When Tastes Affect Asset Prices But Not Expected Returns

February 11, 2026

Abstract

Investor tastes for sustainability can move prices without moving expected returns. We develop an asset pricing framework in which fundamental investors can *span* any desired exposure to financial risk while holding zero exposure to non-pecuniary tastes. In the equilibrium, taste-driven demand creates systematic return comovement, but systematic taste exposure commands no risk premium; noise traders supply the liquidity that allows markets to clear without pricing taste risk. Empirically, we construct three taste factors from United Nations Sustainable Development Goal indicators, Sustainability and Climate Resiliency, Human Development and Social Inclusion, and Institutional Strength and Innovation Capacity, and estimate exposures for 36,077 firms in 45 countries. The factors load significantly on the latent factor space yet earn zero premia in cross-sectional tests. Removing taste exposure from conventional factors raises the out-of-sample squared Sharpe ratio of the five-factor model by about 20 percent, with gains concentrated when arbitrage constraints bind, when sustainability is salient, or when taste investors' wealth share is high. Our framework delineates the conditions under which tastes create systematic yet unpriced risks, reconciling evidence on ESG investment flows with the absence of taste risk premia.

JEL Classification: G11, G12, G14, G23, Q56
Keywords: Arbitrage Pricing Theory, Investor Tastes, Taste Factors, Unpriced Taste Risk, Taste-Neutral Portfolios.

1 Introduction

Do investor preferences for sustainability, social impact, and governance affect equilibrium asset prices? And if so, how? Recent influential work argues that such preferences reduce expected returns: investors are willing to accept lower compensation for holding high-sustainability assets (Pástor et al., 2021; Pedersen et al., 2021). This outcome, however, requires that fundamental investors, those who care only about financial consumption, cannot offset the demand pressures introduced by taste investors.

This paper shows that whether investor tastes affect expected returns depends on market structure and the nature of taste exposure. Using an Arbitrage Pricing Theory framework, we demonstrate that when fundamental investors can *span* their desired exposure to fundamental risk while holding zero exposure to tastes, systematic taste risk is not priced. In this equilibrium, taste-driven demand generates pervasive return covariation but does not affect expected returns. The intuition parallels standard asset pricing logic: idiosyncratic cash-flow shocks influence firm valuations without commanding a risk premium. Analogously, taste-driven demand can raise valuations of high-sustainability firms, affecting capital allocation and incentivizing sustainable production. Yet systematic taste exposure carries no risk premium when it can be hedged. Noise traders provide the liquidity that enables fundamental investors to maintain taste-neutral portfolios, thereby severing the link between aggregate taste demand and expected returns.

This framework yields four testable predictions. First, taste factors should generate systematic covariation but earn zero risk premia. Second, conventional factor portfolios should inherit taste exposure through correlations between taste and financial characteristics. Third, removing this exposure should improve risk-adjusted performance. Fourth, these gains should be largest when arbitrage capacity is constrained, or sustainability concerns are salient.

We use the United Nations Sustainable Development Goals (SDG), a policy framework increasingly adopted by corporations for sustainability reporting and impact measurement, which capture three non-pecuniary dimensions: *sustainability and climate resiliency*, *human development and social inclusion*, and *institutional strength and innovation capacity*. We construct three taste factors from country-level SDG indicators and monthly index returns for 67 countries, then estimate firm-level exposures for 36,077 firms across 45 countries. Importantly, these exposures are inferred solely from return covariation, without relying on ESG ratings or firm disclosures. We externally validate the taste interpretation using data on corporate misconduct: firms with higher estimated SDG exposure are significantly less likely to violate United Nations Global Compact (UNGC) principles, providing corroborating evidence that return-based exposures capture differences in realized firm behavior. Relatedly, sustainability-focused mutual funds hold portfolios tilted toward high-SDG-exposure firms, and SDG factor returns exhibit negative autocorrelation, consistent with temporary price pressure rather than permanent differences in expected returns.

We find empirical support for each of the aforementioned predictions. SDG factors capture systematic return variation but do not earn a risk premium in Fama-MacBeth regressions. Conventional factor portfolios are contaminated by taste exposure: removing it increases squared Sharpe ratios by approximately 20 percent for the five-factor model. These gains concentrate when arbitrage capital is constrained, or sustainability is salient. Together, these results are consistent with the existence of unpriced but economically relevant taste risk.

