}/P_{j,t-1}$ is firm j's gross price inflation. Consistent with Table 8, the green firm has the higher adjustment cost, $\phi_{P,G} > \phi_{P,B}$, and therefore the stickier prices. Firm j's free cash flow in numeraire units is

$$D_{j,t} = p_{j,t} Y_{j,t} - W_t L_{j,t} - I_{j,t} - p_{j,t}\, \varPhi_{p,j,t}, \tag{18}$$

and each firm maximizes the present value of (18) discounted with the SDF (12). The resulting optimal-pricing condition is the two-firm analog of FLR2026's Rotemberg first-order condition, and its linearization gives the firm-level Phillips curve

$$\pi_{j,t} = \beta_E \, E_t \, \pi_{j,t+1} + \kappa_j \big(\widehat{mc}_t - \hat{p}_{j,t}\big), \qquad \kappa_j = \frac{\nu_j - 1}{\phi_{P,j}}, \tag{19}$$

where mc_t is the marginal cost shared across firms and β_E is the Phillips-curve discount coefficient.[15]

The slope κ_j summarizes the risk channel. Both price-setting differences flatten the green firm's Phillips curve, since $\nu_G < \nu_B$ lowers the numerator and $\phi_{P,G} > \phi_{P,B}$ raises the denominator. After a negative productivity realization, marginal cost and core inflation rise while the green firm passes through less of the cost increase. Its margin absorbs the shock, and its value falls in the states in which core inflation rises. Green cash flows therefore have a more negative core inflation beta. Because core inflation is supply-driven and countercyclical in this economy, its price of risk is negative, and the green firm earns a higher expected return, the risk component of the greenium.

6.1.4 Energy, monetary policy, and equity claims

The remaining blocks follow FLR2026, and we state them here so that the model is self-contained. Energy is an exogenous endowment. Its supply and the relative energy-demand shifter η_t of (10) follow

$$\log C_{e,t} = (1 - \rho_e) \log C_{e,ss} + \rho_e \log C_{e,t-1} + \sigma_e \, \varepsilon_{e,t}, \qquad \eta_t = \rho_\eta \, \eta_{t-1} + \sigma_\eta \, \varepsilon_{\eta,t} + \delta_a \, \varepsilon_{n,t}, \tag{20}$$

[15] The full nonlinear system (factor demands, capital accumulation, the sectoral resource constraints $Y_{j,t} = C_{j,t} + I_{j,t} + \Phi_{p,j,t}$, and the aggregate core inflation identity $\log \Pi_t = \sum_j s_j [\log \Pi_{j,t} + \log p_{j,t-1} - \log p_{j,t}]$) parallels FLR2026 firm by firm and collapses to their one-sector economy when $\nu_G = \nu_B$, $\phi_{P,G} = \phi_{P,B}$, and $\sigma_\chi = 0$ (Online Appendix C). We solve the model by third-order perturbation with pruning and compute unconditional moments on a 25,000-quarter simulation.

where $\varepsilon_{n,t}$ is the common productivity shock and the loading $\delta_a > 0$ makes energy demand procyclical. The household's intratemporal first-order condition prices energy in core-bundle (numeraire) units,

$$P_{e,t} = \frac{1-\alpha_c}{\alpha_c}\, e^{\eta_t \frac{\phi-1}{\phi}} \left(\frac{C_{c,t}}{C_{e,t}}\right)^{1/\phi}. \tag{21}$$

Monetary policy sets the gross one-period nominal rate R_t through a Taylor rule on core inflation Π_t and output Y_t,

$$\log R_t = \rho_r \log R_{t-1} + (1-\rho_r)\Big[\log R_{ss} + \rho_\pi \log \tfrac{\Pi_t}{\Pi_{ss}} + \rho_y \log \tfrac{Y_t}{Y_{ss}}\Big] + \sigma_m\, \varepsilon_{m,t}, \tag{22}$$

and the headline good combines one unit of core with one unit of energy, which links the model's core inflation to the measured CPI against which our betas are estimated,

$$\Pi_{h,t} = \frac{1+P_{e,t}}{1+P_{e,t-1}}\, \Pi_t. \tag{23}$$

Nominal claims are valued in units of the core price index, and the nominal stochastic discount factor is M_{t+1}/Π_{t+1}. The one-period bond, the n-period term-structure cascade, and the complete-markets nominal exchange rate S_t satisfy

$$1 = E_t\big[M_{t+1} R_t/\Pi_{t+1}\big], \qquad P_t^{(n)} = E_t\big[M_{t+1} P_{t+1}^{(n-1)}/\Pi_{t+1}\big], \qquad \frac{S_t}{S_{t-1}} = \frac{M^*_{t+1}/\Pi^*_{t+1}}{M_{t+1}/\Pi_{t+1}}, \tag{24}$$

where the foreign nominal discount factor M^*_{t+1}/Π^*_{t+1} is exogenous with persistence ρ_{fx} and innovation ξ_{t+1}. The economy is driven by six structural shocks, namely the common productivity shock $\varepsilon_{n,t}$ with transitory and permanent components and stochastic volatility, the energy-supply shock $\varepsilon_{e,t}$, the energy-demand shock $\varepsilon_{\eta,t}$, the monetary shock $\varepsilon_{m,t}$, the foreign-discount-factor shock ξ_t, and the taste shock $\varepsilon_{\chi,t}$.

Each firm has a traded equity claim on its dividend stream. Using (13), the price equation is

$$P_{s,j,t}\,\big(1-\chi_t\,g_j\big)=E_t\big[M_{t+1}\big(P_{s,j,t+1}+D_{j,t+1}\big)\big],\qquad j\in\{G,B\},\tag{25}$$

and reported returns apply FLR2026's leverage convention. An unexpected shock of green preference lowers the green discount rate and raises the brown one. Because ρ_χ is close to one and equity duration is long, small convenience-yield surprises generate large repricing.[16] Over a sample with repeated positive surprises, green outperforms brown for reasons unrelated to inflation exposure, even though by the end of such a sample the accumulated convenience yield makes green's expected return lower. This is the expected-versus-realized distinction stressed by Pástor et al. (2022). For the nesting exercises, we also track the aggregate equity claim on $D_{G,t}+D_{B,t}$ plus the energy dividend $\alpha\,C_{e,t}P_{e,t}$, which has no taste wedge.

6.2 Calibration

Table 11 reports the selected parameter values for calibration. For all parameters that are common with FLR2026, we take their values, which preserves the macroeconomic and aggregate asset-pricing performance of the nested model (Online Appendix Table A4). The elasticity of substitution between the two firms' goods and share are symmetric, $\phi_f=2$ and $s_G=0.5$.

The price-setting gap is disciplined by our own evidence in Section 5. We set $(\nu_G,\nu_B)=(3.5,12)$, implying steady-state markups of 1.40 versus 1.09, consistent with the markup differential documented in Table 9 and anchored near FLR2026's baseline of $\nu=6$. We set

[16] Log-linearizing (25), the price impact of a taste surprise is approximately $g_j\,\chi_t/(1-\overline{Mg}\,\rho_\chi)$ with $\overline{Mg}\approx 0.995$, a multiplier of about 170. The effective revaluation in the third-order solution is smaller and state-dependent because equity is priced at a risky price–dividend ratio well below its deterministic value. The drift calibration in Section 6.3 is performed on the full nonlinear simulation and absorbs this automatically.

$(\phi_{P,G}, \phi_{P,B}) = (130, 30)$, which maps through the standard Calvo–Rotemberg bridge into average price durations of 7.9 versus 2.2 quarters, the model counterpart of the frequency-of-price-adjustment gap in Table 8.[17]

The taste process has three parameters. The persistence $\rho_\chi = 0.999$ follows Avramov et al. (2024), who constrain green preference to be near unit root, and the loading $\sigma_\chi = 8.6 \times 10^{-5}$ is of the same order as their estimate.[18] The remaining parameter, the average greening surprise d^* defined in the next subsection, is calibrated so that the controlled greenium matches its empirical value of 0.21% per month.

6.3 The greening decade and the model double sort

We now ask whether the calibrated model generates the greenium and its reduction once controlling for core inflation risk exposure with similar magnitudes as in empirical counterparts. We generate 4,000 simulated economies. Each simulation path consists of a 60-quarter burn-in period in which the taste innovations are set to zero, followed by a 50-quarter sample that reflect our sample period from June 2009 to December 2021, in which taste shocks are drawn with a positive mean, $\varepsilon_{\chi,t} \sim N(d^*, 1)$ with $d^* > 0$. Within each 50-quarter sample, we compute quarterly levered excess returns for the two stocks and record the mean green-minus-brown spread in percent per month, averaging across 4,000 simulated economies. We conduct this calibration exercise under four cases of the model: (1) the full case has heterogeneous price-setting parameters $(\nu_G, \phi_{P,G}) \neq (\nu_B, \phi_{P,B})$ and green

[17] The bridge equates the linearized Phillips-curve slopes of the two pricing schemes, $\phi_{P,j} = (\nu_j - 1)\theta_j / [(1-\theta_j)(1 - \delta\theta_j)]$, where θ_j is the Calvo (1983) probability of not resetting the price and the implied average price duration is $1/(1-\theta_j)$.

[18] Avramov et al. (2024) set the persistence of green preference to 0.9999 and estimate a mean of 0.00046 and an innovation volatility of 0.00004. We set $\bar{\chi} = 0$ so that the model's pre-2009 economy is taste-neutral and the greening decade arrives as a sequence of surprises.

preference $\chi_t \neq 0$, and its greenium is the model counterpart of the empirically observed raw greenium in Table 4; (2) the controlled case keeps green preference on but equalizes the two firms' price-setting parameters. Setting $(\nu_j, \phi_{P,j})$ equal across firms eliminates the difference in firms' core inflation betas by construction while leaving the investor's green preference intact, which makes the case (2) the structural analog of our double sort in Table 5: it compares green and brown firms with a matched level of core inflation exposure; (3) The risk-only case keeps the heterogeneous frictions but shuts off green preference $\chi_t = 0$, which isolates the inflation risk component; and (4) the placebo case shuts both channels off. Because all shock draws are identical across model cases, comparisons across cases are not subject to simulation noise.

