Responsible Consumption, Demand Elasticity, and the Green Premium*

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Abstract

We study equilibrium asset prices in a model where investors favor "green" over "brown" goods. We show that demand elasticity of *goods* crucially affects *assets*' riskiness. When demand elasticity is high, brown assets are safer than green, because they hedge against consumption risk. The opposite holds when goods' demand elasticity is low. Our model therefore predicts that the "green minus brown" stock return spread (green premium) varies in the cross section and increases in the price elasticity of demand. We test this novel prediction on US stocks and find that over the 2012–2022 period the annual green premium is 11.7% for firms with high demand elasticity, while it is much smaller and insignificant for firms with low demand elasticity. The high green premium for high demand elasticity firms is robust to standard risk adjustments and to alternative measures of demand elasticity; it cannot be explained by unanticipated shocks to investors' environmental concerns, and remains strong after using option-implied measures of expected returns. These findings underscore the critical role of goods' demand elasticity for understanding the impact of responsible consumption on asset prices.

JEL Classification: G11, G12

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1 Introduction

Individuals manifest their preference for social responsibility through their investment and consumption decisions. Socially responsible investors aim at achieving pro-social objectives by divestment or shareholder engagement. Similarly, socially responsible consumers aim to influence corporate behavior through their purchasing decisions.[1] Spurred by the widespread attention to environmental, social, and governance ("ESG") concerns in investment decisions, the finance literature has directed its focus toward exploring the impact of socially responsible investments on asset prices. Much less attention, however, has been devoted to the financial repercussions of socially responsible consumption. This gap in the literature is surprising given the pervasive and frequent nature of households consumption decisions and their economic relevance.[2] Tariq Fancy, BlackRock's former global chief investment officer for sustainable investing effectively underscores the relevance of responsible consumption: "...10% of the market not buying your stock is not the same as 10% of your customers not buying your product."[3]

In this paper we study the implications of responsible consumption for asset prices. In an equilibrium consumption-based asset pricing model where agents prefer goods produced by socially-responsible firms, we show that the price elasticity of demands for goods is a crucial determinant of the riskiness of "green" (socially responsible) and "brown" stocks. Specifically, the return spread between green and brown stocks is *increasing* in the price elasticity of demand. Empirically, we find that a large part of the documented outperformance of green stocks over the last decade can be attributed to firms facing high demand elasticity. Our empirical results suggests that responsible consumption plays an important role in the cross sectional pricing of securities in the US equity market.

To illustrate the main mechanism of our model, consider an endowment economy with two types of goods, "green" and "brown" and a consumer who prefers green over brown goods. Assume also that the agent can trade green and brown stocks, representing financial claims on the green and brown good endowments, respectively. The agent holds financial assets as a way to smooth

[1] The Free-produce Movement, an international boycott of goods produced by slave labor or the late 1700s, is credited as one of the earliest form of responsible consumption in the US, see, Glickman (2004). Notable instances of responsible consumption include movements such as the boycott against South African goods during apartheid, the 1960s consumer rights movement in the United States, and more recent campaigns promoting ethical sourcing and sustainability in consumer products.

[2] Final goods consumption expenditure represents 68.21% of GDP in the US (OECD, 2023).

[3] https://medium.com/@sosofancy/the-secret-diary-of-a-sustainable-investor-part-1-70b6987fa139.

consumption and maximize lifetime utility. Our main result is that responsible consumption affects the risk of green and brown *assets* differently, depending on the level of the price elasticity: when goods' demand elasticity is high, green stocks are riskier than brown and vice-versa when demand elasticity is low.

To understand this result, suppose that the economy is in a state where the green endowment is scarce relative to the brown. Because the consumer favors the green good, states of the world where the green endowment is scarce are "bad" for the consumer, relative to states where the brown good is scarce. If demand elasticity is high, the consumer can easily substitute green for brown goods, making the green good is less "special". A green stock is therefore risky as the drop in quantity occurring in bad states is not compensated by an increase in desirability of the green good. Although brown goods are less desirable to the consumer, when demand elasticity is high, they act as a good substitute for green goods in bad states. Therefore, brown stocks provide a natural hedge against the risk of green goods shortages. In sum, when demand elasticity is high, green stock are riskier than brown. The opposite is true when demand elasticity is low. In this case green goods are difficult to substitute with brown, making them very valuable in states where they are in short supply. In this case green stocks are safer, as they deliver the highly desirable green goods in bad states of the economy while brown stocks are riskier. The mechanism at play is similar to the "terms of trade hedge" in international finance, e.g., Cole and Obstfeld (1991) and Martin (2010), that is, price response (terms-of-trade) can provide insurance against output shocks. Hence a key prediction from our theory is that the"green premium"—that is, the difference between the expected return of green and brown stocks—is an increasing function of goods' demand elasticity.

We first illustrate the main idea in a two-period model where a representative agent has constant elasticity of substitution (CES) preferences over two consumption goods. We explicitly show that the demand elasticity determines the relative riskiness of assets in the economy. When demand elasticity is greater than one, the asset that produces the favored good is riskier than the asset that produces the disfavored good. The opposite is true when demand elasticity is less than one. While informative about the effect of demand elasticity on asset prices, the simple CES model implies that all goods in the economy have the *same* demand elasticity, which corresponds to the elasticity of substitution across goods. Because of this limitation, the simple intuition from the CES endowment model cannot be extended to a realistic cross section with heterogeneity in goods demand elasticity.

To break the link between elasticity of substitution and demand elasticity in the simple CES model, we propose a general equilibrium model with multiple goods where the agents form habits over individual goods, as in Ravn, Schmitt-Grohé, and Uribe (2006) and van Binsbergen (2016). Our model can be thought of as a version of the "Lucas Orchard" with "deep habits."[4] The presence of good-specific habits allows us to generate a representative cross section of goods' demand elasticities, consistent with reality. As in van Binsbergen (2016), goods with high habit level have low demand elasticity and hence the asset producing such goods hedges against aggregate shocks. In equilibrium, these assets are less risky than those producing goods with low habit levels. If consumers favor some goods over others, the positive relation between demand elasticity and expected returns becomes "steeper" for the asset assets producing favored goods (e.g., green asset) than for assets producing disfavored goods (e.g., brown assets). We construct an equilibrium in this economy and calibrate it to reproduce key asset pricing moments. We then simulate representative cross sections of stocks from this equilibrium, and find that green assets are indeed riskier than brown for high level of demand elasticity, and safer for low levels of demand elasticity. Therefore, the model predicts that the green premium increases with demand elasticity.

We empirically investigate our model predictions using US stock return data from CRSP and ESG scores from MSCI. Following van Binsbergen (2016), we use cumulative price changes (CPC) as a proxy of demand elasticity: decreasing product price are signals of high price competition and hence high demand elasticity. We sort firms into portfolios based on their demand elasticity and their ESG score. Specifically, for each demand elasticity portfolio, we form a zero-cost portfolio that shorts firm with low ESG scores and long firms with high ESG score. We refer the spread return on this portfolio as the Green Minus Brown (GMB) spread, or green premium. Similar to Pastor, Stambaugh, and Taylor (2022), we find that over the 2012–2022 sample period green stocks outperform brown in our sample period with a cumulative return difference of 68.3%. However, we also find that virtually all of this out-performance comes form stocks in the high-demand elasticity tercile. From our time series analysis we estimate that the annual equal-weighted GMB spread for high demand elasticity stocks is 11.7% and statistically significant. In contrast, the GMB spread for low demand elasticity stocks is 2.6% and statistically insignificant. The positive GBM spread in the high demand elasticity portfolios remains economically and statistically significant after controlling

[4]Similar to Cochrane, Longstaff, and Santa-Clara (2008) and Martin (2013), our model features multiple trees. However, unlike these papers where all trees produce the same fruit, in our model each tree produces a unique fruit. The overall utility is derived by aggregating the different fruits through a CES function.

for exposures to common asset pricing factors, such as the CAPM, the Fama and French (1993) three-factor model and the Fama and French (2015) five-factor model. This results is striking and confirms that consumption preferences and demand elasticity have a first order effect in the determination of the green premium in the cross section of US stocks.

The relatively short sample period, 2012–2022, raises the concern that our results, based on realized returns might not be informative of the theoretical predictions of our model, that instead refer to *expected* returns. To address this concern, we also perform our analysis using two alternative measures of expected returns provided by the existing literature. First, following Pastor, Stambaugh, and Taylor (2022) we estimate expected return based on the intercept of the regression of realized returns on shocks to climate concerns and earnings to obtain a "counterfactual", or purified, measure of the GMB spread. Second, we construct a measure of conditional expected returns at the stock level from forward-looking information contained in traded option contracts, as in Martin (2017) and Martin and Wagner (2019).

We find that, while the unconditional GMB spread can be explained by climate and earning surprises, the same cannot be said for the GMB spread within high demand elasticity stocks. Unanticipated shocks to climate concerns and firms' earnings only explain approximately half of the GMB spread and the counterfactual spread remains positive and significant. Fama-Macbeth regressions of option-implied expected returns further show that, unconditionally, firms with high ESG scores have low expected returns. These results confirm the finding of Pastor, Stambaugh, and Taylor (2021) and Pastor, Stambaugh, and Taylor (2022) that the recent outperformance of green over brown stocks is largely driven by "surprises" and that the expected GMB return is negative. However, our analysis also shows that the relation between ESG scores and expected returns is negative for low demand elasticity and positive for high demand elasticity. These findings provide novel evidence that GMB spread varies across demand elasticities, suggesting the existence of a risk compensation channel, as predicted by our model.

Our findings have implications for strategies that responsible consumers undertake to impact firms' behavior. We show that responsible consumption raises the cost of capital for green firms with high price elasticity of demand and lowers it for green firms with low elasticity. Hence, consumers' strategies that target goods with inelastic demand have a greater impact on the cost of capital of the targeted firms. Such strategies can be an effective tool to incentivize firms to embrace the values championed by consumers.[5] To the best of our knowledge, ours is the first study to document, both theoretically and empirically, the relevance of responsible consumption and goods' demand elasticity for asset prices.

Literature. Our paper contributes to two strands of literature. First, we contribute to the rapidly growing literature investigating the effect of social preferences on returns, starting with the pioneering contribution of Heinkel, Kraus, and Zechner (2001) who offer a model in which the divestment by green investors raises the cost of polluting capital. Papers in this literature typically model the impact of responsible investment on the cost of capital.[6] In contrast, our work emphasizes the role of responsible consumption on asset prices. We show that for a green consumer it might be optimal to counterintuitively hold a brown asset because it provides insurance against shortages of the green endowment. Baker, Hollifield, and Osambela (2022) first highlighted this channel in a single-good economy where environmentalists who dislike pollution optimally hold more shares of polluting firms for hedging motives. By allowing for good-specific habits, our model shows that the hedging property of green assets is crucially determined by the demand elasticity. Importantly, we also provide novel empirical evidence emphasizing the role of goods' demand elasticities on the relative return of green and brown assets. In doing so, we offer a theoretically motivated refinement of the existing evidence on the riskiness of green and brown stocks.

Second, we contribute to the recent literature that studies the market implications of consumption consciousness. Aghion, Bénabou, Martin, and Roulet (2023) show how responsible consumption induce firms to pursue greener innovations while Kaufmann and Koszegi (2023) shows that responsible consumption may induce non-price taking behavior in general equilibrium. We add to this literature by evaluating the implication of responsible consumption on asset return and showing that the relation between responsible consumption and the green premium is intermediated by the goods' demand elasticity. Sauzet and Zerbib (2022) also study the implication of green consumption on asset return in a general equilibrium model. The key difference from their paper is that our model features a cross section of goods with heterogeneous demand elasticities, whereas

[5] Jagannathan, Kim, McDonald, and Xia (2023) examines the effectiveness of three different strategies used by environmental activists, namely Exit, Boycott, and Voice, on asset prices. They find that consumption Boycott is at least as effective as Exit, and Voice to be the most effective, in that it requires the fewest amount of coordination among activists.

[6] See, e.g., Luo and Balvers (2017); Baker, Bergstresser, Serafeim, and Wurgler (2018); Pedersen, Fitzgibbons, and Pomorski (2021); Pastor, Stambaugh, and Taylor (2021); Landier and Lovo (2020); Berk and van Binsbergen (2021); Pastor, Stambaugh, and Taylor (2022); Bolton and Kacperczyk (2021); Zerbib (2022); Oehmke and Opp (2022); Hartzmark and Shue (2023).

the two goods in their economy have the *same* demand elasticity, equal to an exogenously specified elasticity of substitution. Importantly, we provide extensive empirical evidence that the green premium varies in the cross section, depending on the price elasticity of demand. Our work also shares commonalities with Albuquerque, Koskinen, and Zhang (2019), who present an industry equilibrium model where firms invest in corporate social responsibility (CSR) to increase product differentiation, leading to lower systematic risk. However, our model differs from theirs in that green firms do not inherently possess a more loyal customer base. Instead, by exploiting good-specific habits, our model can generate a cross section of demand elasticities. This feature enables us to explore the equilibrium relationship between green and brown returns based on the price elasticity of demand.

The rest of the paper proceeds as follows. Section 2 present a simple two-period model of consumption bias. Section 3 presents a general equilibrium model with multiple goods and deep habits that we calibrate to the data. Section 4 contains our empirical analysis. Section 5 concludes. Appendix A contains proofs and Appendix B describes the numerical solution of the model presented in Section 3.

2 A simple equilibrium model of responsible consumption

In this section, we develop a stylized two-goods static model in which a representative agent trades two securities, each representing a claim to the goods included in the agent's consumption basket. The model illustrates how responsible consumption—modeled as a preference bias in favor of one good relative to the other affects equilibrium asset prices.

2.1 Setup

We consider an economy with two dates, $t = 0, 1$, and two assets, or "trees" in unit supply, which we label as G ("green") and B ("brown"). At time $t = 0, 1$ each tree $i = G, B$ produces a random quantity of perishable good $Y_{i,t}$. The two assets G and B are tradable in a frictionless financial market and the two goods are traded in competitive product markets.

The representative agent is endowed with the outstanding shares of the two trees, selects a preferred consumption plan of the two goods, and chooses a portfolio strategy of the two assets that attains the desired consumption plan. Assets and goods are priced such that the representative investor's optimal strategy is not to trade at either time period and to consume the goods produced by the two trees.

Preferences. The preferences of the representative agent exhibit an "ideological bias" that favor one type of consumption over the other. We assume that good G is favored over good B. This bias represents, for example, a preference towards goods produced locally or with an environmentally-friendly technology, and dislike for goods with negative environmental or social impact, such as such tobacco or firearms or other "sin" goods.

We assume that the intertemporal preferences of the representative agent have a standard constant relative risk aversion (CRRA) representation

$$\frac{\mathcal{C}_0^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}\left[\frac{\mathcal{C}_1^{1-\gamma}}{1-\gamma}\right], \tag{1}$$

where $\gamma > 1$ is the coefficient of relative risk aversion, β a time-preference parameter and $\mathcal{C}_t$ denotes a "composite good" consisting of a constant elasticity of substitution (CES) aggregation of consumption in each of the two goods, $C_{i,t}$, that is,

$$\mathcal{C}_t = \left(\frac{1+\phi}{2} C_{G,t}^{1-\frac{1}{\eta}} + \frac{1-\phi}{2} C_{B,t}^{1-\frac{1}{\eta}}\right)^{\frac{1}{1-\frac{1}{\eta}}}, \quad t = 0, 1, \tag{2}$$

with $\phi \in [0,1]$ and $\eta > 0$. The parameter $\eta \in (0, \infty)$ denotes the elasticity of substitution across goods.[7] The parameter ϕ represents the agent's preference bias in favor of good G and against good B. For $\phi = 0$ the agent does not exhibit consumption bias. The bias ϕ is a reduced-form way to introduce responsible consumption in the model. Large value of ϕ imply strong desire for good G against good B. The case of $\phi \to 1$ can be interpreted as an extreme form of responsible consumption, such as a boycott campaign against good B.