Our theoretical contribution identifies a distinct equilibrium mechanism. In models without noise traders (Pástor et al., 2021; Pedersen et al., 2021), taste-driven demand must be absorbed by fundamental investors, forcing expected returns to adjust. We show that when cross-sectional heterogeneity allows fundamental investors to span desired exposures while neutralizing taste risk, and noise traders supply residual liquidity, systematic taste exposure is not priced. When taste-driven demand is large relative to available liquidity, such that fundamental investors cannot maintain taste-neutral portfolios, the equilibrium mechanism emphasized in Pástor et al. (2021) applies and systematic taste exposure becomes priced. By contrast, when cross-sectional heterogeneity allows spanning and noise traders supply sufficient liquidity, taste risk remains unpriced despite generating pervasive comovement. This defines distinct pricing regimes: concentrated preferences that overwhelm available liquidity affect expected returns, whereas granular taste dimensions with rich cross-sectional dispersion remain diversifiable.

Our framework connects to the distinction between tastes and beliefs emphasized by Fama and French (2007). In their formulation, disagreement about cash flows affects prices but does not necessarily generate return predictability unless it is correlated with priced risk. Investor tastes operate analogously: taste shocks influence portfolio demand and induce systematic return covariation, yet when spanning holds, they do not affect expected returns. This clarifies why sustainability-related trading can have significant and persistent effects on prices and covariances without implying predictable excess returns.

An immediate implication is that the market portfolio is no longer mean–variance efficient. Taste-driven demand and noise-trader positions tilt the market toward taste-exposed assets, introducing systematic variation that is not compensated by higher expected returns. Fundamental investors can exploit spanning to construct portfolios that replicate the market's exposure to priced fundamental risks while neutralizing taste exposure, thereby lying strictly closer to the efficient frontier than the market portfolio. This contrasts with Pástor et al. (2021), where the market portfolio, though inefficient, remains useful: investors combine it with a taste portfolio to span the efficient frontier. In our framework, the market portfolio plays no such role–it is contaminated by both unpriced taste exposure and noise-trader positions, and does not help span the set of priced risks. This is consistent with the well-documented finding that market beta has little explanatory power for the cross-section of expected returns (Fama and French, 1992, 1996).

Empirically, our paper contributes to multiple strands of literature. First, we provide evidence that distinguishes among competing models of how tastes affect returns. An extensive literature examines how investor preferences for sustainability affect firm behavior and capital allocation (Heinkel et al., 2001; Hong and Kacperczyk, 2009; Hartzmark and Sussman, 2019; Bolton and Kacperczyk, 2021, 2022; Chowdhry et al., 2019; Bolton and Kacperczyk, 2023). Existing work documents mixed results: some studies find ESG characteristics predict returns, while others find little systematic relation (Larcker and Watts, 2020; Alves et al., 2023; Eskildsen et al., 2024; Zhang, 2025). We reconcile these findings by showing that tastes create systematic covariation without affecting expected returns, consistent with unpriced systematic risk but inconsistent with models where tastes enter expected returns directly.

Second, we contribute to the literature on factor contamination. Grinblatt and Saxena (2018) and Daniel et al. (2020) show that traditional factor construction produces portfolios contaminated by unpriced systematic risks. We identify taste-driven covariation as a specific source of such contamination, demonstrating that factor portfolios inherit taste exposures through market-cap weighting or characteristic sorts.

Third, we document that taste contamination is state-dependent. The benefits of removing taste exposures concentrate when liquidity and arbitrage capital are scarce or when sustainability is salient. This state-dependence is consistent with limits to arbitrage (Shleifer and Vishny, 1997; Mitchell et al., 2007; He et al., 2017): when fundamental investors face binding constraints, they cannot fully exploit spanning, amplifying contamination, and magnifying the benefits of taste-neutral construction. Consistent with this mechanism, Darolles et al. (2025) document that some mutual funds profitably anticipate the trading behavior of taste-driven investors by predicting ESG rating changes before they are published; however, this arbitrage activity is concentrated in liquid large-cap stocks, and taste-driven mispricing persists in small caps where arbitrage is more constrained.

Lastly, our return-based approach offers a transparent alternative to vendor ESG scores, which are externally validated against UNGC violations. Exposures reflect market-based aggregation of investor preferences, support high-frequency estimation, and limit susceptibility to manipulation or self-reported disclosures shaped by managerial incentives.

Our findings also speak to sustainable investing and fiduciary duty. Taste-driven capital allocation creates measurable price effects through the covariance matrix rather than expected returns. For investors who wish to hold sustainable assets, our framework offers a different trade-off than models in which taste investors accept lower expected returns (Pástor et al., 2021). In our setting, noise traders absorb taste-driven demand, making taste-related price movements unpredictable, and taste investors do not sacrifice expected returns; they only accept higher volatility from taste factor exposure. Investors may derive sufficient non-pecuniary utility to justify this tradeoff. For investors focused solely on risk-adjusted performance, our results suggest avoiding both very green and very brown stocks–those that most attract taste-driven demand–to eliminate uncompensated volatility. The Sharpe ratio gains from this approach are economically meaningful and discernible during market stress. For researchers, controlling for conventional risk factors may be insufficient when taste-driven covariation pervades returns.