Panel A of Table 12 presents the model's greenium with its empirical counterpart. Case (1) shows that the model's raw greenium is 0.337% per month compared to 0.33% in the data presented in Table 4. Case (2) shows that controlling for core inflation exposure lowers it to 0.209% compared to 0.21% in Table 5, which is targeted in choosing d^*. The implied reduction is 38.0% against 36% in the data. Given that we only target the greenium after controlling for core inflation exposure, the calibrated model generates the raw greenium reasonably well. Case (3) shows that without green preference, the greenium is 0.128%, which completely stems from the green firm's compensation for higher core inflation risk exposure. Case (4) shows that when both the price-setting gap and green preference are shut off (placebo case), the greenium is virtually zero.[19]

Panel B reports the green-minus-brown core inflation beta differential. In the full model

[19]The two firms are identical in the placebo, and the 0.009% in Table 12 is residual simulation noise indistinguishable from zero.

(case (1)), it is -2.34, close to the -2.41 that we estimate in the data. Once the price-setting parameters are equalized (case (2)), the core inflation beta differential falls to -0.3, which is not zero due to a positive green preference. Green preference pushes up the green stock price, which leads to a higher price-dividend ratio and a longer duration, and a longer-duration claim loads more negatively on the discount-rate movements that core inflation drives. Therefore, the green stock is more negatively exposed to core inflation risk than the brown stock even when the two share the same markup and price stickiness.

Taken together, the calibrated model quantitatively explains the greenium and its decomposition. About two-thirds of the greenium stems from green preference, and the remaining one-third is from compensation for core inflation risk, consistent with the data. The model also reproduces the green-minus-brown core inflation beta difference, close to the data counterpart. Online Appendix C confirms that our extended model of FLR2026 nests FLR2026 when both extensions (two firms and green preference) are shut down and isolates the contribution of each price-setting parameter separately.

7 Conclusion

In this paper, we examine whether the greenium, the observed outperformance of green assets relative to brown assets, can be interpreted as a reflection of inflation risk compensation. We document several key empirical facts that hold consistently in both equity and corporate bond markets. First, green assets carry significantly higher core inflation risk than brown assets, underperforming during periods of unexpected core inflation. Second, core inflation risk is priced in the cross-section of asset returns, with investors requiring higher compensation for holding assets exposed to high core inflation risk during the recent sample period. Importantly, after accounting for differences in core inflation risk exposure, the greenium declines by 36% and 23% for Scopes 1 and 2 in the equity market, respectively, and becomes statistically insignificant at conventional levels. A comparable reduction is observed for the Scope 1 greenium in the bond market. These results remain robust even after excluding the industries with the highest inflation beta. We further document three mechanisms that explain green firms' greater inflation risk: green firms operate in industries with stickier output prices, they carry higher markups, and their cash flows are concentrated further in the future.

We embed these mechanisms and a time-varying investor green preference in a calibrated two-firm New Keynesian asset-pricing model. The model quantitatively reproduces both the raw greenium and its reduction once core inflation exposure is taken into account, with the implied 38% reduction not targeted by the calibration. About two-thirds of the model's greenium reflects the green preference and the remaining one-third reflects compensation for core inflation risk, consistent with the data.

Our results have important implications for understanding the drivers of the greenium and for asset pricing models that incorporate environmental factors. While previous literature has largely attributed the greenium to investor preferences or ongoing transitions to carbon-aware equilibria, our findings suggest that traditional risk-based explanations also play a significant role. This highlights the importance of accounting for macroeconomic risk when evaluating the performance of environmentally focused investment strategies.

Future research could explore how the relationship between the greenium and inflation risk varies across different economic regimes, particularly as the global economy continues to transition toward more sustainable practices. Furthermore, investigating how climate-focused policies impact the inflation risk of green versus brown companies could offer useful insights for investors and policymakers alike.

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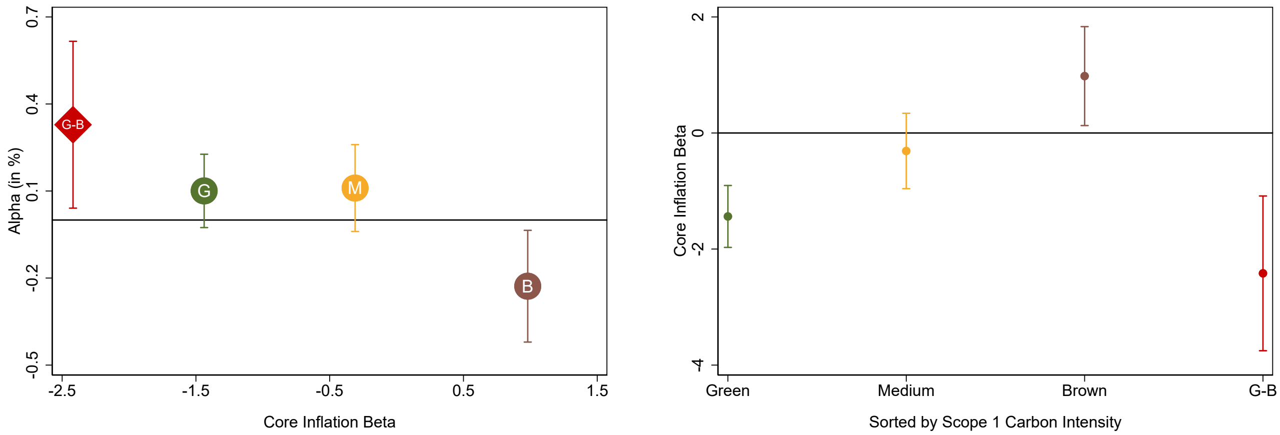
Panel A. Equity



Panel B. Bond

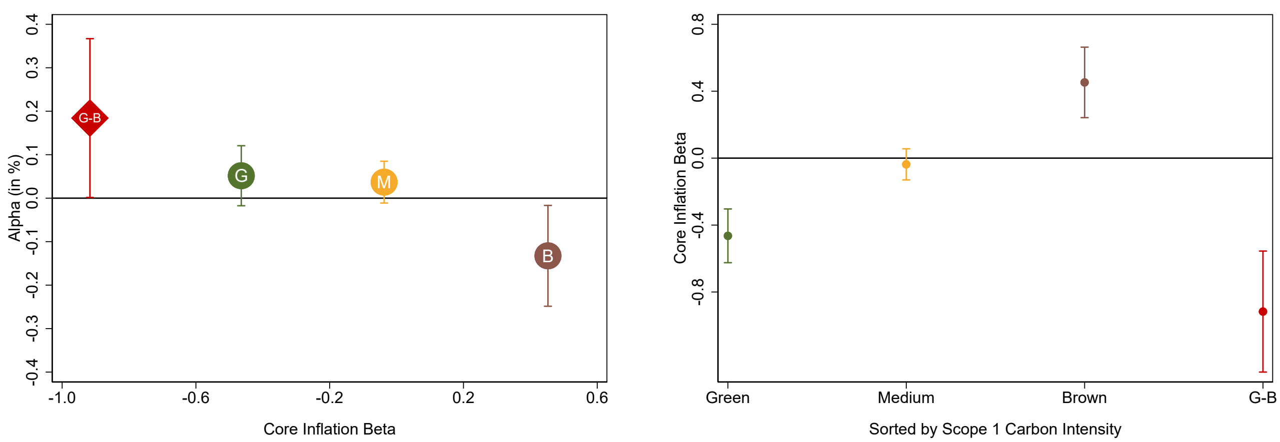
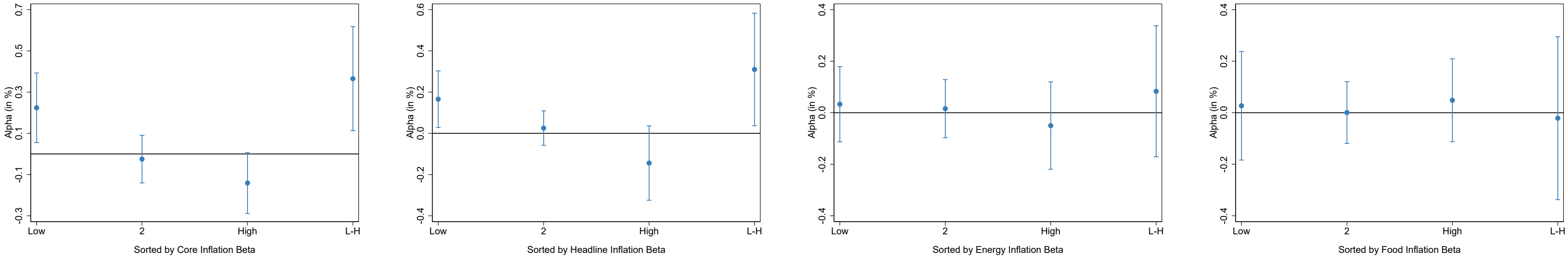


Figure 1. **Risk-Adjusted Returns (Alpha) and Core Inflation Exposure of Carbon Intensity-Sorted Portfolios**

This figure plots the 95% confidence intervals of monthly risk-adjusted returns (α in %) and core inflation exposure of value-weighted tercile portfolios sorted by Scope 1 carbon intensity. '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). 'G-B' is a long-short portfolio that longs the Green portfolio and shorts the Brown portfolio. Every month, we separately sort stocks and corporate bonds into tercile portfolios based on their Scope 1 carbon intensity. Once we obtain these portfolios, we compute their value-weighted monthly returns for the next month for each portfolio. Inflation betas are estimated at the carbon-sorted portfolio level using a 60-month rolling regression of excess returns on contemporaneous inflation shock, one-month-lagged inflation shock, and relevant risk factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Risk adjustment is conducted using the Fama and French (2018) six equity factors for equity portfolios and, for bond portfolios, a corporate bond market factor in addition to Fama and French (1993) term and default factors. 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.