Equilibrium. An equilibrium consists of asset prices V_i and goods prices $P_{i,t}$, $i = G, B$, $t = 0, 1$, such that the representative agent maximizes its lifetime utility (1) and goods and asset markets clear. Given the preferences representation in equations (1)–(2), constructing an equilibrium in

[7] For $\eta \to \infty$, $\mathcal{C}_t \to \frac{1+\phi}{2} C_{G,t} + \frac{1-\phi}{2} C_{B,t}$, implying that goods G and B are substitute. For $\eta \to 0$, $\mathcal{C}_t \to \min\{C_{G,t}, C_{B,t}\}$ and the two goods are perfect complement. For $\eta \to 1$, the composite good $\mathcal{C}_t$ has the "Cobb-Douglas" representation $\mathcal{C}_t = C_{G,t}^{\frac{1+\phi}{2}} C_{B,t}^{\frac{1-\phi}{2}}$.

this economy requires two steps. First, we solve the intertemporal problem of the representative agent by considering a fictitious model with a single tree, representing a claim to the aggregate quantity of the composite good $\mathcal{C}_t$. The price of the G and B assets are such that the representative agent holds the endowed tree. Second, at each time t, we solve the intra-temporal problem of the agent, consisting of finding the optimal finding the optimal demand for goods and the corresponding market clearing prices.

Asset prices. We consider a fictitious one-tree economy with an endowment processes $\mathcal{Y}_t$ given by

$$\mathcal{Y}_t = \left(\frac{1+\phi}{2} Y_{G,t}^{1-\frac{1}{\eta}} + \frac{1-\phi}{2} Y_{B,t}^{1-\frac{1}{\eta}} \right)^{\frac{1}{1-\frac{1}{\eta}}} . \tag{3}$$

and a representative investor with the preferences described in equation (1). Imposing market clearing, $\mathcal{C}_t = \mathcal{Y}_t$, $t = 0, 1$, we obtain that the pricing kernel in this fictitious single-tree economy is

$$\mathbb{M}_1 = \beta \left(\frac{\mathcal{Y}_1}{\mathcal{Y}_0} \right)^{-\gamma} . \tag{4}$$

Goods prices. Without loss of generality, all prices of goods and assets will be expressed in units of the composite good, $\mathcal{Y}_t$. The representative agent maximizes the intraperiod utility (2) under the constraint that the endowed budget $\mathcal{Y}_t$ is spent on the purchase of goods G and B, that is, $\mathcal{Y}_t = P_{G,t}C_{G,t} + P_{B,t}C_{B,t}$. The solution of this problem leads to the following demand functions

$$C_{G,t} = \left(\frac{1+\phi}{2} \right)^{\eta} P_{G,t}^{-\eta} \mathcal{Y}_t, \quad C_{B,t} = \left(\frac{1-\phi}{2} \right)^{\eta} P_{B,t}^{-\eta} \mathcal{Y}_t. \tag{5}$$

Equation (5) show that the demand of both goods have the same price elasticity, that is,

$$-\frac{\partial \ln C_{i,t}}{\partial \ln P_{i,t}} = \eta, \quad i = G, B. \tag{6}$$

Therefore, in this economy, the parameter η captures both the elasticity of substitution across good and the demand elasticity of each good. Imposing market clearing, $C_{i,t} = Y_{i,t}$, in equation (5) we obtain the equilibrium goods prices

$$P_{G,t} = \frac{1+\phi}{2} \left(\frac{Y_{G,t}}{\mathcal{Y}_t} \right)^{-\frac{1}{\eta}}, \ P_{B,t} = \frac{1-\phi}{2} \left(\frac{Y_{B,t}}{\mathcal{Y}_t} \right)^{-\frac{1}{\eta}} . \tag{7}$$

Because each asset i delivers a payoff of $Y_{i,t}P_{i,t}$ units of the composite good, the expected return of asset $i = G, B$ at time 0 is

$$\mathbb{E}[R_i] = \frac{\mathbb{E}[Y_{i,1}P_{i,1}]}{\mathbb{E}\left[\mathbb{M}_1 Y_{i,1}P_{i,1}\right]}, \quad i = G, B. \tag{8}$$

Substituting the expression for the pricing kernel from equation (4) and the equilibrium goods prices from equation (7) in equation (8), we obtain that asset i's expected return is

$$\mathbb{E}[R_i] = \frac{\mathbb{E}\left[\mathcal{Y}_1^{\frac{1}{\eta}} Y_{i,1}^{1-\frac{1}{\eta}}\right]}{\mathcal{Y}_0^{-\gamma}\beta\mathbb{E}\left[\mathcal{Y}_1^{\frac{1}{\eta}-\gamma} Y_{i,1}^{1-\frac{1}{\eta}}\right]}, \quad i = G, B. \tag{9}$$

An inspection of equation (9) shows that when $\eta = 1$, the expected return on asset G and B are identical, that is,

$$\mathbb{E}[R_G] = \mathbb{E}[R_B] = \frac{\mathbb{E}\left[\mathcal{Y}_1\right]}{\mathcal{Y}_0^{-\gamma}\beta\mathbb{E}\left[\mathcal{Y}_1^{1-\gamma}\right]}. \tag{10}$$

The green and brown expected return are aligned when $\eta = 1$ because the CES aggregator (2) becomes Cobb-Douglas and, as a result, the dividend of both the green and the brown securities is linear in the quantity of composite good $\mathcal{Y}_1$.

To build intuitions on how the demand elasticity impacts expected returns when $\eta \neq 1$, consider a two-state economy where, at time $t = 0$, the supply of G and B goods are identical, $Y_{G,0} = Y_{B,0} = 1$ and at time $t = 1$ the endowment $(Y_{G,1}, Y_{B,1})$ is

$$(Y_{G,1}, Y_{B,1}) = \begin{cases} (h, 1), & \text{if } \omega = \omega_G \\ (1, h), & \text{if } \omega = \omega_B \end{cases}, \tag{11}$$

where $h > 1$ is a given constant and the two states ω_G and ω_B are equally likely. The following proposition shows that the expected return of the green asset in this example is larger than the brown asset if and only if $\eta > 1$.

Proposition 1. *Suppose the time $t = 1$ endowment of green and brown goods is given by equation (11). If the representative agent's preferences exhibit a bias $\phi > 0$ in favor of green goods, the "green-minus-brown (GMB)" expected return spread, $\mathbb{E}[R_G] - \mathbb{E}[R_B] > 0$ if and only if $\eta > 1$.*

To understand the result in Proposition 1, it is helpful to consider how changes in the endowment $Y_{i,1}$ affect the asset dividend, $D_{i,1}$. In a multi-good economy, the dividend $D_{i,t}$ represents the purchasing power of composite goods that ownership of asset i entails, that is $D_{i,t} = Y_{i,t} \times P_{i,t}$, $i = G, B$. Using the equilibrium demand and price functions (5) and (7) and imposing market clearing $C_{i,t} = Y_{i,t}$, we obtain that the sensitivity of asset i's dividend to shocks to endowment $Y_{i,1}$ is

$$\Delta \ln D_{i,t} = \underbrace{\Delta \ln Y_{i,t}}_{\text{quantity effect}} + \underbrace{\Delta \ln P_{i,t}}_{\text{price effect}} = \Delta \ln Y_{i,t}\left(1 - \frac{1}{\eta}\right), \tag{12}$$

where the last equality follows from equation (6) and market clearing. Equation (7) shows that a positive supply shock to either good $i = G$ or B will always lead to a decrease in the price of that good. However, by equation (12) the impact of the shock on the dividend is determined by the interplay of two opposing forces. The first is a positive force resulting from the increase in the good *quantity*, while the second is a negative force resulting from the decrease in *price*. Equation (12) shows that the dominance of either force depends on the demand elasticity of the affected good. In particular, when the demand is inelastic (i.e., $\eta < 1$), quantity and dividends move in the opposite direction because the decrease in price following a positive supply shock may offset the increase in quantity, leading to a decrease in dividends. On the other hand, when the demand is elastic (i.e., $\eta > 1$), quantity and dividends move in the same direction.

In Proposition 1 we have assumed that the consumption bias $\phi > 0$, therefore the state in which the green endowment is relatively scarce represents a bad state, that is, it exhibits a higher marginal utility relative to a state where the brown endowment is scarce. Consider a shock to the endowment of the two goods that leads the economy from the good state ω_G to the bad state ω_B. By equation (12), when $\eta > 1$, the negative shock $\Delta Y_{G,1}$ implies a decrease of asset G's dividend; on the other hand, the dividend of asset B (whose endowment is subject to a positive shock) increases. Therefore, asset G is *riskier* than B, because it delivers a lower dividend when marginal utility is high. In contrast, asset B is a *hedging* asset, as it delivers a higher dividend in the same state. The opposite result obtains when $\eta < 1$. In this case, the asset G is a hedging asset while the asset B is riskier.

To further explore the role of elasticity and consumption bias on expected returns, Figure 1 shows the GMB spread $\mathbb{E}[R_G] - \mathbb{E}[R_B]$ as a function of demand elasticity η. We consider three

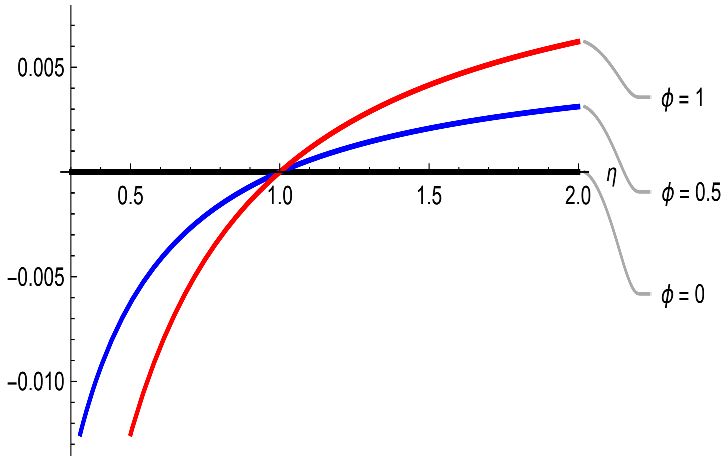


Figure 1: **GMB spread and consumption bias in Proposition 1**

The figure shows the equilibrium GMB spread $\mathbb{E}[R_G] - \mathbb{E}[R_B]$ as a function of demand elasticity for different values of the consumption bias ϕ. Parameter values: $\gamma = 2$, $\beta = 0.8$, $Y_{0,G} = Y_{0,B} = 1$, $h = 1.1$.

different values for the consumption bias: $\phi = 0$, $\phi = 0.5$ and $\phi \to 1$. The figure shows that the GMB spread is increasing in demand elasticity η: the G asset is riskier than B when $\eta > 1$ and safer when $\eta < 1$. Furthermore, the figure shows that consumption bias ϕ amplifies the magnitudes of the spread. In fact, the spread is zero when $\phi = 0$ (black line) and increases, in absolute value, as $\phi \to 1$ (red line).

In sum, the stylized model of this section highlights that in an otherwise standard endowment economy with multiple goods, if the representative agent is a responsible consumer, favoring some goods over others in the consumption basket, then the expected return spread between the asset paying dividends in the favored good and the asset paying dividends in the disfavored good is increasing in demand elasticity. This implies that, when green goods are favored over brown goods, our model predicts that the "green-minus-brown" expected return spread increases with demand elasticity. This effect is amplified when activism motives are stronger, that is if the agent has a stronger preference bias ϕ.

3 A dynamic model of responsible consumption

The simple model of the previous section highlights goods' demand elasticity as a key channel through which responsible consumption impacts asset prices. However, this simple model suffers from the limitation that all goods in the economy have the same demand elasticity, corresponding to the constant elasticity of substitution across goods. This assumption fails to capture the heterogeneity in the demand elasticity across different types of goods that we see in the data. In this section, we break this link by considering an economy with multiple goods that differ in demand elasticity and level of "greenness". We capture difference in demand elasticity by allowing good-specific ("deep") habits as in Ravn, Schmitt-Grohé, and Uribe (2006), and van Binsbergen (2016). We show that the presence of consumption bias towards green goods implies that the GMB return spread is increasing in demand elasticity. We formally test this prediction in the data in Section 4.

Preference and demand functions. We consider an economy with a continuum products and a continuum technologies that differ in their "greenness", which, for example, can be captured by an ESG score. For tractability, we assume that there is a continuum of measure one of products and a continuum of measure one of technologies. We label by $i \in [0,1]$ the product index and by $j \in [0,1]$ the technology. We assume that each product i is available in all technologies. This assumption aims to mimic the empirical sorting procedures we perform in Section 4.

We denote by $\phi_j \in (-1,+1)$ the index that tracks the greenness of the technology and define a "good" as the pair (i,j) consisting of a product i and a greenness technology j. We consider an economy with a continuum of homogeneous and infinitely-lived investors with time-separable CRRA preferences and a bias towards goods produced with greener technologies. Since the continuum of investors has a total mass of 1, individual consumption and portfolio holdings also represent the aggregate consumption and portfolio holdings, respectively. The intertemporal preferences of the agent are

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{\mathcal{C}_t^{1-\gamma}}{1-\gamma}, \tag{13}$$

with β the time-preference parameter and γ denoting the coefficient of relative risk aversion. We assume that $\mathcal{C}_t$ represents consumption of a bundle of goods in excess of good-specific habits. In addition, to account for the agent's consumption bias, we also assume that $\mathcal{C}_t$ depends on the greenness score ϕ_j. Specifically, denoting by $C_t(i,j)$ the agent's consumption and $H_t(i,j)$ the habit level for good (i,j), we define the intra-period utility as

$$\mathcal{C}_t = \left[\int_0^1 (1+\phi_j)^{1/\eta} \, \mathcal{C}_t(j)^{1-\frac{1}{\eta}} \mathrm{d}j \right]^{\frac{1}{1-\frac{1}{\eta}}}, \tag{14}$$

where η is the elasticity of substitution between the goods, as in Dixit and Stiglitz (1977) and $\mathcal{C}_t(j)$ denotes the habit-adjusted consumption of goods produced by the technology j, defined as

$$\mathcal{C}_t(j) = \left[\int_0^1 \left(C_t(i,j) - \theta H_t(i,j)\right)^{1-\frac{1}{\eta}} \mathrm{d}i\right]^{\frac{1}{1-\frac{1}{\eta}}}. \tag{15}$$

where $\theta \in [0,1]$ is a parameter that controls the habit strength. Equation (14) corresponds to the consumption basket defined in equation (2) in the stylized model of Section 2. As in that model, the parameter ϕ_j captures responsible consumption, by introducing a preference bias in favor of some goods over other in the consumption basket. In equation (14), the agent's preferences favor goods with a positive green score, $\phi_j > 0$, over goods with a negative scores, $\phi_j < 0$.

Because there is a continuum of consumer, every consumer takes as given the menu of good prices $P_t(i,j)$ and the menu of (external) habit $H_t(i,j)$ for all goods (i,j) when forming demand functions. Therefore, we can derive the optimal consumer's demand $C_t(i,j)$ for good (i,j) by minimizing the expenditure needed to attain the consumption bundle $\mathcal{C}_t$.