The remainder of the paper proceeds as follows. Section 2 develops our theoretical framework. Section 3 describes our data sources and factor construction. Section 4 reports empirical results, and Section 5 concludes.

2 Theoretical Framework

We develop an asset-pricing framework in which investor preferences for non-pecuniary attributes generate systematic return covariation without commanding a risk premium. The central mechanism is *spanning*: when fundamental investors can construct portfolios that replicate any desired exposure to fundamental risk while maintaining zero exposure to tastes, systematic taste risk becomes redundant for pricing. In this case, tastes affect valuations and the covariance structure of returns, but not expected returns. This spanning property emerges when there is sufficient cross-sectional heterogeneity in firms' taste characteristics relative to their fundamental risk characteristics. The framework builds on an Arbitrage Pricing Theory (APT) perspective and highlights how market structure, specifically cross-sectional heterogeneity and liquidity provision, determines whether taste-driven demand is priced.

2.1 Model Setup

2.1.1 Environment

We consider a two-period economy ($t = 0, 1$) with N firms and three investor types. Each firm j produces two types of output at $t = 1$:

(i) **Fundamental output**, $\tilde{y}_j^F$, which represent financial cash flows (dividends) that provide consumption value and determine payoffs.

(ii) **Taste output**, $\tilde{y}_j^\tau$, which represent non-pecuniary attributes (environmental performance, social impact) that provide direct utility to some investors but have no financial value and are non-tradable.

The non-tradability of taste output implies that non-pecuniary attributes are bundled with share ownership and cannot be sold separately at $t = 1$. Firm outputs follow a two-factor structure:

$$\begin{aligned} \tilde{y}_j^F &= \beta_{j,F}\tilde{Y}^F + \tilde{\epsilon}_j^F \\ \tilde{y}_j^\tau &= \beta_{j,\tau}\tilde{Y}^\tau + \tilde{\epsilon}_j^\tau \end{aligned} \tag{1}$$

where $\tilde{Y}^F$ and $\tilde{Y}^\tau$ are orthogonal aggregate shocks, $\beta_{j,F}$ and $\beta_{j,\tau}$ measure firm j's exposures, and idiosyncratic shocks $\tilde{\epsilon}_j^F$, $\tilde{\epsilon}_j^\tau$ are uncorrelated across firms and with aggregate shocks.

2.1.2 Investors

Fundamental investors, denoted by subscript a, derive utility only from fundamental consumption:

$$U_a(\mathbf{X}_a) = E\left[\sum_{j=1}^{N} X_{a,j}\tilde{y}_j^F\right] - \frac{A}{2}\text{Var}\left(\sum_{j=1}^{N} X_{a,j}\tilde{y}_j^F\right) \tag{2}$$

where $\mathbf{X}_a$ is the portfolio weight vector and $A > 0$ measures risk aversion. Taste output does not enter their utility.

Taste investors, denoted by subscript s, value both fundamental and taste consumption:

$$U_s(\mathbf{X}_s) = E\left[\sum_{j=1}^{N} X_{s,j}\tilde{y}_j^F\right] - \frac{A}{2}\mathrm{Var}\left(\sum_{j=1}^{N} X_{s,j}\tilde{y}_j^F\right) + \delta \cdot E\left[\sum_{j=1}^{N} X_{s,j}\tilde{y}_j^\tau\right] \tag{3}$$

where $\delta > 0$ measures taste preference intensity.

Noise traders, denoted by subscript n, trade for exogenous reasons (liquidity needs, institutional constraints) unrelated to utility maximization. They provide liquidity, enabling fundamental investors to span desired consumption using taste-neutral portfolios. We provide more details in section A.4.1.