Panel A. Equity



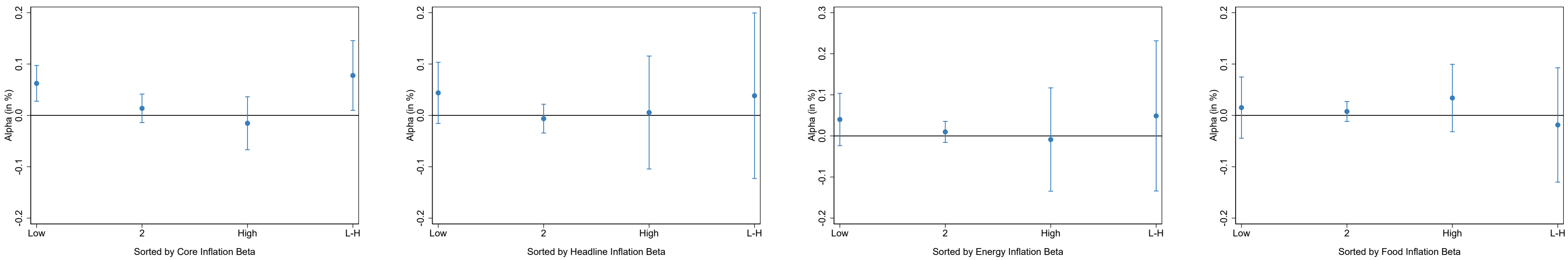
A-a. Core

A-b. Headline

A-c. Energy

A-d. Food

Panel B. Bond



B-a. Core

B-b. Headline

B-c. Energy

B-d. Food

Figure 2. **Risk-Adjusted Returns of Inflation-Sorted 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 the inflation beta-sorted portfolios (x-axis). Sub-panels a, b, c, and d sort portfolios by core, headline, energy, and food inflation betas, respectively.'Low' ('High') denotes the portfolio with the lowest (highest) inflation beta, while 'Medium' denotes the portfolio with intermediate inflation beta. 'L-H' is a long-short portfolio that longs the low-inflation-beta portfolio and shorts the high-inflation-beta portfolio. Every month, we separately sort stocks and corporate bonds into tercile portfolios based on their inflation betas. Once we obtain these portfolios, we compute their value-weighted monthly returns for the next month for each portfolio. Inflation betas are estimated at the stock level using a 60-month rolling regression of excess stock returns on contemporaneous inflation shock, one-month-lagged inflation shock, and relevant risk factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Risk adjustment is conducted using the Fama and French (2018) six equity factors for equity portfolios and, for bond portfolios, a corporate bond market factor in addition to Fama and French (1993) term and default factors. 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: Firm-Level Variables								
Scope 1 Intensity	218,161	2.67	2.13	-1.04	-0.15	2.66	5.65	8.54
Scope 2 Intensity	218,161	2.69	1.29	-0.55	0.71	2.80	4.12	5.48
RET (in %)	217,967	1.46	14.87	-33.00	-11.59	1.11	13.90	42.32
Core Inflation Beta	212,298	0.01	26.47	-75.37	-23.88	-0.05	23.96	77.46
Headline Inflation Beta	212,298	-0.19	12.00	-33.14	-10.08	-0.27	9.86	33.50
Energy Inflation Beta	212,298	-0.02	1.20	-3.18	-1.09	-0.05	1.10	3.38
Food Inflation Beta	212,298	0.15	13.28	-34.27	-11.56	-0.08	11.58	40.48
Markup (Baseline)	11,209	2.34	2.08	0.97	1.21	1.66	4.05	11.81
Markup (Production Function)	11,209	1.91	1.64	0.82	1.01	1.38	3.25	9.37
Cash Flow Duration	9,867	19.66	4.17	4.48	14.60	20.62	23.41	26.52
Log(Sales)	11,001	14.39	1.61	10.34	12.31	14.46	16.39	18.02
ME/BE	10,117	3.35	5.64	-12.25	0.79	2.37	7.45	24.03
Leverage	10,859	0.34	0.21	0.03	0.09	0.31	0.65	0.88
ROA	10,862	2.99	12.77	-52.07	-9.56	4.75	14.26	26.84
PPE/AT	10,862	0.27	0.24	0.01	0.04	0.18	0.63	1.01
Panel B: Bond-Level Variables								
Bond RET (in %)	855,147	0.53	3.42	-6.83	-1.53	0.34	2.84	8.63
Bond Core Inflation Beta	555,792	-0.05	5.20	-14.07	-3.89	-0.10	3.73	14.37
Bond Headline Inflation Beta	555,792	0.16	2.73	-5.04	-1.83	-0.07	2.34	9.03
Bond Energy Inflation Beta	555,792	0.03	0.32	-0.62	-0.22	0.00	0.31	1.15
Bond Food Inflation Beta	555,792	-0.17	2.70	-7.53	-1.88	-0.10	1.62	6.01
Panel C: Industry-level Variables								
Price Stickiness	753	-0.19	0.18	-0.94	-0.45	-0.12	-0.06	-0.04
Panel D: Time-Series Variables (in %)								
Core Inflation	151	0.18	0.15	-0.13	0.07	0.17	0.26	0.78
Headline Inflation	151	0.18	0.25	-0.64	-0.08	0.20	0.47	0.86
Energy Inflation	151	0.26	2.50	-8.90	-2.57	0.34	3.21	5.45
Food Inflation	151	0.19	0.23	-0.23	-0.03	0.14	0.44	0.95
Core Inflation Shocks	151	0.00	0.13	-0.41	-0.12	-0.01	0.13	0.42
Headline Inflation Shocks	151	-0.01	0.24	-0.60	-0.29	0.01	0.28	0.64
Energy Inflation Shocks	151	-0.07	2.35	-6.24	-2.78	0.06	2.57	5.44
Food Inflation Shocks	151	-0.04	0.22	-0.69	-0.26	-0.04	0.18	0.61
MKTRF	151	1.32	4.14	-9.55	-3.64	1.57	5.83	12.44
SMB	151	0.05	2.61	-4.85	-3.19	0.13	3.25	6.96
HML	151	-0.20	2.96	-7.86	-3.13	-0.39	3.38	7.60
RMW	151	0.25	1.85	-3.65	-1.98	0.26	2.34	6.35
CMA	151	0.05	1.62	-3.14	-1.80	0.00	2.00	4.29
MOM	151	0.15	3.56	-9.10	-4.35	0.39	3.91	8.21
CBMKTRF	151	0.48	1.46	-2.65	-0.87	0.43	2.17	4.22
DEF	151	0.18	1.96	-6.22	-1.54	0.19	2.24	4.26
TERM	151	0.49	2.96	-6.00	-3.02	0.22	4.45	7.81

This table reports summary statistics of stock and bond-level characteristics, time-series variables, and mechanism variables. *Carbon Intensity* is the logarithm of a firm's carbon emissions (in tonnes of CO2e) divided by revenues (in millions of U.S. dollars). *RET* denotes monthly stock excess returns. Equity (Bond) *Inflation Betas* are estimated from 60-month rolling regressions of excess stock (bond) returns on contemporaneous and one-month-lagged inflation shocks, and Fama and French (2018) six equity factors (bond market factors). Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. *CBMKTRF* denotes the value-weighted average of corporate bond returns in excess of the risk-free rate. *DEF* captures the return differential between long-term corporate bonds and long-term government bonds, and *TERM* captures the return differential between long-term government bonds and the one-month Treasury bill rate, following Fama and French (1993). *Markup (Baseline)* is the ratio of revenues to cost of goods sold. *Markup (Production Function)* is De Loecker et al. (2020) benchmark markup, where output elasticities are estimated from a production function with industry- and year-specific coefficients. Cash Flow Duration is constructed following Weber (2018). *ME/BE* is the market value of equity divided by the book value of equity. *Leverage* is the market leverage. *ROA* is the return on assets. *PPE/AT* is asset tangibility. *Price Stickiness* is the negative of the 6-digit NAICS-level frequency of price adjustment from Pasten et al. (2020). The sample period spans June 2009 to December 2021. Detailed variable definitions are provided in Online Appendix Table A1.

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

	Core Beta	Headline Beta	Energy Beta	Food Beta	Scope 1 Intensity	Scope 2 Intensity
			Panel A. Equity			
Core Beta	1.00					
Headline Beta	0.52	1.00				
	(0.00)					
Energy Beta	0.27	0.88	1.00			
	(0.00)	(0.00)				
Food Beta	-0.21	-0.33	-0.26	1.00		
	(0.00)	(0.00)	(0.00)			
Scope 1 Intensity	0.02	0.04	0.05	0.01	1.00	
	(0.00)	(0.00)	(0.00)	(0.01)		
Scope 2 Intensity	0.02	0.04	0.05	0.01	0.50	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
			Panel B.Bond			
Core Beta	1.00					
Headline Beta	0.44	1.00				
	(0.00)					
Energy Beta	0.23	0.90	1.00			
	(0.00)	(0.00)				
Food Beta	-0.04	-0.40	-0.30	1.00		
	(0.00)	(0.00)	(0.00)			
Scope 1 Intensity	0.07	0.06	0.07	-0.01	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)		
Scope 2 Intensity	0.05	0.05	0.03	-0.02	0.14	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

This table shows pairwise correlations between firms' respective exposure to core, headline, energy, and food inflation shocks, and their carbon intensities. Inflation betas are estimated from 60-month rolling regressions of excess stock returns on contemporaneous and one-month-lagged inflation shocks, and Fama and French (2018) six equity factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Bond inflation betas are estimated analogously using bond-market factors: *CBMKTRF*, *DEF*, and *TERM*. *p*-values that indicate the statistical significance of the correlations are reported in parentheses. The sample period is between June 2009 and December 2021.