The following proposition characterizes the consumers' demand $C_t(i,j)$

Proposition 2. *Given good prices $P_t(i,j)$ and the desired habit-adjusted consumption $\mathcal{C}_t$, defined in equation (14), the demand function for good (i,j) is given by*

$$C_t(i,j) = (1+\phi_j)\left(\frac{P_t(i,j)}{P_t}\right)^{-\eta} \mathcal{C}_t + \theta H_t(i,j), \tag{16}$$

with P_t denoting the price index,

$$P_t = \left[\int_0^1 \int_0^1 (1+\phi_j)\, P_t(i,j)^{1-\eta} \mathrm{d}i \mathrm{d}j\right]^{\frac{1}{1-\eta}}. \tag{17}$$

The price elasticity of demand of good (i,j) is

$$\nu_t(i,j) \equiv -\frac{\partial \ln C_t(i,j)}{\partial \ln P_t(i,j)} = \eta \underbrace{\left(\frac{C_t(i,j) - \theta H_t(i,j)}{C_t(i,j)}\right)}_{\text{Consumption surplus}}. \tag{18}$$

Equation (16) in Proposition 2 shows that the demand function consists of two parts: a price-sensitive part, with price elasticity equal to η and a price-insensitive part, with price elasticity equal to zero. Equation (18) shows that the demand elasticity of good (i,j) is equal to the substitution elasticity η weighted by the consumption surplus, that is, consumption in excess of habit, as a fraction of total demand. Therefore, demand elasticity varies across goods (i, j) because of difference in good specific habit level $H_t(i, j)$. In the absence of habits, $\theta = 0$, all good have the same demand elasticity η, as in Section 2. In contrast, when consumers experience good-specific habit, $\theta > 0$, the demand elasticity varies across goods and, depending on the consumption surplus, can take any value in the interval $\nu_t(i, j) \in (0, \eta)$. The larger the habit $H_t(i, j)$, the smaller is the demand elasticity and the higher the firms' pricing power. van Binsbergen (2016) shows that this habit-induced pricing power provides firms with a natural hedge against negative shocks and result in lower expected returns.

Markets. The households in our economy can trade securities that represent claims on the endowments of each individual good (i, j). These securities are in unit supply and are traded in a frictionless market. We denote by $V_t(i, j)$ the stock price of firm (i, j) and $D_t(i, j) = P_t(i, j)Y_t(i, j)$ the dividend paid by the firm in units of the composite good, that is, we normalize the price index defined in equation (17) to $P_t = 1$.

Habit dynamics. The good-specific habit $H_t(i, j)$ in equation (15) is a persistent process whose evolution is affected by consumers's lagged consumption $C_{t-1}(i, j)$ and exogenous taste shock. Specifically, we assume that the habit for good (i, j) in period t evolves as follows

$$H_t(i, j) = \rho H_{t-1}(i, j) + (1 - \rho)C_{t-1}(i, j) + \varepsilon^h_{ijt} \tag{19}$$

where $\rho \in (0, 1)$ is a persistence parameter; $\varepsilon^h_{ijt} \sim \mathcal{N}\left(0, \sigma^2_h\right)$ represents a demand or taste shock uncorrelated both across firms and with the aggregate shock in the economy; and $C_{t-1}(i, j)$ is the consumption of good (i, j) in period $t - 1$.

Endowment process. The endowment in the economy consists of a continuum of Lucas trees (an orchard). Each tree produces a dividend $Y_t(i, j)$ representing the physical supply of good (i, j). Trees in the same techonology group share the same endowment process, i.e $Y_t(i, j) = Y_t(j)$ for $\forall i$, and receives the same consumption bias ϕ_j, which means that trees within technology group only differ in their habit level $H_t(i, j)$ and are otherwise identical. We define the habit-adjusted endowment of the composite good produced by technology j by

$$\mathcal{Y}_t(j) = \left[\int_0^1 \left(Y_t(j) - \theta H_t(i,j)\right)^{1-\frac{1}{\eta}} \mathrm{d}i\right]^{\frac{1}{1-\frac{1}{\eta}}}. \quad (20)$$

Shocks to the economy are driven by fundamental shocks to the log habit-adjusted endowment $\ln(\mathcal{Y}_t(j))$ that we specify as an exogenous persistent with a time trend g, that is,

$$\ln(\mathcal{Y}_t(j)) = gt + z_t + z_{j,t}, \quad \text{where} \quad z_t = \varrho_z z_{t-1} + \varepsilon_t \quad \text{and} \quad z_{j,t} = \varrho_j z_{j,t-1} + \varepsilon_{j,t}. \quad (21)$$

The growth of $\mathcal{Y}(j)$ is subject to both an economy-wide shock z_t and a technology-specific shock $z_{j,t}$. The shock z_t captures the risk of aggregate consumption fluctuations and is common to all technologies j. The innovation ε_t is uncorrelated with the idiosyncratic demand shocks in firms' habit processes ε_{ijt}^h and also uncorrelated with greenness-specific shock $\varepsilon_{j,t}$. Following van Binsbergen (2016), we assume that the shock ε_t is normally distributed with mean zero and a time-varying, counter-cyclical volatility,

$$\varepsilon_t \sim N\left(0, \sigma^2(z_{t-1})\right), \quad \text{with} \quad \sigma(z) = \frac{2e^{bz}}{1+e^{bz}}\sigma_z, \quad b < 0. \quad (22)$$

The assumption of $b < 0$ insures that the stochastic discount factor has time-varying volatility inversely related to the consumption surplus ratio and drives the time-series variation in aggregate risk premia. The time-varying volatility of the stochastic discount factor helps matching the time-series properties of the risk-free rate and the equity risk premium to the data.

Moreover, the variable $z_{j,t}$ is a deviation from the growth of aggregate demand and $\varepsilon_{j,t}$ is a shock to the technology endowment. We assume the shock $\varepsilon_{j,t}$ is normally distributed with mean zero and a constant volatility σ_j, $\varepsilon_{j,t} \sim N\left(0, \sigma_j^2\right)$. The shocks $\varepsilon_{j,t}$ represents technology specific shocks.

Equilibrium. An equilibrium is therefore a set of good prices $P_t(i,j)$ and equity prices $V_t(i,j)$ such that household maximize lifetime utility in equation (13), goods market clear, $C_t(i,j) = Y_t(i,j)$, where $C_t(i,j)$ is the optimal demand of good (i,j) derived in equation (16), and equity markets clear.[8] In equilibrium, the stochastic discount factor is $\mathbb{M}_t = \beta^t \left(\frac{\mathcal{Y}_t}{\mathcal{Y}_0}\right)^{-\gamma}$ where $\mathcal{Y}_t$ is aggregate habit-adjusted consumption defined as

$$\mathcal{Y}_t = \left[\int_0^1 (1+\phi_j)^{1/\eta} \mathcal{Y}_t(j)^{1-\frac{1}{\eta}} \mathrm{d}j\right]^{\frac{1}{1-\frac{1}{\eta}}}, \tag{23}$$

with $\mathcal{Y}_t(j)$ defined in equation (20). Denoting by $R_{t+1}(i,j)$ firm (i,j)'s realized return, defined by

$$R_{t+1}(i,j) = \frac{V_{t+1}(i,j) + D_{t+1}(i,j)}{V_t(i,j)}. \tag{24}$$

The optimality of equilibrium and market clearing implies that returns satisfy the Euler equation

$$\mathbb{E}_t\left[\frac{\mathbb{M}_{t+1}}{\mathbb{M}_t} R_{t+1}(i,j)\right] = 1, \quad \text{for all } i,j, \tag{25}$$

From the market clearing condition $C_t(i,j) = Y_t(i,j)$ for all (i,j) and the habit dynamics in equation (19) we have that in equilibrium $\mathcal{Y}_t = \mathcal{C}_t$ and $\mathcal{Y}_t(j) = \mathcal{C}_t(j)$ for all $j \in [0,1]$. Appendix B describes the equilibrium construction and its numerical implementation.

3.1 Calibration

We assume that the continuum of technologies can be partitioned into two types: brown, $j \in [0, \delta_B]$ and green, $j \in (\delta_B, 1]$. Technologies that belong to the same type share the same greenness and productivity. Specifically, consumption goods produced by the same technology type share the same greenness level, that is, $\phi_j = \phi_B$ for $j \in [0, \delta_B]$ and $\phi_j = \phi_G$ for $j \in (\delta_B, 1]$, with $\phi_G > \phi_B$ and the consumption surplus originating from technologies in the same group are identical, that is, $\mathcal{Y}_t(j) = \mathcal{Y}_t(B)$ for $\forall j \in [0, \delta_B]$ and $\mathcal{Y}_t(j) = \mathcal{Y}_t(G)$ for $\forall j \in [\delta_G, 1]$. This is tantamount to calibrating the model with only two types of technology: green and brown. Under this assumption, imposing market clearing , $\mathcal{C}_t = \mathcal{Y}_t$, and using equations (14)–(15), we obtain that the aggregate endowment of composite good is given by

$$\mathcal{Y}_t = \left[\delta_B (1+\phi_B)^{1/\eta} \mathcal{Y}_t(B)^{1-\frac{1}{\eta}} + \delta_G (1+\phi_G)^{1/\eta} \mathcal{Y}_t(G)^{1-\frac{1}{\eta}}\right]^{\frac{1}{1-\frac{1}{\eta}}}, \tag{26}$$

[8]In the numerical implementation, we specify the endowment and habit processes to insure that the goods market clearing condition is satisfied for a finite price.

where $\delta_G \equiv 1 - \delta_B$. The endowment processes of $\mathcal{Y}_t(B)$ and $\mathcal{Y}_t(G)$ are subject to economy-wide shock z_t and technology specific shocks $z_{B,t}$ and $z_{G,t}$ as specified in equation (21). We assume that $\varepsilon_{G,t} = -\varepsilon_{B,t}$. Because both endowments are subject to a common shocks the green and brown endowments are imperfectly correlated. This assumption allows us to match consumption growth volatility in the data. The negative correlation between the two technologies also captures the idea that the success of green technologies comes at the expense of a decline of brown technologies.

We calibrate the model at a quarterly frequency and solve the model using third-order perturbations around the steady state. Table 1 contains the parameter values we used in our solution. We set consumption bias to $\phi_G = -\phi_B = \phi = 0.25$, risk aversion to $\gamma = 6.3$, and time preference to $\beta^* \equiv \beta(\exp(g))^{1-\gamma} = 0.986$, where g denotes the deterministic log growth rate. We let $g = 0.00425$ to match an annual consumption growth rate of 1.7%, as in Campbell and Cochrane (1999). We choose a value for the elasticity of substitution $\eta = 2$, as in Sauzet and Zerbib (2022) and a habit strength of $\theta = 0.82$ as in Jermann (1998). We set persistence of endowment process $\varrho_z = \varrho_j = 0.98$ as in van Binsbergen (2016); habit persistence $\varrho_h = 0.98$ and volatility of habit shock $\sigma_h = 0.06$ to insure that equilibrium good prices are well defined.[9] Finally, we set the volatility of the economy-wide consumption surplus shock to be $\sigma_z = 0.0216$ and the volatility of technology shocks to $\sigma_j = 0.08$ to match the first moments of asset prices. Finally, to match the volatility of risk free rate, we set $b = -7$ in the dynamics of the volatility of the economy-wide shock in equation (22).

3.2 Model results

Aggregate moments. To compute aggregate asset pricing moments, we first solve the model with no idiosyncratic habit shocks ($\sigma_h = 0$) and perform 500 simulations of 2,000 quarters each (500 years). To minimize the effect of initial values, we use a 100-year burn-in period and base our analysis on the remaining 400 years. We compute the consumption and asset pricing moments from the simulated data and compare them to the equivalent quantity in the real data. Table 2 shows that the model matches the key asset pricing moments reasonably well.

[9] To guarantee that equilibrium product prices are finite, we need to insure that habit adjusted consumption is positive, see equation (B17). Our parameter choice generates values of demand elasticity ranging from 0 to 1.2, implying, by equation (18), that consumption surplus is always positive and good prices are hence well-defined.

Cross sectional moments. Using the simulated data panel we then mimic the empirical analysis of Section 4 and analyze the return properties of green and brown firms in the cross section. Our theory predicts that the green premium, that is, the GMB spread, increases with demand elasticity.

We simulate a cross-section of 5,000 green firms and 5,000 brown firms for 700 years. To minimize the effect of initial values, we ignore the first 100 years. In each period, we sort demand elasticity into bins and compute the average expected return in each bin for green and brown stocks. Figure 2 shows average excess returns of the Green-minus-brown portfolios conditional on different demand elasticity rankings. Consistent with the model prediction, the GMB return spread is increasing in demand elasticity, with a negative value at the bottom demand elasticity decile and a positive value at the top demand elasticity decile.

A key measurement challenge to bring our model predictions to the data is that demand elasticity is not directly observable. In the empirical analysis of Section 4 we follow van Binsbergen (2016) and use product price changes to analyze the relation between expected returns and demand elasticity. The main idea is to exploit the fact that firms with low demand elasticity tend to charge higher prices. We define the relative price as follows:

$$\mathrm{RP}_t(i,j) = \ln\left(\frac{P_t(i,j)}{P^{ss}(i,j)}\right), \tag{27}$$

where $P^{ss}(i,j)$ denotes good (i,j)'s steady state price, that is, the initial price in each model simulation. In the steady state, all stocks have the same habit level and hence the same demand elasticity. Overtime, firms that experience positive habit shocks face a lower demand elasticity and can raise their product prices and firms that experience negative habit shocks face high demand elasticity and cannot raise their product prices. Therefore, changes in product prices reflect shifts in demand elasticity. Because the initial demand elasticity level is uniform across all stocks, the inverse of the product price change in equation (27) effectively serves as a proxy for demand elasticity in the model. In the empirical analysis of Section 4 we use the cumulative price change as metric for tracking price changes (see equation (28) below). This measure is consistent with the model price change in equation (27) where the steady state price is replaced by the first time in which the price $P(i,j)$ is observable. Because the GMB return spread is increasing in demand elasticity and high demand elasticity is associated with low relative price, we should expect that a decrease in relative price is associated with a high GMB return spread. Figure 3 is the equivalent of Figure 2 where on the horizontal axis we report the *inverse* of relative price, that is equal to $-RP_t(i,j)$, instead of demand elasticity. Confirming the conjectured negative relation between relative product price and demand elasticity, Figure 3 shows that the GMB spread is negative for stocks of firms that have experienced an increase in good price (low inverse RP) and positive for stocks of firms that have experienced a decrease in good price (high inverse RP). This suggest that the upward GMB spread trend can be observed by sorting firms into portfolios according to their price changes.

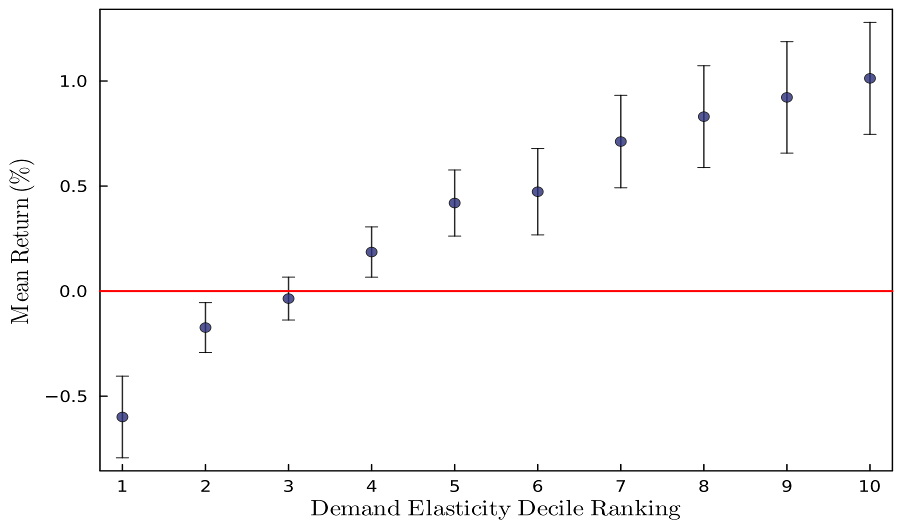


Figure 2: **GMB spread and demand elasticity**

The graph shows average excess returns of Green-Minus-Brown (GMB) portfolios and associated two-tailed 95% confidence intervals conditional on different demand elasticity rankings. Using simulated data, we first sort stocks into 10 groups in each period according to their demand elasticity defined in equation (18). Then, within each ranking, we calculate the average return of green and brown stocks and obtain the GMB return spread as the difference between the average returns. The x-axis is the demand-elasticity decile ranking and the y-axis is the over-time average GMB return spread in each ranking. The expected excess returns are annualized. Parameter values are in Table 1.