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

	Low	2	High	L-H
		Panel A. Equity		
Excess Return	1.53***	1.20***	1.18***	0.35***
	(5.01)	(4.70)	(3.74)	(2.67)
α	0.22***	-0.03	-0.14*	0.37***
	(2.63)	(-0.43)	(-1.88)	(2.86)
MKTRF	1.03***	0.94***	1.07***	-0.04
	(49.42)	(71.18)	(49.32)	(-1.05)
SMB	0.01	-0.09***	-0.00	0.01
	(0.28)	(-3.54)	(-0.02)	(0.19)
HML	0.02	0.06*	-0.07*	0.09
	(0.55)	(1.94)	(-1.67)	(1.50)
RMW	-0.04	0.13***	-0.15***	0.12
	(-0.82)	(3.84)	(-3.33)	(1.59)
CMA	0.00	-0.00	-0.00	0.00
	(0.02)	(-0.00)	(-0.02)	(0.02)
MOM	0.02	0.01	-0.09**	0.11**
	(0.92)	(0.66)	(-2.58)	(2.24)
R^2	0.96	0.97	0.95	0.04
Obs.	151	151	151	151
		Panel B. Bond		
Excess Return	0.52***	0.34***	0.49***	0.03
	(4.07)	(3.82)	(3.71)	(0.64)
α	0.06***	0.01	-0.02	0.08**
	(3.53)	(0.97)	(-0.59)	(2.26)
CBMKTRF	0.94***	0.70***	1.21***	-0.27***
	(31.76)	(30.38)	(20.77)	(-3.38)
DEF	0.06***	-0.02	-0.01	0.07
	(2.75)	(-1.55)	(-0.28)	(1.60)
TERM	0.06***	0.04***	-0.07***	0.13***
	(3.94)	(3.82)	(-2.97)	(3.92)
R^2	0.98	0.99	0.98	0.42
Obs.	151	151	151	151

This table presents monthly excess returns and risk-adjusted returns (α in %) for value-weighted tercile portfolios sorted by core inflation betas. Every month, we separately sort stocks and corporate bonds into tercile portfolios based on their core inflation betas. Then, we construct a Low-minus-High long-short portfolio (L-H) by taking a long position in the Low portfolio and a short position in the High portfolio. Once we obtain these portfolios, we compute their value-weighted monthly returns for the next month. Inflation betas are defined in Table 1. Risk adjustment is conducted using the Fama and French (2018) six equity factors for equity portfolios and, for bond portfolios, the combination of a corporate bond market factor with Fama and French (1993) term and default factors. 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 Portfolio Returns**

	Scope 1				Scope 2			
	Low	2	High	L-H	Low	2	High	L-H
				Panel A. Equity				
Excess Return	1.37***	1.46***	1.00***	0.37**	1.44***	1.22***	1.25***	0.18
	(4.70)	(5.03)	(3.45)	(2.54)	(5.06)	(4.17)	(4.54)	(1.51)
α	0.10	0.11	-0.23**	0.33**	0.16**	-0.05	-0.06	0.22*
	(1.57)	(1.45)	(-2.34)	(2.26)	(2.22)	(-0.82)	(-0.89)	(1.79)
MKTRF	1.05***	1.01***	0.93***	0.12**	1.01***	1.02***	0.98***	0.04
	(55.10)	(59.56)	(28.56)	(2.56)	(52.78)	(50.00)	(43.37)	(1.05)
SMB	-0.16***	0.06	0.01	-0.16***	-0.07*	-0.09***	0.02	-0.10
	(-6.47)	(1.61)	(0.23)	(-2.86)	(-1.97)	(-2.83)	(0.66)	(-1.64)
HML	0.14***	-0.19***	0.05	0.09	0.04	0.02	-0.02	0.06
	(5.02)	(-4.83)	(1.30)	(1.49)	(1.42)	(0.55)	(-0.35)	(0.88)
RMW	-0.14***	0.13***	0.11*	-0.25**	0.01	-0.12***	0.18***	-0.18**
	(-2.90)	(2.63)	(1.91)	(-2.55)	(0.12)	(-2.85)	(3.95)	(-2.10)
CMA	-0.17***	0.09	0.21***	-0.38***	-0.14***	-0.01	0.14**	-0.28***
	(-3.73)	(1.27)	(3.15)	(-3.73)	(-2.92)	(-0.24)	(2.53)	(-3.34)
MOM	-0.01	0.02	-0.05	0.04	0.01	-0.04	0.01	0.01
	(-0.25)	(0.72)	(-1.28)	(0.76)	(0.52)	(-1.37)	(0.28)	(0.15)
R^2	0.97	0.96	0.93	0.19	0.96	0.97	0.96	0.09
Obs.	151	151	151	151	151	151	151	151
				Panel B. Bond				
Excess Return	0.45***	0.45***	0.45***	0.01	0.46***	0.43***	0.47***	-0.01
	(3.95)	(4.10)	(3.14)	(0.08)	(3.95)	(3.79)	(3.65)	(-0.19)
α	0.05	0.04	-0.13**	0.18**	0.04	-0.01	-0.03	0.07
	(1.48)	(1.52)	(-2.26)	(1.99)	(1.57)	(-0.46)	(-0.91)	(1.21)
CBMKTRF	0.76***	0.88***	1.44***	-0.67***	0.79***	0.94***	1.22***	-0.43***
	(9.38)	(23.77)	(8.09)	(-2.61)	(15.74)	(38.95)	(12.65)	(-2.97)
DEF	0.11***	-0.02	-0.13	0.24**	0.08***	0.01	-0.06	0.14**
	(2.99)	(-0.75)	(-1.58)	(2.04)	(3.65)	(0.69)	(-1.55)	(2.38)
TERM	0.10***	0.04**	-0.09	0.18*	0.11***	0.04***	-0.07	0.18***
	(2.79)	(2.50)	(-1.24)	(1.77)	(5.54)	(2.99)	(-1.62)	(2.95)
R^2	0.96	0.98	0.94	0.42	0.98	0.99	0.97	0.45
Obs.	151	151	151	151	151	151	151	151

This table presents monthly excess returns and risk-adjusted returns (α in %) for value-weighted tercile portfolios sorted by carbon intensity. Every month, we separately sort stocks and corporate bonds into tercile portfolios based on either their Scope 1 or Scope 2 carbon intensities. Then, we construct a low-minus-high long-short portfolio (L-H) by taking a long position in the Low (Green) portfolio and a short position in the High (Brown) portfolio. Once we obtain these portfolios, we compute their value-weighted monthly returns for the next month for each portfolio. Risk adjustment is conducted using the Fama and French (2018) six equity factors for equity portfolios and, for bond portfolios, the combination of a corporate bond market factor with Fama and French (1993) term and default factors. 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 Portfolio Returns after controlling for Core Inflation Betas**

	Double sorted (Control: Core Inflation beta)		Single sorted (Table 4)	
	Scope 1	Scope 2	Scope 1	Scope 2
	Panel A. Equity			
Low Carbon	1.35***	1.40***	1.37***	1.44***
	(4.49)	(4.86)	(4.70)	(5.06)
2	1.45***	1.28***	1.46***	1.22***
	(5.01)	(4.25)	(5.03)	(4.17)
High Carbon	1.12***	1.27***	1.00***	1.25***
	(3.57)	(4.43)	(3.45)	(4.54)
L-H Return	0.24	0.14	0.37**	0.18
Difference	(1.49)	(1.11)	(2.54)	(1.51)
L-H α	0.21	0.17	0.33**	0.22*
Difference	(1.51)	(1.48)	(2.26)	(1.79)
	Panel B. Bond			
Low Carbon	0.46***	0.45***	0.45***	0.46***
	(4.13)	(4.08)	(3.95)	(3.95)
2	0.45***	0.44***	0.45***	0.43***
	(4.17)	(3.91)	(4.10)	(3.79)
High Carbon	0.45***	0.47***	0.45***	0.47***
	(3.35)	(3.81)	(3.14)	(3.65)
L-H Return	0.00	-0.02	0.01	-0.01
Difference	(0.06)	(-0.39)	(0.08)	(-0.19)
L-H α	0.16*	0.04	0.18**	0.07
Difference	(1.95)	(0.73)	(1.99)	(1.21)

This table presents monthly excess 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 separately sort stocks and corporate bonds into tercile portfolios using core inflation beta, then within each tercile portfolio, we sort stocks or bonds into tercile portfolios based on either their 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. Inflation betas and carbon intensities are defined in Table 1. Risk adjustment is conducted using the Fama and French (2018) six equity factors for equity portfolios and, for bond portfolios, the combination of a corporate bond market factor with Fama and French (1993) term and default factors. 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 Portfolio Returns after Excluding High Core Inflation Beta Industries**

	Panel A. Equity							
	All industries (Table 5)		Ex: Steel		Ex: Steel + Coal		Ex: Steel + Coal + Fun	
	Single	Double	Single	Double	Single	Double	Single	Double
Scope 1 Intensity	0.33**	0.21	0.32**	0.21	0.31**	0.21	0.30**	0.20
	(2.26)	(1.51)	(2.19)	(1.50)	(2.10)	(1.46)	(2.05)	(1.45)
Scope 2 Intensity	0.22*	0.17	0.20*	0.16	0.20*	0.16	0.19	0.15
	(1.79)	(1.48)	(1.68)	(1.34)	(1.69)	(1.39)	(1.55)	(1.30)

	Panel B. Bond							
	All industries (Table 5)		Ex: Mines		Ex: Mines + Rubbr		Ex: Mines + Rubbr + Oil	
	Single	Double	Single	Double	Single	Double	Single	Double
Scope 1 Intensity	0.18**	0.16*	0.19**	0.15*	0.19**	0.15*	0.11*	0.11*
	(1.99)	(1.95)	(2.01)	(1.92)	(2.02)	(1.93)	(1.91)	(1.84)
Scope 2 Intensity	0.07	0.04	0.08	0.04	0.07	0.04	0.02	0.00
	(1.21)	(0.73)	(1.22)	(0.81)	(1.21)	(0.82)	(0.45)	(0.11)

This table presents monthly risk-adjusted returns (α in %) of the long-short (Green-minus-Brown) portfolios that long the Green portfolio and short the Brown 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'). Inflation betas and carbon intensities are defined in Table 1. Risk adjustment is conducted using the Fama and French (2018) six equity factors for equity portfolios and, for bond portfolios, the combination of a corporate bond market factor with Fama and French (1993) term and default factors. 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. **Core Inflation Beta-Sorted Portfolio Returns after controlling for Carbon Intensity**