4 Empirical Analysis

In this section, we investigate the key empirical predictions of our model: green stocks are riskier than brown when goods' demand elasticity is high and are safer than brown when elasticity is low. This implies that the GMB return spread increases in demand elasticity. Section 4.1 describes the data; Section 4.3 provides a first test of our main prediction using realized stock returns as a main dependent variables; Section 4.4 extends the analysis to expected returns which we construct by purifying realized returns from climate concerns and earning surprises and by using option-implied bounds.

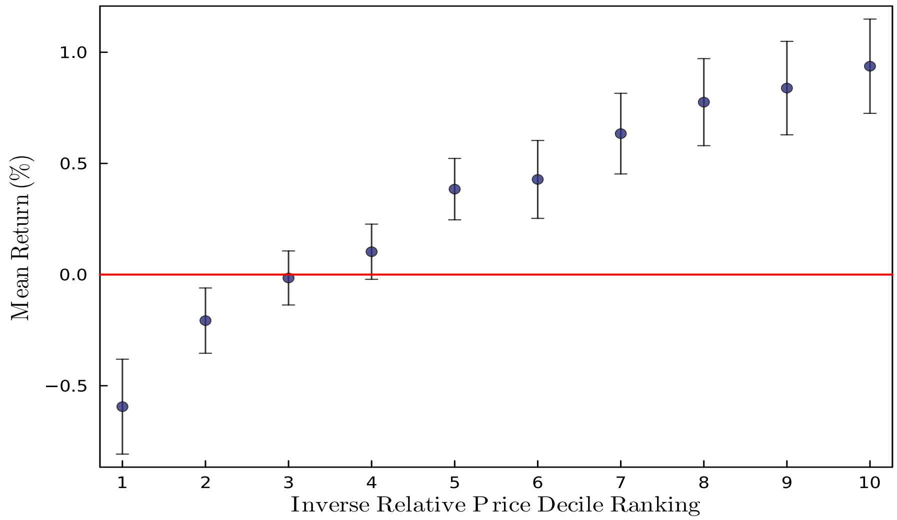


Figure 3: **GMB spread and inverse relative price change**

The graph shows average excess returns of Green-Minus-Brown (GMB) portfolios and associated two-tailed 95% confidence intervals conditional on different inverse ranking of relative price (RP) defined in equation (27). Using simulated data, we first sort stocks into 10 groups in each period according to their RP ranking. Then, within each ranking, we calculate the average return of green and brown stocks and obtain the GMB return spread as the difference between the average returns. The x-axis is the inverse RP decile ranking and the y-axis is the over-time average GMB return spread in each ranking. The expected excess returns are annualized. Parameter values are in Table 1.

4.1 Data and Measurements

U.S. Bureau of Economic Analysis Producer Price Index. We obtain the industry-level price index between January 1926 and November 2022 from the Producer Price Index (PPI) program published by the U.S. Bureau of Economic Analysis. The U.S. Bureau of Economic Analysis started to publish the PPI program as of 1902.[10] The PPI program's original intent was to measure changes in prices received for goods sold in primary markets.[11] In the early years, the PPI program mainly covers the price index in goods-producing sectors: agriculture, forestry, fisheries, mining, scrap, and manufacturing. In recent years, the PPI has extended coverage to many of the non-goods producing sectors of the economy, including transportation, retail trade, insurance, real estate, health, legal, and professional services. New PPIs are gradually being introduced for the products of industries in the utilities, finance, business services, and construction sectors of the economy.[12] Since 2003, producer prices by sector are based on NAICS codes. We use PPI data based on six-digit NAICS

[10] Until 1978 the index was known as the Wholesale Price Index, or WPI.
[11] Source: https://www.bls.gov/opub/hom/pdf/ppi-20111028.pdf
[12] Source: https://www.bls.gov/ppi/

codes, resulting in monthly observations for 900 NAICS industries from 2003 to 2022. Following van Binsbergen (2016), we use the cumulative price change (CPC) as a measure of product price change and take this measure as a proxy for goods' demand elasticity. Specifically, after removing positive outliers from the PPI database,[13] we compute the geometric mean of the overall price changes from the time the industry PPI appears in the database using an expanding window. For industry i, entering the PPI database at time s, the cumulative price change $\text{CPC}_{i,t}$ at time t is measured as

$$\text{CPC}_{i,t} = (P_{i,t}/P_{i,s})^{\frac{1}{t-s}} - 1. \tag{28}$$

MSCI ESG scores. We obtain stock-level ESG ratings from MSCI, the largest provider of ESG ratings (Eccles and Stroehle, 2018). MSCI ESG rating data are used by more than 1,700 clients, including pension funds, asset managers, consultants, advisers, banks, and insurers. Furthermore, MSCI covers more firms than other ESG raters, such as Asset4, KLD, RobescoSAM, Sustainalytics, and Vigeo Eiris (Berg, Koelbel, and Rigobon, 2022). MSCI's coverage increases dramatically in October 2012, when MSCI began covering small U.S. stocks.[14] Hence, as in Pastor, Stambaugh, and Taylor (2022), we choose November 2012 as the start of our sample period. Our sample of ESG ends in December 2022.

4.2 Summary Statistics

Figure 4 shows the number of stocks covered by our databases every month. We match stock return data in CRSP with $\text{CPC}_{i,t}$ in PPI price data by using six-digit NAICS codes. On average, during our sample period, about 70% of the firms in CRSP can be matched. Then, we merge CRSP and MSCI by CUSIP, resulting in about 1,500 observations every month.

The sorting procedure we discuss in the next section takes the BLS and CRPS industry classification as given. Merging on the basis of this classifications may lead to measurement errors. Large firms (conglomerates) may have business in multiple industries that are harder to classify

[13]In certain time intervals, we identify notable positive outliers within the PPI database. To address the impact of these outliers, we exclude the most significant 1% price change for each interval. This approach bears resemblance to the technique employed by van Binsbergen (2016), who eliminates the most substantial 10% of price changes in each interval; however, we exercise a more conservative approach. The results are unaffected if, instead of truncating, we winsorize price changes at the 1% level.

[14]According to Pastor, Stambaugh, and Taylor (2022), before October 2012, MSCI covered only the largest 1,500 companies in the MSCI World Index, plus large companies in the UK and Australia MSCI indexes. In October 2012 MSCI added many smaller U.S. firms when it began covering also the MSCI U.S. Investible Market Index.

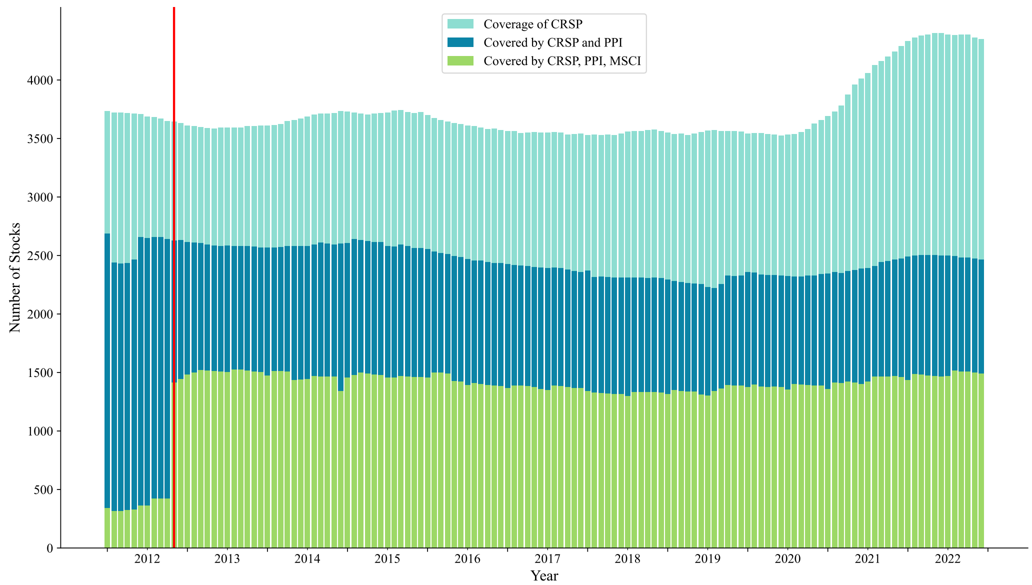


Figure 4: Data coverage

The figure shows the number of stocks in our sample covered by CRSP, the number of stocks covered by both CRSP and PPI, and the number of stocks covered by all databases every month. The red line refers to November 2012, where our sample begins. MSCI expanded its coverage in October 2012 and expanded ESG rating data are available as of November 1st.

into a single NAICS industry compared to smaller firms. Classification differences between the two sources would then weaken the channel identified in our model. For example, suppose a large firm has relevant businesses in two industries: one industry has a CPC ranking of 1 while the other has CPC (elasticity) ranking of 3. The firm is actually of approximate elasticity ranking 2. However, because the firm has to be assigned to one of the two groups, it will be defined as either CPC 1 or 3. Value-weighting will exaggerate this error because it allocates more weight to large firms, which are more likely to be misclassified. Because small firms are less likely to be misclassified, we follow van Binsbergen (2016) and use an equal-weighting scheme when forming portfolios unless otherwise specified.

4.3 Demand elasticity and the green premium: realized returns

Our model predicts that the green premium increases in the price elasticity of demand. To test this prediction, we sort the universe of US stocks into three portfolios according to demand elasticity—proxied by the CPC measure in equation (28)—as of month $t-1$, and then, within each CPC portfolio we sort socks based on their ESG scores as of the first day of month t. For ease of exposition, we will refer to low (high) CPC portfolios as high (low) demand elasticity portfolios.

For each demand elasticity tercile, we form a zero-cost portfolio that longs firms in the top greennes quartile and shorts firms in the bottom greennes quartile. Hence for each demand elasticity tercile we obtain a GMB (green minus brown) zero-cost portfolio. Figure 5 shows the cumulative equally-weighted return of the GMB portfolio in the top (red line) and bottom (blue line) demand elasticity terciles. For reference, we also report the unconditional GMB (dashed black line). Similar to Pastor, Stambaugh, and Taylor (2022),[15] we find that the cumulative return of GMB portfolio is 68.3%. However, virtually all of this out-performance comes form stocks in the high demand elasticity tercile (red line). The GMB portfolios in the top demand elasticity tercile outperforms that in the bottom tercile by $195.9 - 27.7 = 168.2$ percentage points over this period. This results is striking and confirms that consumption preferences and demand elasticity have a first order effect in the determination of the GMB spread, as predicted by our model.

In Table 3 we provide summary statistics of the characteristics of stocks for demand elasticity portfolios (Panel A) and, for ESG portfolios, within the set of firms with high demand elasticity (Panel B). Panel A shows that stocks with high demand elasticity tend to have lower ESG score overall. Over our sample period, CPC and ESG ratings have a correlation of 0.128. This correlation is largely driven by the environmental pillar—the average E score for firms in high CPC tercile (low demand elasticity) is 27% higher than that for firms in low CPC tercile (high demand elasticity): 4.8 vs 3.8, t-statistic: 12.24. High demand elasticity portfolio tend to have low Herfindhal-Hirschman Index (HHI).[16] This fact is consistent with Corhay, Kung, and Schmid (2020), who show that the equilibrium price elasticity of demand is a inverse function of industry concentration. Hence, HHI provides an alternative way to assess the channel from our model. High-demand elasticity firms are similar in term of size to low-demand elasticity firms but tend to have higher book to market and lower asset growth. Panel B shows characteristics of ESG portfolios within the class of high-demand

[15] While the GMB return in Pastor, Stambaugh, and Taylor (2022) is based on the environmental pillar of the ESG score, our results are based on the overall score. We obtain similar results if we construct GMB returns using only the environmental score. Specifically, the unconditional cumulative GMB return is 42%. This return spread is largely driven by firms in the high demand elasticity tercile (62.5%) with firms in the low demand elasticity tercile earning a negative spread (3.8%). The E score is positively correlated with CPC ranking. Repeating our analysis with independent sorts to account for this fact, we find that the unconditional cumulative GMB return is 50.0%, largely driven by firms in the high demand elasticity tercile (99.4%) with firms in the low demand elasticity tercile earning a negative spread (-6.1%).

[16] Similar to Corhay, Kung, and Schmid (2020), we compute HHI by summing all firms' squared market share in the same 4-digit SIC industry and multiplying the sum by 1000. The firm's market share is define as the firm's sales (Compustat Quarterly item SALEQ) scaled by the sum of the sales of the its peers.

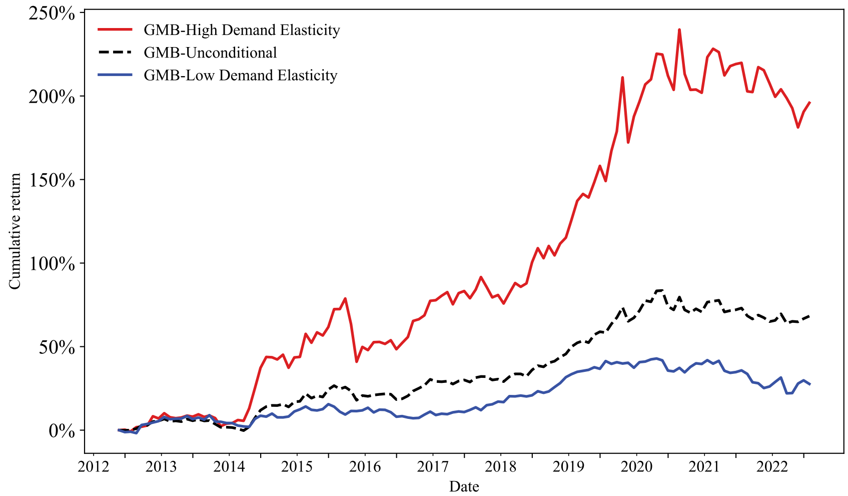


Figure 5: Cumulative GMB returns and cumulative price changes
The figure reports the cumulative returns to the GMB portfolio conditional on cumulative price changes. The red (blue) line reports the GMB spread for firms with low (high) cumulative price changes. The dashed black line is the unconditional GMB spread.

elasticity firms. Within this class, high ESG firms tend to be larger, growth firms, more profitable and with low asset growth. This underscores the importance of adjusting for related asset pricing factors when assessing GMB returns. For instance, the observation that companies in the "G" leg exhibit larger size and lower book-to-market ratios implies that, upon accounting for SMB (Small Minus Big) and HML (High Minus Low) factors, the GMB spread might potentially be stronger than the raw GMB return.