	Double Sorted (Control: Carbon intensity)		Single Sorted (Table 3)
	Scope 1	Scope 2	
	Panel A. Equity		
Low Inflation Beta	1.46***	1.51***	1.53***
	(4.68)	(4.86)	(5.01)
2	1.21***	1.23***	1.20***
	(4.90)	(4.82)	(4.70)
High Inflation Beta	1.19***	1.18***	1.18***
	(3.52)	(3.68)	(3.74)
L-H Return	0.27**	0.34***	0.35***
Difference	(2.08)	(2.76)	(2.67)
L-H α	0.29**	0.31***	0.37***
Difference	(2.14)	(2.81)	(2.86)
	Panel B. Bond		
Low Inflation Beta	0.51***	0.51***	0.52***
	(3.96)	(4.05)	(4.07)
2	0.35***	0.34***	0.34***
	(3.80)	(3.82)	(3.82)
High Inflation Beta	0.50***	0.50***	0.49***
	(3.86)	(3.91)	(3.71)
L-H Return	0.01	0.01	0.03
Difference	(0.23)	(0.31)	(0.64)
L-H α	0.05	0.05	0.08**
Difference	(1.29)	(1.50)	(2.26)

This table presents monthly excess returns and risk-adjusted returns (α in %) for value-weighted tercile portfolios sorted by core inflation betas after controlling for carbon intensities. Every month, we separately sort stocks and corporate bonds into tercile portfolios using either Scope 1 or Scope 2 carbon intensities, then within each tercile portfolio, we sort stocks or bonds 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. Inflation betas and carbon intensities are defined in Table 1. Risk adjustment is conducted using the Fama and French (2018) six equity factors for equity portfolios and, for bond portfolios, the combination of a corporate bond market factor with Fama and French (1993) term and default factors. 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 8. **Carbon Intensity and Price Stickiness**

	(1)	(2)	(3)	(4)
	Price Stickiness			
Scope 1 Carbon Intensity	-0.04***	-0.03***		
	(-5.59)	(-4.42)		
Scope 2 Carbon Intensity			-0.04***	-0.02*
			(-3.71)	(-1.84)
log(Sales)		-0.02***		-0.02***
		(-3.07)		(-2.60)
ME/BE		0.00***		0.00***
		(4.73)		(5.32)
Leverage		-0.01		-0.01
		(-0.12)		(-0.27)
ROA		0.00**		0.00**
		(2.18)		(2.06)
PPE/AT		-0.17***		-0.26***
		(-3.74)		(-4.47)
Year FE	Yes	Yes	Yes	Yes
R^2	0.17	0.26	0.06	0.21
Obs.	2,577	2,488	2,577	2,488

This table presents industry-level regressions of price stickiness on carbon intensity. Price stickiness is measured as the negative of the frequency of price adjustment (FPA) at the NAICS 6-digit level computed by Pasten et al. (2020), following the construction in Li et al. (2021). Additional industry-level control variables are included as specified using firm-level controls. The firm-level controls are trimmed at the 1st and 99th percentiles by year. All variables are aggregated to the NAICS 6-digit level using firm-sales-weighted averages of the corresponding firm characteristics, and they are defined in Table 1. All specifications include year fixed effects. Standard errors are clustered at the NAICS 6-digit level, and *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans 2009 to 2021.

Table 9. **Carbon Intensity and Markup**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Markup (Baseline)				Markup (Production Function)			
Scope 1 Carbon Intensity	-0.28***	-0.20***			-0.19***	-0.13***		
	(-10.86)	(-9.28)			(-10.07)	(-7.99)		
Scope 2 Carbon Intensity			-0.47***	-0.34***			-0.33***	-0.23***
			(-9.76)	(-8.02)			(-9.09)	(-7.20)
Log(Sales)		-0.13***		-0.11***		-0.10***		-0.08***
		(-4.56)		(-3.63)		(-4.15)		(-3.36)
ME/BE		0.02***		0.02***		0.02***		0.02***
		(3.95)		(3.96)		(3.99)		(3.97)
Leverage		-1.85***		-1.91***		-1.51***		-1.54***
		(-9.36)		(-9.58)		(-9.55)		(-9.75)
ROA		-0.00		-0.00		-0.00		-0.00
		(-0.71)		(-0.57)		(-0.50)		(-0.38)
PPE/AT		-0.23*		-0.35***		-0.25**		-0.31***
		(-1.66)		(-2.59)		(-2.27)		(-2.88)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.05	0.12	0.05	0.13	0.04	0.12	0.04	0.12
Obs.	11,209	9,367	11,209	9,367	11,209	9,367	11,209	9,367

This table presents regressions of markup on carbon intensity, controlling for a set of firm characteristics. Columns 1-4 report results for the baseline markup, defined as the ratio of revenues to cost of goods sold. Columns 5-8 report results for De Loecker et al. (2020) benchmark markup, where output elasticities are estimated from a production function with industry- and year-specific coefficients. Following De Loecker et al. (2020), we drop firm-years with non-positive deflated revenues, cost of goods sold, or SG&A and trim the sales-to-cost-of-goods-sold ratio and the underlying cost shares at the 1st and 99th percentiles by year before computing the markup measures. The firm-level controls are trimmed at the same percentiles. All variables are defined in Table 1. Regressions include year fixed effects as indicated. Standard errors are clustered at the firm level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample covers the period from 2009 to 2021.

Table 10. **Carbon Intensity and Cash Flow Duration**

	(1)	(2)	(3)	(4)
	Cash Flow Duration			
Scope 1 Carbon Intensity	-0.50***	-0.25***		
	(-8.85)	(-4.56)		
Scope 2 Carbon Intensity			-0.42***	-0.06
			(-4.65)	(-0.82)
Log(Sales)		0.32***		0.33***
		(6.31)		(6.45)
ME/BE		0.11***		0.12***
		(7.28)		(7.37)
Leverage		-8.27***		-8.33***
		(-17.23)		(-17.15)
ROA		0.01**		0.01**
		(1.99)		(2.00)
PPE/AT		-1.34***		-2.01***
		(-3.86)		(-5.61)
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.06	0.29	0.03	0.28
Obs.	9,867	9,127	9,867	9,127

This table presents regressions of cash flow duration on carbon intensity, controlling for a set of firm characteristics. Cash flow duration is constructed following Weber (2018). The duration measure and the firm-level controls are trimmed at the 1st and 99th percentiles by year. All variables are defined in Table 1. Regressions include year fixed effects as indicated. Standard errors are clustered at the firm level, and *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample covers the period from 2009 to 2021.

Table 11. **Model Calibration**

Parameter	Symbol	Value	Source/Target
Panel A: Households and macro block (inherited from FLR2026)			
Discount factor	δ	0.9929	FLR2026; $E[r_f] \approx 1.45\%$
Risk aversion	γ	10	FLR2026
IES	ψ	2	FLR2026
Consumption–leisure elasticity	ξ_l	0.5	FLR2026
Core/energy elasticity	ϕ	5	FLR2026
Core weight	α_c	0.9	10% energy share
Capital share	α	0.33	FLR2026
Depreciation	δ_k	0.02	FLR2026
Capital adjustment elasticity	ξ_k	4.8	FLR2026
Across-firm CES	ϕ_f	2	symmetric baseline
Firm shares	$s_G = s_B$	0.5	symmetric baseline
Taylor rule	$(\rho_r, \rho_\pi, \rho_y)$	(0.7, 1.5, 0.1)	FLR2026
Equity leverage	ϕ_{lev}, σ_d	2, 0.08	FLR2026
Shocks, productivity, energy	—	—	FLR2026
Panel B: Green/brown price-setting parameters (Scope 1)			
Variety elasticity	ν_G, ν_B	3.5, 12	risk component $= 0.12\%$/mo
implied markup	μ_G, μ_B	1.40, 1.09	markup gap (Table 9)
Rotemberg cost	$\phi_{P,G}$, $\phi_{P,B}$	130, 30	stickiness gap (Table 8)
implied Calvo duration	—	$\approx$ 7.9q, 2.2q	green stickier
Panel C: Green preference (ESG demand)			
Greenness	g_G, g_B	$+0.5$, -0.5	normalization
Mean ESG demand	$\bar{\chi}$	0	taste emerges in sample
Persistence	ρ_χ	0.999	Avramov et al. (2024), near unit root
Shock loading	σ_χ	8.6×10^{-5}	Avramov et al. (2024), same order
Greening drift	d^*	0.56 (calibrated)	controlled greenium $= 0.21\%$/mo

This table reports the calibration of the model of Section 6 at the quarterly frequency. Panel A lists the parameters inherited from FLR2026, including the productivity, energy, monetary, and foreign-block processes (see their Internet Appendix C for the complete list). Panel B reports the green/brown price-setting gap: the variety elasticities ν_j imply the steady-state markups $\mu_j = \nu_j/(\nu_j - 1)$, and the Rotemberg coefficients $\phi_{P,j}$ map into Calvo-equivalent average price durations through the first-order equivalence $\phi_{P,j} = (\nu_j - 1)\theta_j/[(1-\theta_j)(1-\delta\theta_j)]$ with duration $1/(1-\theta_j)$. The gap is set so that the model's risk component matches the empirically explained component of the Scope 1 greenium, $0.33 - 0.21 = 0.12\%$ per month, with the direction of each price-setting parameter disciplined by Tables 8 and 9. Panel C reports the ESG demand block: the persistence and the scale of σ_χ follow Avramov et al. (2024), and the greening drift d^* is calibrated so that the controlled greenium of case (2) matches its empirical value in Table 5.

Table 12. **The Greenium and Core inflation beta difference: Model vs. Data**

In % per month	Green Preference	Hetero price-setting	Model	Data
Panel A: Greenium				
Case (1)	Yes	Yes	0.337	0.33
Case (2)	Yes	No	0.209	0.21
Reduction (1)→(2) in %			38%	36%
Case (3) = (1) - (2)	No	Yes	0.128	0.12
Case (4)	No	No	0.009	0
Panel B: Core inflation beta difference $\beta_G^{core} - \beta_B^{core}$				
Case (1)	Yes	Yes	-2.34	-2.419
Case (2)	Yes	No	-0.30	-0.051

This table reports the grenium in the model and its empirical counterpart for Scope 1. Model entries average the levered green-minus-brown excess return across 4,000 independent simulations of the calibrated economy under the indicated case. All shock draws are shared across model cases, and differences between model cases are therefore free of simulation noise. For each simulated path, there is a 60-quarter burn-in in which the taste innovations are set to zero, $\varepsilon_{\chi,t} = 0$, followed by a 50-quarter greening sample in which taste shocks are drawn with mean d^*, corresponding to June 2009 to December 2021. Case (1) presents the greenium with heterogeneous price-setting parameters that generate the differential core inflation risk exposure and green preference. In case (2), the two firms' price-setting parameters are equalized—i.e., $(\nu_G, \phi_{P,G}) = (\nu_B, \phi_{P,B})$—so that their core inflation betas are matched by construction, which is the model analog of the double sort in Table 5. In case (3), green preference is switched off, $\chi_t = 0$, while the price-setting gap is retained, which isolates the risk component. In case (4), green preference is switched off, $\chi_t = 0$, and the price-setting parameters are equalized, a placebo that shuts both channels and should deliver no greenium. Data: Scope 1 risk-adjusted greenium estimates from Tables 4 and 5.

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

June 23, 2026

A Construction of De Loecker et al. (2020) Production-Function Markup

Building on the production approach of Hall (1988) and De Loecker and Warzynski (2012), De Loecker et al. (2020) treat the cost of goods sold (COGS) as the variable input and define the production-function markup of firm i in year t as

$$Markup_{it} = \theta_{it} \times \frac{Sales_{it}^{D}}{COGS_{it}^{D}}, \tag{26}$$

where θ_{it} is the output elasticity of COGS and $Sales_{it}^{D}/COGS_{it}^{D}$ is the ratio of deflated sales to deflated COGS.

Following De Loecker et al. (2020), we build this measure in three steps. We first construct a deflated Compustat firm-year panel, then estimate the output elasticity, and finally compute the markup.

A.1 Build Deflated Compustat Firm-Year Panel

We start from the annual Compustat data and merge in three macroeconomic series from the Federal Reserve Economic Data (FRED) at the St. Louis Fed: (i) the annual U.S. GDP Implicit Price Deflator (`A191RD3A086NBEA`, rebased to 100 in 2015), (ii) the year-over-year percent change in the same deflator (quarterly series `A191RI1Q225SBEA` capturing inflation), and (iii) the Effective Federal Funds Rate (daily series `DFF`). We average the inflation and federal funds series to the annual frequency and denote them π_t and i_t, respectively.

We then deflate nominal sales, COGS, selling, general, and administrative expenses (SG&A), and gross property, plant, and equipment (PPE) by the GDP deflator as follows:

$$X_{it}^{D} = \frac{X_{it}}{Deflator_t} \times 100, \tag{27}$$

where X_{it} is a nominal accounting variable of firm i at time t, and X_{it}^{D} is its real counterpart.

De Loecker et al. (2020) define the user cost of capital as

$$r_t = i_t - \pi_t + \delta, \tag{28}$$

where i_t is the effective federal funds rate at time t, π_t is the inflation rate, and δ, set to 12%, is an adjustment for depreciation and risk premium.

From the deflated accounting variables and the user cost of capital, we then construct two cost shares:

$$CS1_{it} = \frac{COGS_{it}^{D}}{COGS_{it}^{D} + r_t \times PPE_{it}^{D}}, \tag{29}$$

$$CS2_{it} = \frac{COGS_{it}^{D}}{COGS_{it}^{D} + SG\&A_{it}^{D} + r_t \times PPE_{it}^{D}}, \tag{30}$$

where $CS1_{it}$ excludes SG&A from total cost and $CS2_{it}$ includes it.

Finally, following De Loecker et al. (2020), we exclude firm-years with non-positive deflated sales, deflated COGS, deflated SG&A, or sales-to-COGS ratio. We then trim the sales-to-COGS ratio and the cost shares at the 1st and 99th percentiles within each year.

A.2 Estimate Output Elasticities

We recover the output elasticity θ_{it} from a Cobb-Douglas production function with time-varying, sector-specific coefficients:

$$y_{it} = \theta_{st}^{c}\, c_{it} + \theta_{st}^{k}\, k_{it} + \omega_{it} + \varepsilon_{it}, \tag{31}$$

where y_{it} is log deflated sales, c_{it} is log deflated COGS, k_{it} is log deflated capital, and ω_{it} is firm productivity. The output elasticity of COGS is θ_{st}^{c}.

To address the simultaneity between productivity and the variable input, we follow De Loecker et al. (2020) and adopt the proxy-variable approach of Olley and Pakes (1996) and Ackerberg et al. (2015), implemented through the one-step generalized method of moments estimator of Wooldridge (2009). In practice, we regress log deflated sales on log deflated COGS, instrumented by its first lag, together with log deflated PPE and lagged investment and capital terms that proxy for productivity. The coefficient on log deflated COGS is the output elasticity θ_{st}^{c}.

We estimate Equation (31) separately for each 2-digit NAICS sector using a five-year window from $t-2$ to $t+2$. This yields an output elasticity of COGS for every industry-year, which serves as θ_{it} in Equation (26).

A.3 Compute Production-Function Markups

Using Equation (26), we form the production-function markup by multiplying the industry-year output elasticity from the previous step by the firm-year ratio of deflated sales to deflated COGS. This measure is reported in columns (5) to (8) of Table 9.

Online Appendix Table A3 reports three alternative markups from De Loecker et al. (2020). These markups share the same structure but differ in how the output elasticity θ_{it} is computed. The constant-elasticity markup, reported in columns (1) to (4) of Table A3, replaces the estimated elasticity with a fixed value of 0.85. The two cost-share markups instead use the within-industry-year median cost share of COGS, which under cost minimization is a nonparametric proxy for θ_{it}. The cost-share markups in columns (5) to (8) and columns (9) to (12) of Table A3 are built from $CS1_{it}$ and $CS2_{it}$ in Equations (29) and (30), respectively.

B Construction of Weber (2018) Equity Cash-Flow Duration

Equity cash-flow duration measures the weighted-average time at which a firm's equity cash flows are expected to arrive, analogous to the Macaulay duration of a bond (Weber, 2018; Dechow et al., 2004). Following Weber (2018), we compute duration for each firm i at the end of each fiscal year t as

$$Dur_{it} = \frac{\sum_{s=1}^{T} s \times CF_{i,t+s}/(1+r)^s}{P_{it}} + \left(T + \frac{1+r}{r}\right) \times \frac{P_{it} - \sum_{s=1}^{T} CF_{i,t+s}/(1+r)^s}{P_{it}}, \quad (32)$$

where $CF_{i,t+s}$ is the forecast equity cash flow s years ahead, P_{it} is current market equity, r is the discount rate, and T is the length of the explicit forecast horizon. The first term captures the duration of the explicitly forecast cash flows. The second term applies the duration of a level perpetuity, $T + (1+r)/r$, to the share of current price not explained by the discounted cash flows over the explicit horizon.

We compute cash flow in each year as earnings minus the change in book equity:

$$CF_{i,t+s} = E_{i,t+s} - (BV_{i,t+s} - BV_{i,t+s-1}), \quad (33)$$

where $E_{i,t+s}$ is earnings and $BV_{i,t+s}$ is book equity. Earnings equal return on equity times lagged book equity, $E_{i,t+s} = ROE_{i,t+s} \times BV_{i,t+s-1}$. Book equity grows at the forecast rate $g_{i,t+s}$, so that $BV_{i,t+s} = BV_{i,t+s-1}(1 + g_{i,t+s})$. Following Weber (2018), we model return on equity and growth as first-order autoregressive processes that revert to long-run means,

$$ROE_{i,t+s} = \rho_{ROE}\, ROE_{i,t+s-1} + (1 - \rho_{ROE})\, \bar{r}, \quad (34)$$

$$g_{i,t+s} = \rho_g\, g_{i,t+s-1} + (1 - \rho_g)\, \bar{g}. \quad (35)$$

We construct the constituent accounting variables using annual Compustat data. Book equity BV_{it} is stockholders' equity plus deferred taxes and investment tax credit minus the book value of preferred stock. Preferred stock is measured by its redemption, liquidation, or par value in that order of availability. Market equity P_{it} is common shares outstanding times the fiscal-year-end share price. Return on equity ROE_{it} is income before extraordinary items over lagged book equity. Finally, growth is the annual growth rate of net sales.

We estimate the persistence parameters ρ_{ROE} and ρ_g by pooled ordinary least squares. Return on equity starts from the firm's most recent realized value and reverts to the cost of equity $\bar{r}$, set to 12%. The growth process starts from the firm's realized sales growth and reverts to the long-run nominal growth rate of the economy $\bar{g}$, set to 6%. Following Weber (2018), we also set the discount rate $r = 12\%$ and the forecast horizon $T = 15$ years. We winsorize the resulting duration measure at the 1st and 99th percentiles within each year.

C Model Validation: Nesting and Single-Parameter Experiments

This appendix validates the model of Section 6 in two steps. First, we shut down both extensions, the two-firm split and the green preference, and verify that the model collapses to the one-sector economy of FLR2026 and reproduces its published moments. Second, with the green preference still off, we allow the two firms to differ in one parameter at a time. These experiments isolate the contribution of price stickiness and of markup to the cross-section of core inflation betas and provide the within-economy model counterpart of Hypotheses 1 and 2 in Section 5, in the spirit of the multi-sector New Keynesian literature on heterogeneous price-setting frictions (Weber, 2015; Gorodnichenko and Weber, 2016; Pasten et al., 2020). Throughout, parameters are those of Table 11 except for the parameter pairs listed in each experiment. The model is solved by third-order perturbation with pruning, and moments are computed on a 25,000-quarter simulation initialized at the deterministic steady state.

C.1 Collapsing the model to FLR2026

With the green preference shut down ($\bar{\chi} = \sigma_\chi = 0$) and symmetric price-setting parameters ($\nu_G = \nu_B = 6$, $\phi_{P,G} = \phi_{P,B} = 80$), the two firms of Section 6 are identical: the taste state is inert, relative prices equal one, sectoral inflations coincide with aggregate core inflation, and the sectoral optimality conditions and resource constraints aggregate to their single-sector counterparts. The model is then the representative-firm economy of FLR2026, and its moments constitute a replication check. Table A4 reports the performance. The aggregate stock excess return is 6.67% (vs. 6.87% in FLR2026), and aggregate stock volatility is 18.60% (vs. 18.58%). The bond excess return is 1.15% (vs. 1.13%), and the core inflation β of the aggregate stock is -5.37 (vs. -5.70). The macroeconomic moments, inflation volatility, and the real risk-free rate match FLR2026 to a comparable degree, with the remaining differences within Monte Carlo noise. We conclude that the model nests FLR2026 correctly, and that the extensions of Section 6 are added to a sound replication of the parent economy.