In Table 4 we estimate monthly time-series regressions from November 2012 to December 2022. We regress the GMB return spread on a constant and various factors, capturing different asset pricing models. MKTRF refers to the Market factor in the CAPM; SMB and HML are the size and value factors in Fama and French (1993); RMW and CMA refer to the profitability and investment factors in Fama and French (2015). Panel A reports estimates conditional on high demand elasticity; Panel B reports estimates conditional on low demand elasticity. In parenthesis we report t-statistics adjusted for autocorrelation using Newey and West (1987).

Comparing Panel A and Panel B of Table 4, we see that the annual equal-weighted GMB spread in the low demand elasticity portfolio is 2.6% (t-statistic: 1.454) while the annual GMB spread in the high demand elasticity portfolio is 11.7% (t-statistic: 2.808). Consistent with the

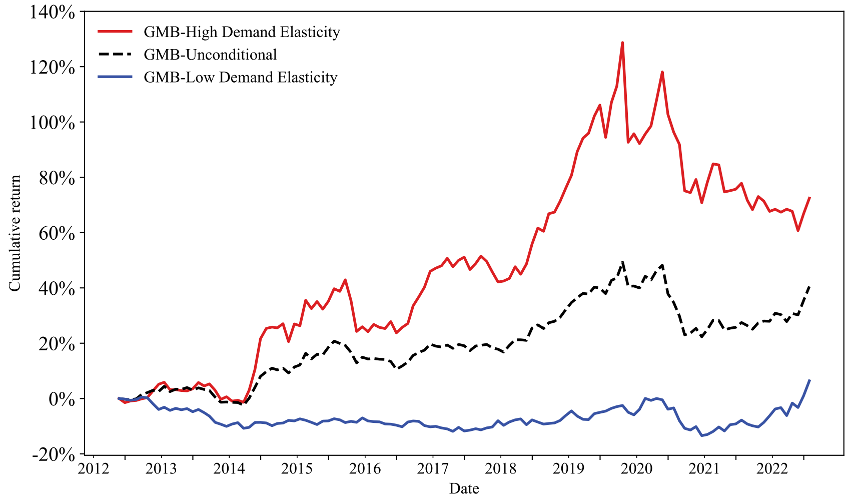


Figure 6: Cumulative GMB returns and HHI
The figure reports the cumulative returns to the GMB portfolio conditional on the Hirschman-Herfindhal Index (HHI). The red (blue) line reports the GMB spread for firms with low (high) HHI index. The dashed black line is the unconditional GMB spread.

summary statistics in Table 3, Firms in the "G" leg of the spread have higher size and lower book-to-market ratio than those in the "B" leg, leading to negative loadings of GMB on SMB and HML. Therefore, the positive GBM spread in the high demand elasticity portfolios is even larger and more significant after adjusting for exposures to common asset pricing factors. The results for value-weighted portfolios are qualitatively similar. Finally, Panel C shows that the difference between GMB spread in high-demand elasticity and low demand elasticity portfolios is positive and significant. Upon accounting for asset pricing factors, the disparity in alpha becomes even more pronounced, primarily because of the negative loadings on these factors.

Figure 7 shows raw and risk-adjusted excess returns of the GMB portfolio for each demand elasticity tercile. The estimates for the first and third tercile are also reported in Table 4. The figure shows that, consistent with the prediction of our model, the GMB spread is increasing in demand elasticity. This figure represents the empirical counterpart of the return spread in Figure 1, from the simple model of Section 2 and Figure 2, from the dynamic model of Section 3.

The strong relation between demand elasticity (CPC) and industry concentration (HHI) documented in Table 3 indicates that high industry concentration (HHI) is typically associated with low demand elasticity. This fact suggest that HHI can serve as an alternative way to assess the

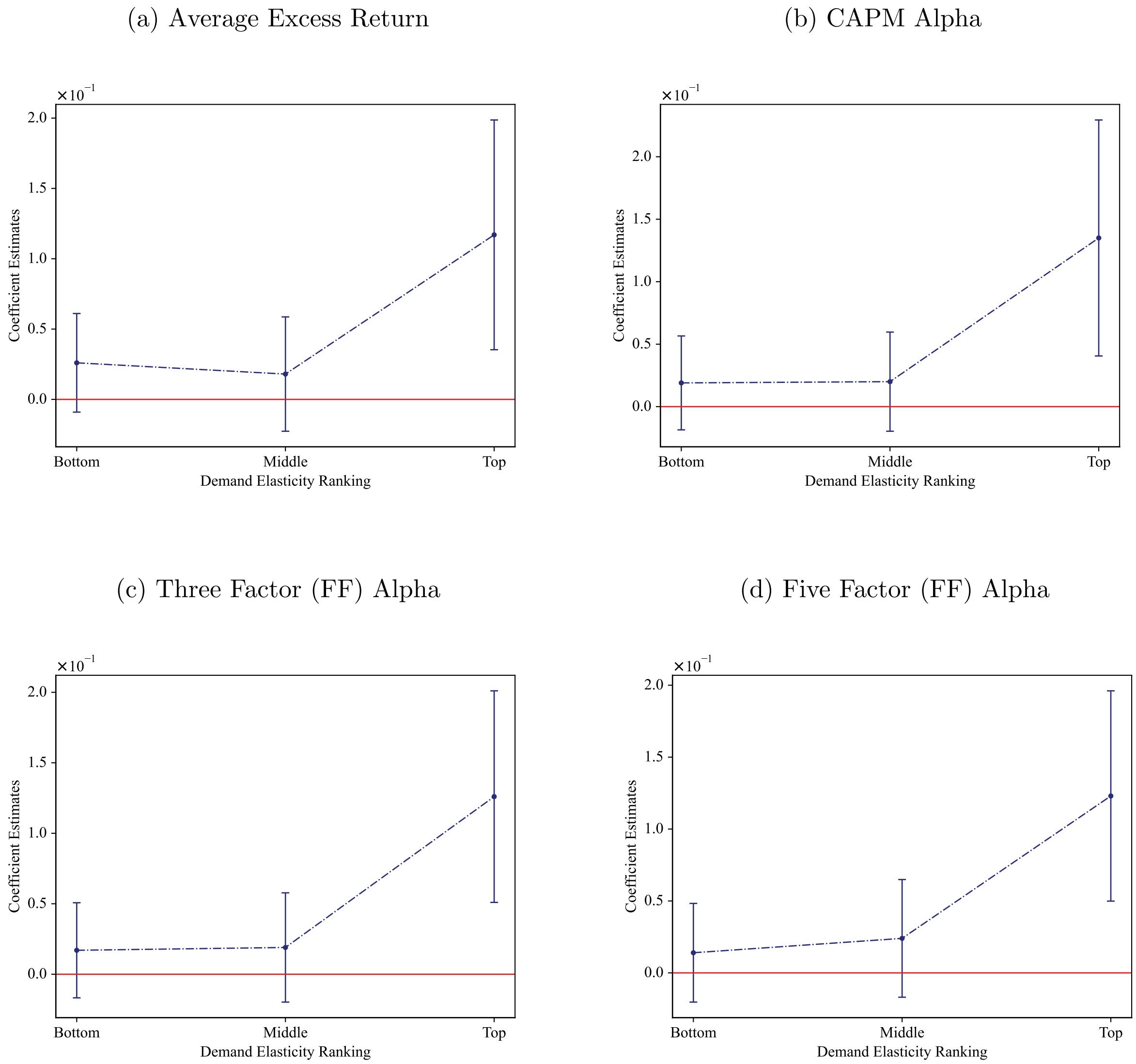


Figure 7: GMB portfolio returns and cumulative price changes

Panel (a) reports the equally-weighted GMB spread in each demand elasticity tercile. Panels (b)–(d) show alpha estimates with respect to the factor models considered in Table 4. The sample period is from November 2012 to December 2022. The solid vertical lines represent 95 percent confidence intervals.

effect of demand elasticity on the GMB spread. Figure 6 shows the cumulative return of the GMB portfolio conditional on high and low HHI terciles. This figures is the equivalent of Figure 5 where instead of CPC we use HHI as a proxy for demand elasticity. Consistent with the intuition that high industry concentration is associated with low demand elasticity, Figure 6 shows that over the 2012–2022 sample period, the GMB spread is positive for low HHI and negative for high HHI.

Similarly, Table 5 replicates Table 4 using HHI as a proxy of demand elasticity. The results are qualitatively similar to those obtained using the CPC proxy.

A limitation of the above portfolio analysis is the potential for variations in returns among portfolios driven by factors other than demand elasticity and ESG scores. For instance, it is conceivable that certain high-risk stocks coincidentally fall into the top ESG quartile within the high demand tercile, thereby driving the GMB spread in that tercile. To address this issue, we exploit the cross-sectional variation in returns, measured demand elasticity, and other firm well-known stock return characteristics to explore possible alternative explanations. We conduct monthly Fama-Macbeth regressions at the individual firm level. Specifically, we standardize the ESG score and demand elasticity measures and, in each month, we estimate the following cross-sectional regression:[17]

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_{t-1} + \beta_1 \,\text{Demand Elasticity}_{i,t-1} \times \text{ESG score}_{i,t-1} + \beta_2 \,\text{Demand Elasticity}_{i,t-1} \\ + \beta_3 \,\text{ESG score}_{i,t-1} + \beta_4^{'} X_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{29}$$

where $X_{i,t-1}$ is a vector of firm characteristics, including size, book-to-market ratio, profitability, asset growth and momentum return. The coefficient β_1 captures how the sensitivity of expected return to ESG score varies with demand elasticity. Table 6 reports the average coefficients and associated t-statistics of the estimated regression, computed over the entire sample. Panel A shows that the coefficient of the interaction term, β_1, is positive and weakly significant, suggesting that for higher demand elasticities, ESG score is associated with higher stock returns. Furthermore, we explore whether ESG score has different predictive implications for stocks in the high demand elasticity tercile compared to the low demand elasticity tercile. The positive and significant coefficient of ESG score_{-1} in columns (2) and the economically small and statistically insignificant coefficient in (3) are consistent with the portfolio analysis above in which we document a large GMB spread for high demand elasticity and an insignificant spread for low demand elasticity. Results are qualitatively similar for HHI, the alternative measure of demand elasticity in Panel B. The results in Table 6 confirm that the observed pattern regarding GMB and demand elasticity is consistent across both portfolio analysis and cross-sectional regression analysis, and it remains robust to different measures of demand elasticity.

[17]Specifically, we obtain the measures of demand elasticity by standardizing the negative values of CPC and HHI, that is, we subtract the sample mean and dividing by the sample standard deviation.

4.4 Demand elasticity and the green premium: expected returns

Our theoretical model predicts that the *expected* return spread of green and brown stocks increases in goods' demand elasticity. In the previous section, we measured expected returns through time-series average of monthly realized returns. Because of the relatively short sample period, 2012–2022, there is an obvious concern that, as pointed out by Pastor, Stambaugh, and Taylor (2022), the realized GMB returns in past decade are largely driven by "surprises" and hence the results we documented may not be informative about expected returns. To address this concern, in this section we accomplish this task in two different ways: (i) by exploiting information about unanticipated shocks that could drive realized returns, such as surprises in climate concerns and firm earnings, as in Pastor, Stambaugh, and Taylor (2022); (ii) by constructing a measure of conditional expected return at the stock level from forward-looking information contained in traded option contracts, as in following Martin (2017) and Martin and Wagner (2019).

4.4.1 Expected returns from past realizations

We closely follow Pastor, Stambaugh, and Taylor (2022) and use shocks to climate concerns, from the Media Climate Change Concern index (MCCC) of Ardia, Bluteau, Boudt, and Inghelbrecht (2020), and earning news from I/B/E/S as explanatory variables in the above regression.

Climate concerns. Building on the work of Engle, Giglio, Kelly, Lee, and Stroebel (2020), Ardia, Bluteau, Boudt, and Inghelbrecht (2020) construct an index of climate concern gathering information from eight US newspaper. Following their methodology, we obtain shocks to climate concerns (ΔCC_t) as the error from rolling AR(1) models applied to the MCCC index.

Earning news. As in Pastor, Stambaugh, and Taylor (2022), we use two measures of earning news: earning announcements returns (EAR_t) and changes in earning forecasts (ΔEF_t). The first measure is designed to capture short-term earning news while the second captures news at a longer frequency. We measure earning announcement as stock returns in excess of the market during a three-day window around announcement dates. We measure changes in earning forecasts for a firm in a given quarter t as the difference between the earliest median analyst forecast of long-term earning growth in quarter $t+1$ and the latest median earning forecast in quarter $t-1$.

After converting the firm-level earning measures into portfolio quantities that mimic the construction of the GMB spread, we end up estimating the following time-series regressions at the monthly frequency, separately for high- and low-demand elasticity terciles:

$$GMB_t^k = a + b_1 \, \Delta CC_t + b_2 \, \Delta CC_{t-1} \; + b_3 \, EAR_t + b_4 \, \Delta EF_t + \varepsilon_t, \tag{30}$$

where k denotes the demand elasticity tercile. Following Pastor, Stambaugh, and Taylor (2022), we take the estimate of the intercept $\hat{a}$ as a measure of the *counterfactual* monthly GMB spread, that is the GMB that would be observed in the absence of shocks to climate concerns and earning.

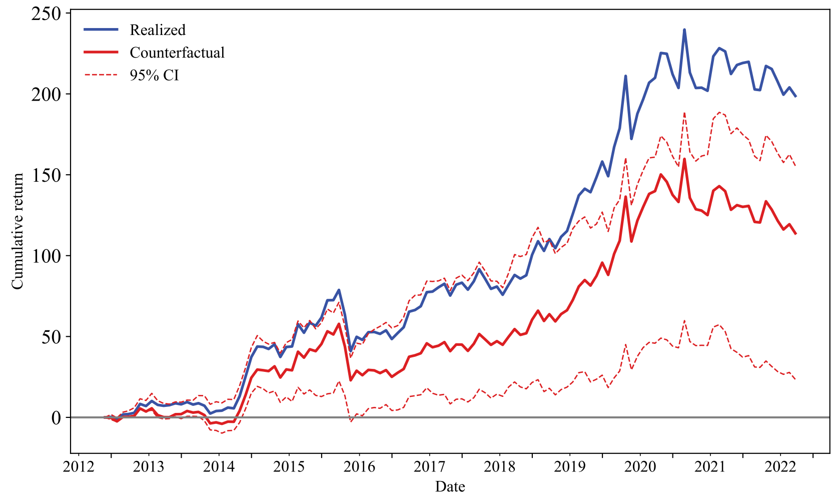
Table 7 presents estimates of the regression equation (30). Panel A shows that for the high demand elasticity tercile, the coefficients b_2 and b_4 for the lagged climate concern and earnings forecasts are positive and significant across most model specifications. This aligns with findings from Pastor, Stambaugh, and Taylor (2022), and indicates the existence of a "surprise" channel affecting the GMB at high demand elasticity. Figure 8 illustrates the counterfactual performance of GMB, revealing that the surprise variables account for approximately half of the cumulative GMB return at high demand elasticity. However, the GMB spread cannot be fully explained by these surprises. The counterfactual GMB spread remains positive and significant after controlling for climate concerns and earning surprises. Finally, Panel C shows that the difference between the counterfactual GMB at high and low demand elasticity remains positive and significant. Overall, we conclude that the GMB spread at high demand elasticity is not solely driven by the "surprise" channel but can be attributed in part to risk compensation, as predicted by our model.