C.2 One parameter at a time

We next test Hypotheses 1 and 2 of Section 5 inside the model, and connect to the growing literature on the cross-section of inflation risk (Hong et al., 2022; Bonelli et al., 2025). With the green preference off, we let the two firms differ in a single price-setting parameter while sharing the same productivity, monetary, and energy shocks; the same SDF; and the same factor markets. Table A5 reports the two experiments (the sector indices 1 and 2 replace the green/brown labels, since with the taste channel off the firms differ only in the parameter listed).

Price stickiness (Panel A). Holding the variety elasticity fixed at $\nu_1 = \nu_2 = 6$, we set $\phi_{P,1} = 30$ and $\phi_{P,2} = 130$, which corresponds to a Calvo-equivalent average price duration of roughly 3 quarters in sector 1 and 5.7 quarters in sector 2 (FLR2026; Weber, 2015). The stickier sector earns a higher equity premium (6.81% vs. 6.39%) and has a more negative core inflation β (-3.33 vs. -3.09). The economic intuition is the one we use in Section 5 and that goes back to Weber (2015): when marginal cost rises, the sticky sector cannot fully reset prices. Its margin and cash flow therefore absorb a larger share of the shock, and its return is more strongly correlated with the rise in inflation. The result confirms Hypothesis 1.

Markup (Panel B). Holding $\phi_{P,1} = \phi_{P,2} = 80$ at the baseline, we set $\nu_1 = 4$ and $\nu_2 = 10$, which delivers steady-state markups of $\mu_1 = 4/3$ and $\mu_2 = 10/9$ in the two sectors. The high-markup sector earns a higher equity premium (6.77% vs. 6.07%) and has a much more negative core inflation β (-6.73 vs. -0.68). The intuition mirrors the markup mechanism in FLR2026 and connects to a broader macro-finance literature linking market power to expected returns (Corhay et al., 2020; Clara, 2023): a lower variety elasticity reduces the marginal benefit of realigning the price with marginal cost. As a result, the high-markup sector's prices respond more sluggishly to cost shocks. Its margin is compressed more strongly when marginal cost rises, and its cash flow co-moves more negatively with core inflation. The result confirms Hypothesis 2 and is consistent with column 2 of Table 12 in FLR2026, where lowering ν from 6 to 3 in the one-sector calibration pushes the aggregate stock core β from -5.70 to -14.32. The two-firm structure turns this comparative-static into a within-economy cross-sectional spread.[20]

The two panels make the same point through different parameters. In Panel A the slow-adjusting sector is the one with stickier prices, and in Panel B it is the one with a higher markup. In both cases the sector whose prices respond more slowly to marginal-cost shocks earns a higher equity premium and has a more negative core inflation β. The mechanism is the same flattening of the New Keynesian Phillips curve, summarized by the slope $\kappa_j = (\nu_j - 1)/\phi_{P,j}$ in Section 6: when the slope is flatter, the sector's inflation response to a productivity shock is muted, but its margins and cash flows still absorb the shock, and its return co-moves more strongly with the rise in core inflation. The two experiments are the model-side counterpart of the cross-sectional evidence in Section 5 and the cross-sectional forces behind the greenium in Section 6.[21]

[20]With heterogeneous markups the two sectors' relative prices deviate from one, and the convention of pricing investment at the numeraire in dividends while sectoral resource constraints allocate it from own-sector output implies a small unmodeled budget item (about 0.24% of core consumption at the Panel B steady state). Re-solving the closely related model of Section 6 with investment purchased as the core consumption bundle, which restores Walras' law, leaves all cross-sector spreads essentially unchanged.

[21]The two experiments are centered on the symmetric baseline ($\nu = 6$, $\phi_P = 80$) and isolate the direction of each channel. They are not a decomposition of the headline green-minus-brown gap of -2.34 in Table 12, and the two spreads do not add up to it, because the core inflation beta is a general-equilibrium object measured against share-weighted aggregate core inflation and each sector's beta depends on both sectors' price-setting jointly. This is why the markup-only spread in Panel B (-6.05) exceeds the headline gap in magnitude even though the headline calibration is more extreme in both parameters: in Panel B the high-markup sector is paired with a baseline counterpart at $\phi_P = 80$, whereas the headline calibration pairs a stickier green firm ($\phi_P = 130$) with a more flexible brown firm ($\phi_P = 30$), and the two channels interact through the stickiness level and the aggregate-inflation weighting.

Table A1. **Variable Definitions**

Variable	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
Food Inflation	Monthly log change in food price index	Federal Reserve Economic Data	Month
Headline Inflation Shocks	Residuals of headline inflation from rolling ARMA(1,1) plus 5 principal components of 127 economic variables	Federal Reserve Economic Data	Month
Core Inflation Shocks	Residuals of core inflation from ARMA(1,1) plus 5 principal components of 127 economic variables	Federal Reserve Economic Data	Month
Energy Inflation Shocks	Residuals of energy inflation from ARMA(1,1) plus 5 principal components of 127 economic variables	Federal Reserve Economic Data	Month
Food Inflation Shocks	Residuals of food inflation from ARMA(1,1) plus 5 principal components of 127 economic variables	Federal Reserve Economic Data	Month
MKTRF	Market excess return factor, defined as the CRSP value-weighted market return minus the one-month Treasury bill rate	Kenneth French website	Month
SMB	Size factor, defined as the return on portfolios of small-cap stocks minus the return on portfolios of large-cap stocks	Kenneth French website	Month
HML	Value factor, defined as the return on portfolios of high book-to-market stocks minus the return on portfolios of low book-to-market stocks	Kenneth French website	Month
RMW	Profitability factor, defined as the return on portfolios of firms with robust operating profitability minus the return on portfolios of firms with weak operating profitability	Kenneth French website	Month
CMA	Investment factor, defined as the return on portfolios of firms with conservative investment policies minus the return on portfolios of firms with aggressive investment policies.	Kenneth French website	Month
CBMKTRF	Corporate bond market excess return factor, defined as the ICE value-weighted corporate bond market return minus the one-month Treasury bill rate	Authors	Month
DEF	Term factor, defined as the return on long-term government bonds minus the return on short-term Treasury bills	Amit Goyal website	Month
TERM	Default factor, defined as the return on long-term corporate bonds minus the return on long-term government bonds	Amit Goyal website	Month
Principal Components	Five principal components from 127 economic and financial variables	Michael McCracken website	Month
RET	Excess returns of stocks	CRSP	Firm-month

(continued)

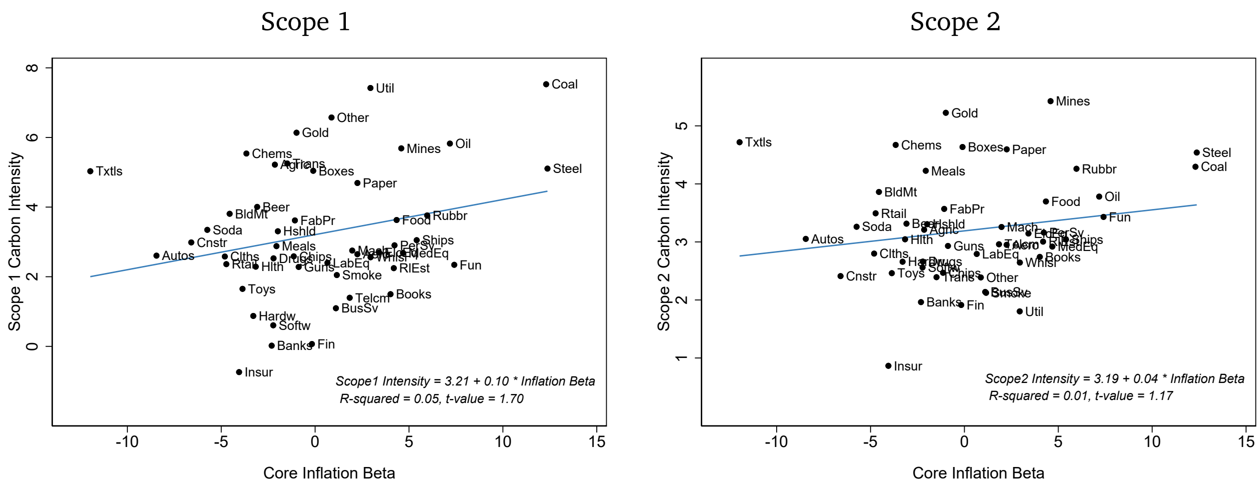
Continued

Variable	Description	Source	Level
Core Beta	Core inflation beta	Authors	Firm-month
Headline Beta	Headline inflation beta	Authors	Firm-month
Energy Beta	Energy inflation beta	Authors	Firm-month
Food Beta	Food 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
Markup (Baseline)	Simple markup, defined as revenues divided by the cost of goods sold	Compustat	Firm-year
Markup (Production Function)	Production-function markup of De Loecker et al. (2020), equal to the industry-year (2-digit NAICS) output elasticity of the cost of goods sold multiplied by the ratio of deflated sales to deflated cost of goods sold	Compustat, Fred	Firm-year
Cash Flow Duration	Equity cash flow duration constructed following Weber (2018)	Compustat	Firm-year
Log(Sales)	Natural logarithm of sales	Compustat	Firm-year
ME/BE	Market value of equity divided by the book value of equity	Compustat	Firm-year
Leverage	Market leverage, defined as book value of debt divided by the sum of the book value of debt and the market value of equity	Compustat	Firm-year
ROA	Return on assets, defined as income before extraordinary items divided by lagged total assets	Compustat	Firm-year
PPE/AT	Asset tangibility, defined as net property, plant, and equipment divided by lagged total assets	Compustat	Firm-year
Price Stickiness	Negative of the frequency of price adjustment from Pasten et al. (2020), aggregated to the 6-digit NAICS industry-year level	Michael Weber Website	Industry (time-invariant)