4.4.2 Option-implied expected returns

Our second measure of expected return uses forward-looking information from option prices, following the methodology of Martin and Wagner (2019). We calculate the risk-neutral volatility for stock i in month t as

$$SVIX_{i,t}^2 = \frac{2}{R_{f,t+1} S_{i,t}^2} \left[\int_0^{F_{i,t}} \text{put}_{i,k}(K) dK + \int_{F_{i,t}}^{\infty} \text{call}_{i,t}(K) dK \right], \tag{31}$$

where $S_{i,t}$ denotes the price of the stock, $R_{f,t+1}$ the gross risk-free rate, $F_{i,t}$ the forward price of the stock, that is, the strike price such that $\text{call}_{i,t}(F_{i,t}) = \text{put}_{i,t}(F_{i,t})$, and $\text{put}_{i,k}(K)$ and $\text{call}_{i,t}(K)$ the put and call prices at the strike K. Martin (2017) and Martin and Wagner (2019) show that, Panel A: GMB–High demand elasticity



Panel B: GMB alpha–High demand elasticity

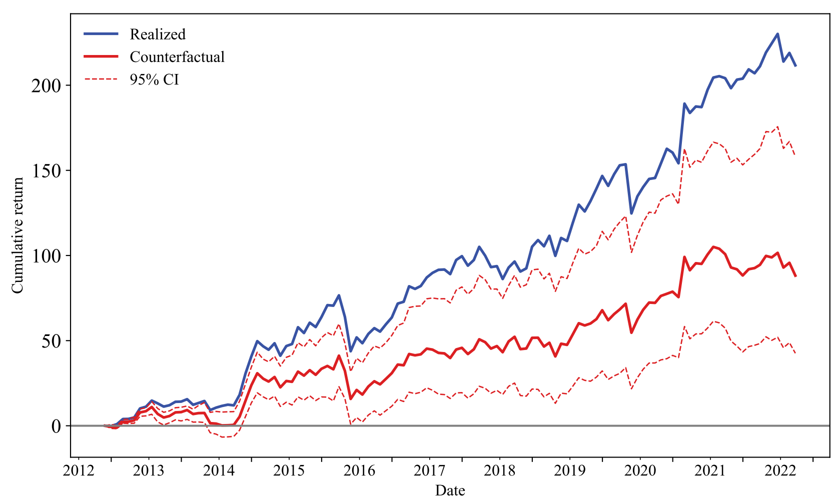


Figure 8: **Counterfactual GMB performance.**

The figure reports the counterfactual cumulative returns to the GMB portfolio conditional on high demand elasticity (low CPC). Panel A shows cumulative, compounded returns on the GMB portfolio. The solid blue lines represent realized returns. The dashed line show the counterfactual returns derived from Panel A in Table 7. The counterfacual reurn is defined as the realized return minus the fitted value from the regression in equation (30). Dotted lines indicate the 95% confidence interval for the counterfactual, computed using the Bootstrap method, as described in Pastor, Stambaugh, and Taylor (2022). Panel B plots the counterparts of cumulative, compounded returns on GMB's Fama-French 5-factor alpha. Alphas are computed as in Table 4.

under some conditions[18] the expected return on stock i in excess of the risk-free rate $R_{f,t+1}$ can be approximated as follows:

$$\mathbb{E}_t[R_{i,t+1} - R_{f,t+1}] = R_{f,t+1}\left(SVIX_{m,t}^2 + \frac{1}{2}\left(SVIX_{i,t}^2 - \overline{SVIX}_t^2\right)\right), \tag{32}$$

where $SVIX_{m,t}$ is the risk-neutral volatility for the value-weighted market portfolio, computed as in equation (31) and $\overline{SVIX}_t$ is the value-weighted average of $SVIX_{i,t}$ across all the stocks in the market portfolio.

After obtaining the expected return for S&P 500 firms with valid option data, we narrow the sample to S&P 500 firms with non-missing variables to ensure that all firms have traded options with sufficient liquidity. We then estimate Fama-Macbeth regressions at the individual firm level similar to the cross-sectional regression in equation (29), where we use instead the option-implied expected return as dependent variable. The results in Table 8 imply that the sensitivity of expected return to the ESG score is given by

$$\frac{\partial \mathbb{E}_{t-1}[R_{i,t} - R_{f,t}]}{\partial \text{ESG score}_{i,t-1}} = \underbrace{\beta_1}_{0.244} \times \text{Demand elasticity}_{i,t-1} + \underbrace{\beta_3}_{-0.309}. \tag{33}$$

Because Demand elasticity$_{i,t-1}$ has zero unconditional mean, the unconditional sensitivity of expected return to ESG score is negative, $\beta_3 = -0.309$. Comparing this result to the positive and significant coefficient of ESG score in Panel A of Table 6 confirms the conjecture of Pastor, Stambaugh, and Taylor (2022): the positive unconditional realized GMB is largely driven by surprises, and likely implies a negative expected unconditional GMB return. However, as equation (33) shows, this sensitivity increases in demand elasticity. Therefore, our analysis adds a novel and complementary perspective to the existing literature by demonstrating that the expected GMB return spread varies in the cross section, depending on the price elasticity of demand.

5 Conclusion

We develop an asset pricing model to study the effect of responsible consumption on asset prices. We model responsible consumption as a preference bias in favor of some good varieties and against

[18] Specifically, that (i) the range of betas from regressing returns on a growth optimal portfolios is not too wide and (ii) the variance of the residual from this regression is not persistently different from the value-weighted average. These conditions are likely satisfied in our cross section of S&P500 stocks.

others. In an otherwise standard consumption-based asset pricing model with multiple varieties of goods, we show that agents might invest in a stock producing a disfavored good as a way to hedge against consumption risk. We show that this hedging motive crucially depends on goods' demand elasticity. For example, when consumers have a "green" bias, green firms producing high demand elasticity goods are *riskier* than brown firms producing high demand elasticity products. The riskiness of these firms flips for firms that produce low demand elasticity goods.

Our empirical analysis provides supporting evidence for the mechanism highlighted by our model. After sorting US stocks according to a proxy of demand elasticity and measures of social responsibility (ESG scores), we find that the green-minus-brown (GMB) spread is increasing in the price elasticity of demand. Specifically, the annual spread is 2.6% and insignificant in the bottom elasticity tercile and 11.7% and significant in the top tercile. Common asset pricing factors do not explain the GMB spread in the high-demand elasticity tercile. Furthermore, we show that the cumulative positive return spread of green vs. brown stocks over the last decade is mainly attributed to high-demand-elasticity stocks, with low demand elasticity stocks earning an insignificant or negative spread. Our findings suggest that responsible consumption, operating through the demand elasticity channel, has a first-order impact on the cross-section of green premium.

Our study has relevant implications for the efficacy of responsible consumption as a channel to achieve social and environmental impact through its effect on asset prices. A direct implication of our model is that strategies of responsible consumption with a negative bias toward low-demand elasticity brown goods can be effective in increasing the cost of capital of firms producing those goods. In contrast, a negative bias towards high-demand elasticity brown-goods firms may lead to the unintended outcome of reducing their cost of capital. Responsible consumption could therefore counteract other socially responsible strategies, such as divestment. Furthermore, our model also hints at the possibility that firms manufacturing goods and services with low demand elasticity have stronger incentive to engage in "greenwashing", as this will reduce their cost of capital. Our model is agnostic on the sources of cross-sectional variation in goods' demand elasticity. Micro-founding such a heterogeneity in a multi-industry equilibrium is an interesting task that we leave for future research.

A Proofs

Proof of Proposition 1

Denoting by $\mathcal{Y}_{i,1}$ the endowment of composite good in state ω_i for $i \in \{G, B\}$, direct calculations show that $\mathcal{Y}_0 = 1$, and

$$\mathcal{Y}_1(\omega) = \begin{cases} \mathcal{Y}_{G,1} \equiv \left(\frac{1+\phi}{2}h^{1-\frac{1}{\eta}} + \frac{1-\phi}{2}\right)^{\frac{1}{1-\frac{1}{\eta}}}, & \text{if } \omega = \omega_G \\ \mathcal{Y}_{B,1} \equiv \left(\frac{1+\phi}{2} + \frac{1-\phi}{2}h^{1-\frac{1}{\eta}}\right)^{\frac{1}{1-\frac{1}{\eta}}}, & \text{if } \omega = \omega_B \end{cases} \tag{A1}$$

Note that, because $\phi > 0$, we have $1 < \mathcal{Y}_{B,1} < \mathcal{Y}_{G,1} < h$ for all $\eta > 0$.[19] Therefore, the quantity of composite good produced in state ω_G is larger than that of state ω_B. In this sense, the state ω_G represents a "good state" in that the marginal utility of the representative agent is lower than in the "bad state" ω_B. If $\phi < 0$, ω_B would be the good state and ω_G the bad state. Therefore, the sign of the bias ϕ implicitly defines good and bad states in the economy.

Using the expression for the equilibrium price in equation (7) we obtain that the dividend of the G and B assets are,

$$D_{G,1}(\omega) = P_{G,1}(\omega) \times Y_{G,1}(\omega) = \frac{1+\phi}{2}\begin{cases} \mathcal{Y}_{G,1}^{\frac{1}{\eta}} h^{1-\frac{1}{\eta}}, & \text{if } \omega = \omega_G \\ \mathcal{Y}_{B,1}^{\frac{1}{\eta}}, & \text{if } \omega = \omega_B \end{cases} \tag{A2}$$

$$D_{B,1}(\omega) = P_{B,1}(\omega) \times Y_{B,1}(\omega) = \frac{1-\phi}{2}\begin{cases} \mathcal{Y}_{G,1}^{\frac{1}{\eta}}, & \text{if } \omega = \omega_G \\ \mathcal{Y}_{B,1}^{\frac{1}{\eta}} h^{1-\frac{1}{\eta}}, & \text{if } \omega = \omega_B \end{cases} \tag{A3}$$

Direct calculations show that the prices of the two assets are

$$V_G = \beta\frac{1+\phi}{2}\left(\frac{1}{2}\mathcal{Y}_{G,1}^{\frac{1}{\eta}-\gamma}h^{1-\frac{1}{\eta}} + \frac{1}{2}\mathcal{Y}_{B,1}^{\frac{1}{\eta}-\gamma}\right), \quad V_B = \beta\frac{1-\phi}{2}\left(\frac{1}{2}\mathcal{Y}_{G,1}^{\frac{1}{\eta}-\gamma} + \frac{1}{2}\mathcal{Y}_{B,1}^{\frac{1}{\eta}-\gamma}h^{1-\frac{1}{\eta}}\right) \tag{A4}$$

[19] To see this, suppose $\eta < 1$, and denote $\theta = 1 - \frac{1}{\eta} < 0$. Similar argument applies for the case $\eta > 1$. The composite good $\mathcal{Y}_{G,1}$ in equation (A1) may be rewritten as $\mathcal{Y}_{G,1}^{\theta} = \frac{1+\phi}{2}h^{\theta} + \frac{1-\phi}{2}$. Since $\frac{1+\phi}{2} + \frac{1-\phi}{2} = 1$, we have $h^{\theta} < \mathcal{Y}_{G,1}^{\theta} < 1$. Taking logs we get $\theta\log(h) < \theta\log(\mathcal{Y}_{G,1}) < 0$. Since $\theta < 0$ this implies $0 < \log(\mathcal{Y}_{G,1}) < \log(h)$, or $1 < \mathcal{Y}_{G,1} < h$. An identical argument can be used to prove that $1 < \mathcal{Y}_{B,1} < h$.

Using the expected return formula (9) and the expressions (A1) gives the following expression of the securities returns

$$\mathbb{E}[R_G] = \frac{\mathcal{Y}_{G,1}^{\frac{1}{\eta}} h^{1-\frac{1}{\eta}} + \mathcal{Y}_{B,1}^{\frac{1}{\eta}}}{\beta \left[\mathcal{Y}_{G,1}^{\frac{1}{\eta}-\gamma} h^{1-\frac{1}{\eta}} + \mathcal{Y}_{B,1}^{\frac{1}{\eta}-\gamma} \right]}, \quad \mathbb{E}[R_B] = \frac{\mathcal{Y}_{G,1}^{\frac{1}{\eta}} + \mathcal{Y}_{B,1}^{\frac{1}{\eta}} h^{1-\frac{1}{\eta}}}{\beta \left[\mathcal{Y}_{G,1}^{\frac{1}{\eta}-\gamma} + \mathcal{Y}_{B,1}^{\frac{1}{\eta}-\gamma} h^{1-\frac{1}{\eta}} \right]}. \tag{A5}$$

Using (A5), direct calculations show that

$$\mathbb{E}[R_G] - \mathbb{E}[R_B] = \frac{\mathcal{Y}_{G,1}^{\frac{1}{\eta}} \mathcal{Y}_{B,1}^{\frac{1}{\eta}} (\mathcal{Y}_{B,1}^{-\gamma} - \mathcal{Y}_{G,1}^{-\gamma})}{\beta \left(\mathcal{Y}_{G,1}^{\frac{1}{\eta}-\gamma} h^{1-\frac{1}{\eta}} + \mathcal{Y}_{B,1}^{\frac{1}{\eta}-\gamma} \right) \cdot \left(\mathcal{Y}_{G,1}^{\frac{1}{\eta}-\gamma} + \mathcal{Y}_{B,1}^{\frac{1}{\eta}-\gamma} h^{1-\frac{1}{\eta}} \right)} \cdot \left(h^{2\left(1-\frac{1}{\eta}\right)} - 1 \right). \tag{A6}$$

The above expression can be rewritten as $\mathbb{E}[R_G] - \mathbb{E}[R_B] = K(h^{1-\frac{1}{\eta}} - 1)$ where the constant K is given by

$$K = \frac{\mathcal{Y}_{G,1}^{\frac{1}{\eta}} \mathcal{Y}_{B,1}^{\frac{1}{\eta}} (\mathcal{Y}_{B,1}^{-\gamma} - \mathcal{Y}_{G,1}^{-\gamma})(h^{1-\frac{1}{\eta}} + 1)}{\beta \left(\mathcal{Y}_{G,1}^{\frac{1}{\eta}-\gamma} h^{1-\frac{1}{\eta}} + \mathcal{Y}_{B,1}^{\frac{1}{\eta}-\gamma} \right) \cdot \left(\mathcal{Y}_{G,1}^{\frac{1}{\eta}-\gamma} + \mathcal{Y}_{B,1}^{\frac{1}{\eta}-\gamma} h^{1-\frac{1}{\eta}} \right)}.$$

Since $Y_{B,1} < \mathcal{Y}_{G,1}$ and $\gamma > 0$ we have, $\left(\mathcal{Y}_{B,1}^{-\gamma} - \mathcal{Y}_{G,1}^{-\gamma} \right) > 0$ and hence the constant K is positive. Therefore, $\mathbb{E}[R_G] > \mathbb{E}[R_B]$ if an only if $\eta > 1$. ∎

Proof of proposition 2

Taking the price $P_t(i,j)$, as given, we derive the optimal demand for $C_t(i,j)$ by solving the following expenditure minimization problem

$$\min_{C_t(i,j)} \int_0^1 \int_0^1 P_t(i,j) C_t(i,j) \mathrm{d}i \mathrm{d}j, \tag{A7}$$

subject to equation (14), defining the quantity $\mathcal{C}_t$. The Lagrangian of this minimization problem is

$$\mathcal{L} = \int_0^1 \int_0^1 P_t(i,j) C_t(i,j) \mathrm{d}i \mathrm{d}j + \lambda \left(\mathcal{C}_t - \left[\int_0^1 \int_0^1 (1+\phi_j)^{1/\nu} \Big(C_t(i,j) - \theta H_t(i,j) \Big)^{1-\frac{1}{\nu}} \mathrm{d}i \mathrm{d}j \right]^{\frac{1}{1-\frac{1}{\nu}}} \right), \tag{A8}$$

where λ is Lagrange multiplier. The solution of the problem in equation (A7) involves pointwise minimization, leading to the first-order condition for $C_t(i,j)$:

$$P_t(i,j) = (1+\phi_j)^{1/\nu}\left(C_t(i,j) - \theta H_t(i,j)\right)^{-1/\nu}\mathcal{C}_t^{1/\nu}\lambda. \tag{A9}$$