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			

Panel A. Equity



Panel B. Bond

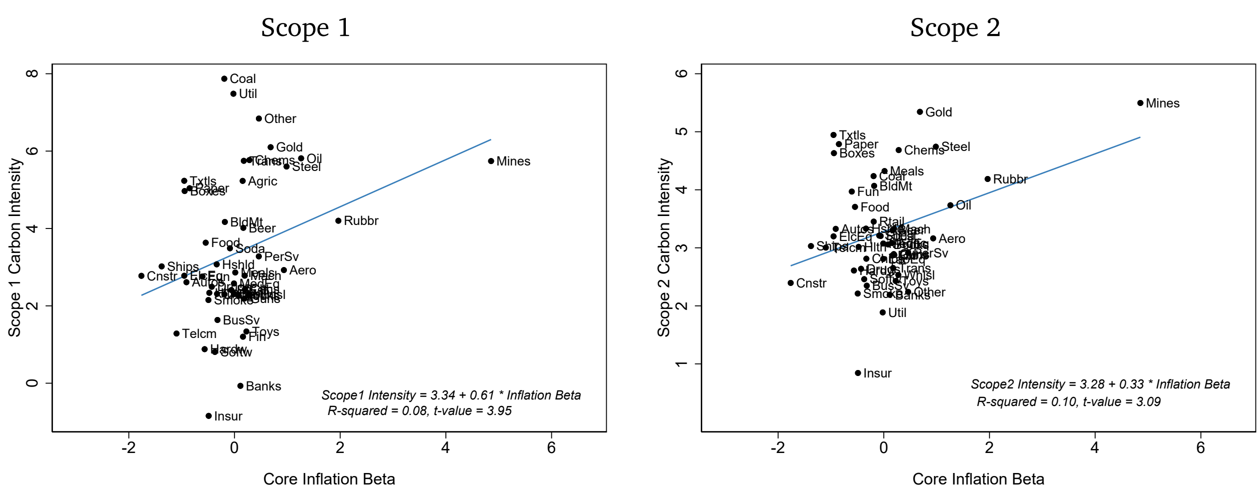


Figure A1. **Carbon Intensity and Core Inflation Exposure of FF49 Industry portfolios**

This figure plots Scope 1 and Scope 2 carbon intensity (y-axis) and core inflation beta (x-axis) for each of the Fama-French 49 industries. Inflation betas are estimated at the industry portfolio level using a 60-month rolling regression of excess returns on contemporaneous and one-month-lagged inflation shocks, and relevant risk factors. Then, inflation beta is the sum of the beta of contemporaneous inflation shock and the beta of one-month-lagged inflation shock. Risk adjustment is conducted using the Fama and French (2018) six equity factors for equity portfolios and, for bond portfolios, a corporate bond market factor in addition to Fama and French (1993) term and default factors. The list of Fama-French 49 industries is presented in Online Appendix Table A2.

Table A3. **Carbon Intensity and Alternative Markup Measures**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Markup (Constant Elasticity)				Markup (Cost Share, SG&A Excluded)				Markup (Cost Share, SG&A Included)			
Scope 1 Carbon Intensity	-0.23***	-0.17***			-0.30***	-0.21***			-0.11***	-0.07***		
	(-10.86)	(-9.28)			(-13.17)	(-10.33)			(-9.92)	(-6.56)		
Scope 2 Carbon Intensity			-0.40***	-0.29***			-0.45***	-0.29***			-0.18***	-0.11***
			(-9.76)	(-8.02)			(-10.28)	(-7.65)			(-8.07)	(-5.60)
log(Sales)		-0.11***		-0.09***		-0.11***		-0.09***		-0.05***		-0.05***
		(-4.56)		(-3.63)		(-4.36)		(-3.37)		(-3.44)		(-2.84)
ME/BE		0.02***		0.02***		0.02***		0.02***		0.01***		0.01***
		(3.95)		(3.96)		(4.07)		(4.14)		(3.73)		(3.72)
Leverage		-1.58***		-1.62***		-1.65***		-1.71***		-0.96***		-0.97***
		(-9.36)		(-9.58)		(-9.35)		(-9.56)		(-9.30)		(-9.45)
ROA		-0.00		-0.00		-0.00		-0.00		0.00		0.00
		(-0.71)		(-0.57)		(-0.51)		(-0.36)		(0.97)		(1.07)
PPE/AT		-0.19*		-0.29***		-0.54***		-0.74***		-0.27***		-0.31***
		(-1.66)		(-2.59)		(-4.75)		(-6.43)		(-3.87)		(-4.53)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.12	0.05	0.13	0.07	0.15	0.05	0.14	0.03	0.11	0.03	0.11
Obs.	11,209	9367	11209	9367	11209	9367	11209	9367	11209	9367	11209	9367

This table presents firm-level panel regressions of alternative markup measures, constructed following De Loecker et al. (2020), on carbon intensity. Columns 1-4 report results for the constant elasticity markup, where the output elasticity is calibrated to a constant value of 0.85. Columns 5-8 and 9-12 report results for cost-share-based markups, where the output elasticity is proxied by the within-industry-year median cost share computed excluding and including SG&A, respectively. For the computation of markups, industries are defined at the 2-digit NAICS level. Following De Loecker et al. (2020), we drop firm-years with non-positive deflated revenues, cost of goods sold, or SG&A and trim the sales-to-cost-of-goods-sold ratio and the underlying cost shares at the 1st and 99th percentiles by year before computing the markup measures. The firm-level controls are trimmed at the same percentiles. All specifications control for firm characteristics defined in Table A1 and include year fixed effects. Standard errors are clustered at the firm level, with *t*-statistics reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 2009 to 2021.

Table A4. **Replication of FLR2026 under the Symmetric Two-Sector Calibration**

Moment	Data	FLR2026 (One Sector)	Two-Sector (Nesting Check)
Panel A: Macroeconomic moments (% per year)			
$E[\Delta y]$	1.96	1.78	1.93
$\sigma(\Delta y)$	3.18	2.67	2.92
$\sigma(\Delta c)$	1.74	1.37	1.53
$\sigma(\Delta i)$	15.15	8.06	8.63
$E[r_f]$	0.93	1.45	1.45
$E[y^{(1)}]$	4.63	4.98	4.92
Panel B: Inflation volatility (% per year)			
Core inflation	3.18	3.29	3.12
Panel C: Asset excess returns (% per year)			
Stock (aggregate), mean	6.80	6.87	6.67
Stock (aggregate), SD	16.79	18.58	18.60
Bond, mean	1.93	1.13	1.15
Panel D: Inflation betas			
Stock core β	-5.60	-5.70	-5.37

Notes: This table reports the symmetric nesting check of the model of Section 6. The two-sector column shuts down the green preference ($\bar{\chi} = \sigma_{\chi} = 0$) and sets $\nu_1 = \nu_2 = 6$ and $\phi_{P,1} = \phi_{P,2} = 80$, which collapses the model to a single representative core sector and should reproduce the one-sector FLR2026 baseline. Other parameters are listed in Table 11. The aggregate stock return is the leverage-adjusted return on the aggregate equity claim, whose dividend is the sum of the two sectors' dividends plus the energy dividend $\alpha C_{e,t} P_{e,t}$, as in FLR2026. Data column reports U.S. data moments from FLR2026. All values annualized in percent per year. The model is solved by third-order perturbation with pruning, and moments are computed on a 25,000-quarter simulation initialized at the deterministic steady state. The two-sector aggregate moments line up with the one-sector FLR2026 moments within Monte Carlo noise, confirming that the extension reduces correctly to the parent model under symmetric calibration.

Table A5. **Two-Sector Cross-Section: Price Stickiness and Markup Heterogeneity**

	Sector 1	Sector 2	Spread $(1-2)$
Panel A: Price-stickiness heterogeneity ($\phi_{P,1}=30$, $\phi_{P,2}=130$; $\nu_1=\nu_2=6$)			
Rotemberg coefficient $\phi_{P,j}$	30	130	
Implied price duration (quarters)	~ 3.0	~ 5.7	
Markup μ_j	1.200	1.200	0
Equity premium (% per year)	6.39	6.81	-0.43
Core inflation β	-3.09	-3.33	0.24
Panel B: Markup heterogeneity ($\nu_1=4$, $\nu_2=10$; $\phi_{P,1}=\phi_{P,2}=80$)			
Variety elasticity ν_j	4	10	
Markup $\mu_j=\nu_j/(\nu_j-1)$	1.333	1.111	0.222
Equity premium (% per year)	6.77	6.07	0.70
Core inflation β	-6.73	-0.68	-6.05

Notes: This table reports the single-parameter cross-sectional experiments of Online Appendix C.2, based on the model of Section 6 with the green preference shut down ($\bar{\chi}=\sigma_\chi=0$). Two ex-ante identical sectors face the same household, the same productivity and monetary shocks, and the same factor prices; they differ only in the parameters listed. Panel A varies the Rotemberg price-adjustment coefficient $\phi_{P,j}$ across sectors while holding the variety elasticity ν_j at 6. Panel B varies ν_j while holding $\phi_{P,j}$ at the baseline value of 80. Implied Calvo-equivalent price duration in Panel A is computed at the linearized New Keynesian Phillips curve. Equity premium is the leverage-adjusted annualized return in excess of the real risk-free rate. Core inflation β is the slope coefficient on $\Delta \log \Pi_t$ in a two-factor regression of the (sector j) excess return on $\Delta \log \Pi_t$ and $\Delta \log \Pi_t^e$ at the quarterly frequency, in line with the inflation-beta convention of FLR2026. The two-sector spread column is sector 1 minus sector 2. In both panels, the sector whose prices respond more slowly to marginal-cost shocks, whether through stickier prices (Panel A) or through a higher markup (Panel B), has a more negative core inflation β and earns a higher equity premium. Other parameters are in Table 11. The model is solved by third-order perturbation with pruning, and moments are computed on a 25,000-quarter simulation initialized at the deterministic steady state.