Raising both the left and right hand side of the above equality to the power of $1-\nu$, multiplying both sides by $(1+\phi_j)$, and then integrating over i and j, we obtain

$$\int_0^1\int_0^1 (1+\phi_j)P_t(i,j)^{1-\nu}\mathrm{d}i\mathrm{d}j = \lambda^{1-\nu}\mathcal{C}_t^{\frac{1}{\nu}-1}\int_0^1\int_0^1 (1+\phi_j)^{1/\nu}\left(C_t(i,j)-\theta H_t(i,j)\right)^{1-\frac{1}{\nu}}\mathrm{d}i\mathrm{d}j = \lambda^{1-\nu}, \tag{A10}$$

where the last equality uses the definition of $\mathcal{C}_t$ in equation (14). The Lagrange multiplier λ represents the shadow price of $\mathcal{C}_t$. Denoting by P_t such a price we have,

$$P_t = \lambda = \left[\int_0^1\int_0^1 (1+\phi_j)P_t(i,j)^{1-\nu}\mathrm{d}i\mathrm{d}j\right]^{\frac{1}{1-\nu}}. \tag{A11}$$

From the first-order condition in equation (A9) we then have that the consumer demand for the bundle $C_t(i,j)$ is

$$C_t(i,j) = (1+\phi_j)\left(\frac{P_t(i,j)}{P_t}\right)^{-\nu}\mathcal{C}_t + \theta H_t(i,j). \tag{A12}$$

Taking the log-derivative of equation (A12) with respect to $P_t(i,j)$, delivers the expression of the demand elasticity shown in equation (18). Note finally that

$$\frac{\partial \ln C_t(i,j)}{\partial \mathcal{C}_t} = \frac{\partial C_t(i,j)}{\mathcal{C}_t}\frac{\mathcal{C}_t}{C_t(i,j)} = \frac{(1+\phi_j)\left(\frac{P_t(i,j)}{P_t}\right)^{-\nu}\mathcal{C}_t}{C_t(i,j)} = \frac{C_t(i,j)-\theta H_t(i,j)}{C_t(i,j)}, \tag{A13}$$

which is the consumption surplus. ∎

B Details of numerical solution of the model of Section 3

We solve the model Section 3 using third-order perturbation methods (Dynare++). In this appendix we summarize the conditions used to construct an equilibrium.

Exogeneous shocks. The process for the exogenous variables $\mathcal{Y}_t(j)$, z_t and $z_{j,t}$ are given in equations (21) and (22) of the main text.

Representative firm. As discussed in Section B.1 we recover the physical endowment $Y_t(j)$ from the exogenous habit-adjusted endowment $\mathcal{Y}_t(j)$ by solving the model with the idiosyncratic habit shock volatility set to zero ($\sigma_h^2 = 0$). This assumption assumes that all trees within greenness group j are identical, thereby allowing for the existence of a representative tree for the group. For the representative firm, the evolution of the physical endowment $\mathcal{Y}_t(j)$ and of habit $H_t(j)$ is[20]

$$Y_t(j) = \mathcal{Y}_t(j) + \theta H_{t-1}(j) \tag{B1}$$

$$H_t(j) = \rho H_{t-1}(j) + (1-\rho) Y_t(j). \tag{B2}$$

The equilibrium good price $P_t(j)$ follows from Proposition 2, that is,

$$P_t(j) = (1+\phi_j)^{1/\nu} \left(\frac{\mathcal{Y}_{t(j)}}{\mathcal{Y}_t} \right)^{-\frac{1}{\nu}} \tag{B3}$$

where the aggregate consumption surplus $\mathcal{Y}_t$ is

$$\mathcal{Y}_t = \left[\delta_B \left(1+\phi_B\right)^{1/\nu} \mathcal{Y}_t(B)^{1-\frac{1}{\nu}} + \delta_G \left(1+\phi_G\right)^{1/\nu} \mathcal{Y}_t(G)^{1-\frac{1}{\nu}} \right]^{\frac{1}{1-\frac{1}{\nu}}} \tag{B4}$$

with $\delta_B \in (0,1)$ and $\delta_G = 1 - \delta_B$ denoting the mass of Brown and Green technologies, as discussed in Section 3.1

Aggregate-level asset pricing quantities. From the representative-firm problem we can obtain the sectoral return $R_t(j)$, and the risk-free rate $R_{f,t}$ from the standard Euler's equations:

$$\mathbb{E}_t \left[\mathbb{M}_{t,t+1} R_{t+1}(j) \right] = 1 \tag{B5}$$

$$\mathbb{E}_t \left[\mathbb{M}_{t,t+1} R_{f,t} \right] = 1 \tag{B6}$$

where $\mathbb{M}_{t,t+1} = \beta \left(\frac{\mathcal{Y}_{t+1}}{\mathcal{Y}_t} \right)^{-\gamma}$, $R_t(j) = \frac{D_t(j)+V_t(j)}{V_{t-1}(j)}$, with $D_t(j) = P_t(j) C_t(j)$ and $V_t(j)$ denoting the representative firm's value. The aggregate dividend $D_{m,t}$, market value, $V_{m,t}$, market return $R_{m,t}$,

[20] Because the habit variable is a "stock" variable, we adhere to the Dynare notation convention and report it as a lagged variable, H_{t-1}, as it is known at time t. We follow the same convention for all stock variables in the model.

and aggregate price-dividend ratio $pd_{m,t}$ are given by

$$D_{m,t} = \delta_b D_t(B) + \delta_g D_t(G) \tag{B7}$$

$$V_{m,t} = \delta_b V_t(B) + \delta_g V_t(G) \tag{B8}$$

$$R_{m,t} = \frac{D_{m,t} + V_{m,t}}{V_{m,t-1}} \tag{B9}$$

$$pd_{m,t} = \frac{V_{m,t}}{D_{m,t}}. \tag{B10}$$

Cross section of individual firm (i,j). As we discuss in Step 3 of the solution method described in Section B.1 below, at each point in time we simulate a cross section of brown and green firms. The conditions that describe the evolution of physical endowment, habit, goods prices and demand elasticity are:

$$Y_t(i,j) = (1+\phi_j)P_t(i,j)^{-\nu}\mathcal{Y}_t + \theta H_{t-1}(i,j), \quad Y_t(i,j) = Y_t(j) \tag{B11}$$

$$H_t(i,j) = \rho H_{t-1}(i,j) + (1-\rho)Y_t(i,j) + \varepsilon^h_{ijt} \tag{B12}$$

$$\eta_t(j) = \nu\left(\frac{Y_t(i,j) - \theta H_{t-1}(i,j)}{Y_t(i,j)}\right) \tag{B13}$$

The return for firm (i,j) is given by the standard Euler's equation

$$\mathbb{E}_t\left[\mathbb{M}_{t,t+1}R_{t+1}(i,j)\right] = 1 \tag{B14}$$

where $R_t(i,j) = \frac{D_t(i,j)+V_t(i,j)}{V_{t-1}(i,j)}$ and the dividend $D_t(i,j) = P_t(i,j)C_t(i,j)$.

Because the exogenous endowment process in equation 21 growth at a rate g, to achieve stationarity, we rescale $\mathcal{Y}_t(j)$, $Y_t(j)$, $H_t(j)$, $D_t(j)$, $V_t(j)$, $Y_t(i,j)$, $H_t(i,j)$, $D_t(i,j)$, and $V_t(i,j)$ by e^{gt}. From the de-trended conditions we obtain the equilibrium dynamics of the models using a third-order perturbation method from Dynare++.

B.1 Solution method

Given the habit-adjusted process $\mathcal{Y}_t(j)$ and the cross sectional distribution of good-specific habits $H_t(i,j)$, the physical endowment process $Y_t(i,j) = Y_t(j)$ is implicitly defined by equation (20). Because the cross-sectional distribution of good-specific habits $H_t(i,j)$ is an infinite-dimensional object, recovering $Y_t(j)$ exactly is numerically unfeasible. To make the problem tractable, we follow

Krusell and Smith (1998) and summarize the distribution of $H_t(i,j)$ with the average habit level in the sector j,

$$\bar{H}_t(j) = \int_0^1 H_t(i,j)\mathrm{d}i, \tag{B15}$$

and verify that such approximation delivers a sufficiently accurate solution for the physical endowment process $Y_t(j)$.

Specifically, we solve the model using third-order perturbation methods, as discussed in Appendix B, using the following steps:

1. We first consider two representative firms $j \in \{B, G\}$ and take as given the habit-adjusted process $\mathcal{Y}_t(j)$. Because the representative firm is an average across all firms i with level of greenness j, we take the habit level of the representative firm as the average habit level $\overline{H}_t(j)$. Formally, we construct such representative firms by solving the model under the assumption that the habit dynamics in equation (19) has no shocks, that is, $\sigma_h = 0$. Using the average habit level $\overline{H}_t(j)$ and the habit-adjusted endowment process $\mathcal{Y}_t(j)$, we obtain the following guess for the physical endowment $Y_t(j)$

$$Y_t(j) = \mathcal{Y}_t(j) + \theta\bar{H}_t(j). \tag{B16}$$

2. Taking as given the process for $\mathcal{Y}_t(j)$ and $Y_t(i,j) = Y_t(j)$ from Step 1, we compute individual habit levels $H_t(i,j)$ from the habit dynamics equation (19), where, by the market clearing condition, $C_{t-1}(i,j) = Y_{t-1}(i,j)$. Using the habit $H_t(i,j)$ thus derived, we can compute the good price $P_t(i,j)$ according to demand function from Proposition 2, that is,

$$P_t(i,j) = \left(\frac{(1+\phi_j)\mathcal{Y}_t}{Y_t(j) - \theta H_t(i,j)}\right)^{\frac{1}{\eta}}, \tag{B17}$$

where $\mathcal{Y}_t$ is computed according to equation (26). From the good price $P_t(i,j)$ we can then derive the dividend $D_t(i,j) = P_t(i,j)Y_t(j)$, which will be used to price the stock of firm (i,j) and hence obtain its required rate of return.

3. At each point in time, we simulate a cross-section of green and brown firms using the solution defined in Step 2, and use the guessed $Y_t(j)$ and the resulting distribution of $H_t(i,j)$ to compute the implied aggregate consumption surplus $\hat{\mathcal{Y}}_t(j)$ according to equation (20).

4. We verify the accuracy of our approximation by comparing the aggregate consumption surplus $\hat{\mathcal{Y}}_t(j)$ from Step 3 with the exogenously specified consumption surplus $\mathcal{Y}_t(j)$ from Step 1. In our solution, we find that $corr(\hat{\mathcal{Y}}_t(j), \mathcal{Y}_t(j)) > 0.9999$, confirming that the guess for the physical endowment $Y_t(j)$ in equation (B16) provides a good approximation.

C Tables

Table 1: Parameter values

The table reports the values of the model coefficients used in the calibration of the model in Section 3. We calibrate the model at a quarterly frequency.

Parameter	Symbol	Value
Time preference	β^*	0.986
Elasticity of substitution	η	2
Curvature parameter	γ	6.3
Deterministic growth rate	g	0.00425
Economy-wide endowment persistence	ϱ_z	0.98
Technology-specific endowment persistence	ϱ_j	0.98
Habit persistence	ρ	0.98
Volatility of economy-wide endowment shock	σ_z	0.0216
Volatility of technology-specific shock	σ_j	0.08
Volatility of idiosyncratic habit shock	σ_h	0.06
Habit strength	θ	0.82
Countercyclical volatity parameter	b	-7
Consumption bias	ϕ	0.25
Technology group size	δ_B, δ_G	0.5

Table 2: Moments from the calibrated model

We run 500 simulations of 500 years each and compute aggregate level moments by discarding the first 100 years in each simulation. The table reports the annualized moments values from the model and the corresponding values in the data. Following Garleanu, Panageas, and Yu (2012), we use all data moments from the long sample (1871–2005) in Campbell and Cochrane (1999) except for the volatility of the 1-year zero coupon yield, which is from Chan and Kogan (2002).

Moment	Data	Model
Mean of consumption growth	0.017	0.017
Volatility of consumption growth	0.033	0.035
Mean of 1-year zero coupon yield	0.029	0.029
Volatility of 1-year zero coupon yield	0.030	0.074
Mean of equity premium (logarithmic returns)	0.039	0.039
Volatility of equity premium	0.180	0.239

Table 3: Characteristics of demand elasticity and ESG portfolios

Panel A shows summary statistics of characteristics of demand elasticity (CPC) portfolios. The sample is all CRSP stocks that are list in NYSE, AMEX and NASDAQ and have non-missing CPC and ESG score variables from November 2012–December 2022. Panel B shows summary statistics of characteristics of ESG portfolios within top demand elasticity tercile. The sample period is from November 2012–December 2022. t-statistics are adjusted for autocorrelation using Newey and West (1987).

Panel A: Characteristics of demand elasticity portfolios

	High Elasticity		Low Elasticity		High-Low	
	Mean	Median	Mean	Median	Mean	t-statistic
ESG						
ESG Score	4.374	4.343	4.444	4.470	-0.070	-3.97
E Score	3.783	3.644	4.765	4.875	-0.982	-12.24
S Score	4.262	4.214	4.251	4.256	0.012	0.53
G Score	5.553	5.670	5.290	5.102	0.263	3.95
Demand elasticity measures						
CPC (monthly %)	-0.356	-0.391	0.306	0.302	-0.661	-28.69
Herfindhal index (HHI)	150.556	149.470	243.895	244.000	-93.339	-39.56
Firm characteristics						
ln(ME)	21.844	0.467	21.812	21.725	0.033	0.82
ln(BM)	-0.782	0.161	-1.084	-1.097	0.303	21.78
Operating profitability (Yr %)	17.141	17.069	15.214	16.229	1.926	1.48
Asset growth (Yr %)	17.325	17.085	23.070	21.518	-5.745	-4.70

Panel B: Characteristics of ESG portfolios with high demand elasticity

	High ESG		Low ESG		High-Low	
	Mean	Median	Mean	Median	Mean	t-statistic
ESG						
ESG Score	5.531	5.440	3.206	3.279	2.325	21.26
E Score	5.381	5.372	2.450	2.573	2.930	17.19
S Score	5.484	5.360	3.204	3.226	2.280	21.54
G Score	6.145	6.011	4.738	4.753	1.407	11.86
Demand elasticity measures						
CPC (monthly %)	-0.272	-0.266	-0.681	-0.811	0.408	8.01
Herfindhal index (HHI)	183.335	180.658	123.987	122.095	59.348	10.47
Firm characteristics						
ln(ME)	22.442	22.447	21.472	21.448	0.970	10.35
ln(BM)	-1.046	-0.978	-0.571	-0.525	-0.475	-9.38
Operating profitability (Yr %)	22.484	21.692	12.515	14.681	9.969	7.02
Asset growth (Yr %)	15.484	14.108	19.147	20.260	-3.663	-3.46

Table 4: GMB spread and demand elasticity

The table shows regression results of the GMB return spread on a constant and various factors, capturing different asset pricing models. GMB is a zero-cost portfolio with a long position in the highest quartile of the overall ESG score and a short position in the lowest quartile of the ESG score. The portfolio is rebalanced monthly. MKTRF refers to the Market factor in the CAPM; SMB and HML are the size and value factors in Fama and French (1993); RMW and CMA refer to the profitability and investment factors in Fama and French (2015). Panel A shows estimates conditional on high demand elasticity (low CPC); Panel B shows estimates conditional on low demand elasticity (high CPC); and Panel C shows estimates of their difference. The sample period is November 2012–December 2022. The underlying portfolio returns are at monthly frequency, and the estimates of the average excess returns and alphas are annualized by multiplying by twelve. In parenthesis we report Newey West t-statistics. In the table we report annualized returns in percentages. *, **, *** indicate significance level at 10, 5, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: High Demand Elasticity								
	Equal weighted excess returns				Value weighted excess returns			
Constant	0.117***	0.135***	0.126***	0.123***	0.115**	0.127*	0.108***	0.104***
t-stat	(2.808)	(2.802)	(3.291)	(3.298)	(2.038)	(1.925)	(2.958)	(2.816)
MKTRF		-0.142	-0.083	-0.048		-0.104	0.025	-0.056
t-stat		(-1.054)	(-0.821)	(-0.497)		(-0.719)	(0.362)	(-0.689)
SMB			-0.218	-0.250			-0.559***	-0.356***
t-stat			(-1.497)	(-1.635)			(-5.543)	(-2.583)
HML			-0.516***	-0.585***			-0.682***	-0.682***
t-stat			(-6.408)	(-4.246)			(-5.171)	(-4.749)
RMW				-0.133				0.557***
t-stat				(-0.760)				(3.497)
CMA				0.216				-0.220
t-stat				(0.812)				(-0.929)
Panel B: Low Demand Elasticity								
	Equal weighted excess returns				Value weighted excess returns			
Constant	0.026	0.019	0.017	0.014	0.015	0.010	0.011	0.019
t-stat	(1.454)	(0.991)	(0.988)	(0.800)	(0.645)	(0.336)	(0.431)	(0.792)
MKTRF		0.061	0.071*	0.052		0.047	0.037	0.039
t-stat		(1.272)	(1.645)	(1.285)		(0.561)	(0.491)	(0.578)
SMB			-0.042	0.028			0.072	-0.013
t-stat			(-0.661)	(0.447)			(1.060)	(-0.182)
HML			-0.085*	-0.112**			-0.092	0.009
t-stat			(-1.843)	(-2.155)			(-1.287)	(0.074)
RMW				0.174				-0.167
t-stat				(1.543)				(-1.601)
CMA				-0.006				-0.174
t-stat				(-0.068)				(-1.132)
Panel C: High demand elasticity GMB - Low demand elasticity GMB								
	Equal weighted excess returns				Value weighted excess returns			
Constant	0.091**	0.116***	0.109***	0.109***	0.099*	0.118**	0.097**	0.085**
t-stat	(2.392)	(2.713)	(2.867)	(2.984)	(1.816)	(1.984)	(2.465)	(2.213)
MKTRF		-0.203*	-0.154*	-0.1		-0.151	-0.012	-0.095
t-stat		(-1.676)	(-1.701)	(-1.087)		(-1.589)	(-0.189)	(-1.149)
SMB			-0.176	-0.278*			-0.631***	-0.343**
t-stat			(-1.112)	(-1.729)			(-6.285)	(-2.503)
HML			-0.431***	-0.473***			-0.590***	-0.691***
t-stat			(-4.822)	(-3.690)			(-4.768)	(-5.782)
RMW				-0.307				0.724***
t-stat				(-1.428)				(3.957)
CMA				0.222				-0.047
t-stat				(0.848)				(-0.192)

Table 5: GMB spread and industry concentration

The table shows regression results of the GMB return spread on a constant and various factors, capturing different asset pricing models. GMB is a zero-cost portfolio with a long position in the highest quartile of the overall ESG score and a short position in the lowest quartile of the ESG score. The portfolio is rebalanced monthly. MKTRF refers to the Market factor in the CAPM; SMB and HML are the size and value factors in Fama and French (1993); RMW and CMA refer to the profitability and investment factors in Fama and French (2015). Panel A shows estimates conditional on high demand elasticity (low HHI); Panel B shows estimates conditional on low demand elasticity (high HHI); and Panel C report estimates of their difference. The sample period is November 2012–December 2022. The underlying portfolio returns are at monthly frequency, and the estimates of the average excess returns and alphas are annualized by multiplying by twelve. In parenthesis we report t-statistics adjusted for autocorrelation using Newey and West (1987). In the table we report annualized returns in percentages. *, **, *** indicate significance level at 10, 5, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Low HHI								
	Equal weighted excess returns				Value weighted excess returns			
Constant	0.061	0.086**	0.075**	0.077**	0.071**	0.078***	0.072***	0.069***
t-stat	(1.557)	(2.196)	(2.362)	(2.417)	(2.538)	(2.812)	(2.791)	(2.847)
MKTRF		-0.204*	-0.130	-0.139		-0.058	-0.013	-0.021
t-stat		(-1.789)	(-1.644)	(-1.604)		(-0.817)	(-0.202)	(-0.324)
SMB			-0.323***	-0.326***			-0.202*	-0.161
t-stat			(-3.717)	(-2.863)			(-1.932)	(-1.392)
HML			-0.382***	-0.351**			-0.208**	-0.234***
t-stat			(-5.263)	(-2.539)			(-2.514)	(-2.818)
RMW				0.014				0.095
t-stat				(0.097)				(0.623)
CMA				-0.077				0.023
t-stat				(-0.410)				(0.114)
Panel B: High HHI								
	Equal weighted excess returns				Value weighted excess returns			
Constant	0.008	0.012	0.009	0.008	0.023	0.038	0.035	0.025
t-stat	(0.416)	(0.615)	(0.434)	(0.448)	(0.879)	(1.428)	(1.448)	(1.069)
MKTRF		-0.036	-0.012	-0.028		-0.122*	-0.106	-0.139**
t-stat		(-0.865)	(-0.307)	(-0.612)		(-1.915)	(-1.509)	(-2.042)
SMB			-0.108	-0.075			-0.099	0.076
t-stat			(-1.608)	(-1.031)			(-1.099)	(0.825)
HML			-0.087**	-0.081			0.079*	-0.038
t-stat			(-2.204)	(-1.454)			(1.645)	(-0.566)
RMW				0.096				0.404***
t-stat				(1.053)				(3.148)
CMA				-0.052				0.115
t-stat				(-0.552)				(0.962)
Panel C: Low HHI − High HHI GMB spread								
	Equal weighted excess returns				Value weighted excess returns			
Constant	0.053	0.074*	0.066*	0.069*	0.048	0.040	0.036	0.044
t-stat	(1.385)	(1.764)	(1.788)	(1.823)	(1.438)	(1.195)	(1.296)	(1.607)
MKTRF		-0.169	-0.118	-0.112		0.064	0.093	0.118
t-stat		(-1.546)	(-1.312)	(-1.075)		(0.619)	(0.976)	(1.168)
SMB			-0.215**	-0.251*			-0.103	-0.237*
t-stat			(-2.255)	(-1.878)			(-0.700)	(-1.696)
HML			-0.295***	-0.271**			-0.287***	-0.196*
t-stat			(-4.622)	(-2.176)			(-2.822)	(-1.948)
RMW				-0.082				-0.309
t-stat				(-0.481)				(-1.460)
CMA				-0.025				-0.092
t-stat				(-0.124)				(-0.361)

Table 6: Fama-MacBeth regressions-Realized return

This table shows Fama-MacBeth regression results when monthly returns (in %) are regressed on lagged firm characteristics. Accounting data come from Compustat. The full sample is all CRSP stocks that are list in NYSE, AMEX and NASDAQ and have non-missing listed independent variables, ranging from November 2012 to December 2022. "High Demand Elasticity" and "Low Demand Elasticity" are subsample of stocks that fall into bottom and top CPC tercile in every month, respectively. In parenthesis we report t-statistics with Newey and West (1987) standard errors.

Panel A: Cumulative Price Change (CPC)			
	(1)	(2)	(3)
	All Sample	High Demand Elasticity	Low Demand Elasticity
ESG score$_{-1}$ × Demand elasticity$_{-1}$	0.098*		
	(1.703)		
Demand elasticity$_{-1}$	0.008		
	(0.096)		
ESG score$_{-1}$	0.129***	0.315***	0.102
	(2.722)	(2.951)	(1.369)
LogSize$_{-1}$	0.026	-0.045	0.051
	(0.436)	(-0.892)	(0.730)
LogB/M$_{\text{Yr -1}}$	0.011	-0.170	0.088
	(0.077)	(-0.832)	(0.515)
OP$_{\text{Yr -1}}$	0.317**	-0.040	0.361**
	(2.295)	(-0.154)	(2.400)
LogAG$_{\text{Yr -1}}$	-0.137	-0.314	-0.139
	(-0.473)	(-0.740)	(-0.448)
LogReturn$_{-2,-12}$	0.412	0.283	0.410
	(1.419)	(0.720)	(1.256)
Constant	0.244	1.787	-0.226
	(0.154)	(1.333)	(-0.127)
Panel B: Herfindhal Index (HHI)			
	All Sample	High Demand Elasticity	Low Demand Elasticity
ESG score$_{-1}$ × Demand elasticity$_{-1}$	0.059		
	(1.636)		
Demand elasticity$_{-1}$	-0.027		
	(-0.593)		
ESG score$_{-1}$	0.137***	0.216**	0.045
	(2.926)	(2.289)	(1.368)
LogSize$_{-1}$	0.029	-0.007	0.016
	(0.506)	(-0.134)	(0.219)
LogB/M$_{\text{Yr -1}}$	0.015	-0.111	0.046
	(0.119)	(-0.579)	(0.327)
OP$_{\text{Yr -1}}$	0.260*	0.276**	0.201
	(1.805)	(2.018)	(1.050)
LogAG$_{\text{Yr -1}}$	-0.335	-0.604*	-0.351
	(-1.309)	(-1.675)	(-1.061)
LogReturn$_{-2,-12}$	0.441	0.577	0.235
	(1.516)	(1.538)	(0.685)
Constant	0.178	0.916	0.554
	(0.116)	(0.690)	(0.286)

Table 7: Dissecting GMB spread

The table shows monthly time-series regressions when realized GMB returns (alpha) are regressed against variables capturing shocks to climate concerns and earnings as in Pastor, Stambaugh, and Taylor (2022). We estimate GMB alpha in time series regressions as in table 4 and set it equal to regression's intercept plus residual. The sample period is November 2012–December 2022. In parenthesis we report t-statistics with Newey and West (1987) standard errors. *, **, *** indicate significance level at 10, 5, and 1%, respectively.

Panel A: High Demand Elasticity GMB								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Return	CAPM α	FF3 α	FF5 α	Return	CAPM α	FF3 α	FF5 α
const	0.082*	0.103**	0.073**	0.069**	0.070*	0.093**	0.077**	0.074**
	(1.790)	(2.292)	(2.288)	(2.223)	(1.769)	(2.345)	(2.390)	(2.424)
Δ Climate concerns (same month)	0.011	0.012	0.015	0.014	0.008	0.008	0.015	0.014
	(0.733)	(0.789)	(1.325)	(1.276)	(0.500)	(0.547)	(1.238)	(1.195)
Δ Climate concerns (prev. month)	0.023*	0.020	0.030***	0.033***	0.019	0.016	0.029***	0.032***
	(1.758)	(1.490)	(2.710)	(3.092)	(1.500)	(1.230)	(2.706)	(3.095)
Δ Earnings forecasts					0.003**	0.003**	0.000	0.000
					(2.224)	(2.297)	(0.192)	(0.063)
Earnings announcement returns					0.001	-0.021	-0.077	-0.092
					(0.006)	(-0.123)	(-0.506)	(-0.602)
Panel B: Low Demand Elasticity GMB								
	Return	CAPM α	FF3 α	FF5 α	Return	CAPM α	FF3 α	FF5 α
const	0.028	0.019	0.014	0.009	0.020	0.011	0.005	0.001
	(1.335)	(0.883)	(0.688)	(0.447)	(1.047)	(0.558)	(0.286)	(0.046)
Climate concerns (same month)	-0.002	-0.002	-0.001	0.001	-0.004	-0.004	-0.003	-0.001
	(-0.371)	(-0.369)	(-0.269)	(0.168)	(-0.856)	(-0.916)	(-0.784)	(-0.234)
Climate concerns (prev. month)	-0.003	-0.002	-0.000	-0.001	-0.005	-0.004	-0.002	-0.002
	(-0.573)	(-0.358)	(-0.062)	(-0.107)	(-0.812)	(-0.637)	(-0.340)	(-0.390)
Earnings forecasts					0.002**	0.002*	0.002**	0.002*
					(1.961)	(1.845)	(2.209)	(1.855)
Earnings announcement returns					0.427***	0.442***	0.450***	0.435***
					(4.826)	(5.203)	(5.416)	(5.269)
Panel C: Counterfactual High demand elasticity GMB - Low demand elasticity GMB								
	Return	CAPM α	FF3 α	FF5 α	Return	CAPM α	FF3 α	FF5 α
Difference	0.054	0.084**	0.059*	0.059*	0.050	0.082**	0.072**	0.073**
	(1.453)	(2.293)	(1.739)	(1.784)	(1.381)	(2.230)	(2.037)	(2.128)

Table 8: Fama-MacBeth regressions-Expected return

This table shows Fama-MacBeth regression results when option-implied expected returns (in %) are regressed on lagged firm characteristics. Option-implied expected returns are the lower bounds of expected returns from Martin (2017) and Martin and Wagner (2019). Following Martin and Wagner (2019), we take monthly average of daily lower bound of expected return for each stock and run regressions at monthly frequency. Accounting data come from Compustat. The full sample is all S&P 500 stocks with non-missing variables, ranging from November 2012 to December 2022. In parenthesis we report t-statistics with Newey and West (1987) standard errors.

Return Horizon	30 days	60 days	91 days	182 days	365 days	730 days
ESG score$_{-1}$ × Demand elasticity$_{-1}$	0.244**	0.218**	0.205**	0.186**	0.167**	0.153**
	(2.234)	(2.139)	(2.142)	(2.180)	(2.268)	(2.328)
ESG score$_{-1}$	-0.309***	-0.293***	-0.285***	-0.270***	-0.260***	-0.267***
	(-6.975)	(-6.656)	(-6.904)	(-7.043)	(-7.207)	(-7.401)
Demand elasticity$_{-1}$	0.589***	0.576***	0.558***	0.530***	0.484***	0.451***
	(7.109)	(7.752)	(8.266)	(8.626)	(9.526)	(9.995)
LogSize$_{-1}$	-1.089***	-0.928***	-0.822***	-0.737***	-0.677***	-0.659***
	(-11.745)	(-11.808)	(-12.314)	(-12.130)	(-10.498)	(-9.491)
LogB/M$_{\text{Yr -1}}$	-0.455***	-0.495***	-0.515***	-0.518***	-0.483***	-0.502***
	(-3.266)	(-3.739)	(-4.062)	(-4.575)	(-5.050)	(-5.972)
OP$_{\text{Yr -1}}$	-1.252***	-1.260***	-1.276***	-1.265***	-1.208***	-1.270***
	(-4.775)	(-4.901)	(-5.082)	(-5.572)	(-6.252)	(-7.545)
LogAG$_{\text{Yr -1}}$	0.768***	0.799***	0.773***	0.721***	0.692***	0.791***
	(3.478)	(3.607)	(3.328)	(2.991)	(3.094)	(3.526)
LogReturn$_{-2,-12}$	-1.894*	-1.651*	-1.446	-1.211	-0.993	-0.826
	(-1.865)	(-1.690)	(-1.557)	(-1.390)	(-1.224)	(-1.078)
Constant	31.029***	27.001***	24.398***	22.346***	20.776***	19.022***
	(10.618)	(10.541)	(10.922)	(11.203)	(10.719)	(9.987)

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