2.2 Portfolio Choice and Taste-Driven Demand

Investors choose portfolios at $t = 0$ to maximize expected utility. Standard mean-variance optimization yields optimal weights (derivation in Appendix A.1):

$$\text{Fundamental investors:} \quad \mathbf{X}_a = \frac{1}{A}\mathbf{\Sigma}^{-1}E[\tilde{\mathbf{y}}^F] \tag{4}$$

$$\text{Taste investors:} \quad \mathbf{X}_s = \frac{1}{A}\mathbf{\Sigma}^{-1}\left(E[\tilde{\mathbf{y}}^F] + \delta E[\tilde{\mathbf{y}}^\tau]\right) \tag{5}$$

where $\mathbf{\Sigma} = \mathrm{Cov}(\tilde{\mathbf{y}}^F)$ and we normalize $\mathrm{Var}(\tilde{Y}^F) = 1$ for simplicity. The taste term $\delta E[\tilde{\mathbf{y}}^\tau] = \delta E[\tilde{Y}^\tau]\boldsymbol{\beta}_\tau$ creates a portfolio tilt toward high-$\beta_{j,\tau}$ stocks. Taste investors' deviation from fundamental investors is:

$$\mathbf{X}_s - \mathbf{X}_a = \frac{\delta E[\tilde{Y}^\tau]}{A}\mathbf{\Sigma}^{-1}\boldsymbol{\beta}_\tau \propto \mathbf{\Sigma}^{-1}\boldsymbol{\beta}_\tau \tag{6}$$

This tilt shifts equilibrium prices and induces correlated return movements among taste-exposed firms.

2.3 Returns

The end-of-period payoffs depend only on fundamental output since taste output has no financial value. However, equilibrium prices reflect taste investor demand: when taste investors bid up high-$\beta_{j,\tau}$ stocks, this affects their market valuations and creates systematic return covariation. Returns follow a two-factor structure:

$$\tilde{r}_j - E[\tilde{r}_j] = \beta_{j,F} f_F + \beta_{j,\tau} f_\tau + \varepsilon_j \tag{7}$$

where f_F and f_τ are fundamental and taste factor shocks, and ε_j captures diversifiable idiosyncratic risk. The fundamental factor f_F arises from unexpected fundamental output shocks $\tilde{Y}^F$. The taste factor f_τ captures systematic covariation that arises because shocks to taste preferences, to the wealth of taste investors, or to aggregate taste characteristics cause correlated price movements among high-$\beta_{j,\tau}$ stocks, even though the underlying taste output has no financial value to fundamental investors.

2.4 Spanning and Unpriced Taste Risk

2.4.1 The Spanning Property

The central insight is that fundamental investors can *span* their desired fundamental consumption using portfolios with zero taste exposure.

Definition 1 (Fundamental Consumption Spanning) *The cross-section spans fundamental consumption if, for any target fundamental exposure β_F^{target}, there exists a portfolio satisfying:*

$$\mathbf{X}'\boldsymbol{\beta}_F = \beta_F^{target}, \quad \mathbf{X}'\boldsymbol{\beta}_\tau = 0, \quad \mathbf{X}'\mathbf{1} = 1 \tag{8}$$

This property holds when there is sufficient cross-sectional heterogeneity in $(\beta_{j,F}, \beta_{j,\tau})$. Intuitively, we need stocks with various combinations of fundamental and taste exposures. We formalize this below.

Assumption 1 (Spanning Condition) *The cross-section satisfies: (i) $Var(\beta_{j,\tau}) > 0$ with $E[\beta_{j,\tau}] \approx 0$, (ii) $Cov(\beta_{j,F}, \beta_{j,\tau}) \approx 0$, and (iii) $[\boldsymbol{\beta}_F \ \boldsymbol{\beta}_\tau]$ has full column rank.*

These conditions ensure taste exposures are dispersed, approximately orthogonal to fundamental loadings, and allow independent control of each exposure dimension.

2.4.2 Main Result

Under spanning, taste exposure cannot affect expected returns in equilibrium.

Proposition 2.1 (Zero Taste Risk Premium) *Suppose returns follow (7) and Assumption 1 holds. Then for well-diversified portfolios:*

$$E[\tilde{r}_p] = \beta_{p,F}\lambda_F + \beta_{p,\tau}\lambda_\tau \tag{9}$$

where $\lambda_F > 0$ is the fundamental risk premium and $\lambda_\tau = 0$.

Proof sketch. Suppose $\lambda_\tau \neq 0$. Consider two portfolios with identical fundamental exposure $\beta_{p,F}$ but different taste exposures $\beta_{p,\tau} \neq 0$ and $\beta'_{p,\tau} = 0$. By Definition 1, both exist. They deliver identical fundamental consumption (same mean and variance as $N \to \infty$), so fundamental investors derive identical utility from both. If $\lambda_\tau \neq 0$, their expected returns differ: $E[\tilde{r}_p] - E[\tilde{r}'_p] = \beta_{p,\tau}\lambda_\tau \neq 0$. One portfolio dominates: same utility, different return. All fundamental investors would borrow at r_f and demand the higher-return portfolio. This creates excess demand that cannot be absorbed, forcing prices to adjust until $\lambda_\tau = 0$. □

The full proof appears in Appendix A. The key insight is that spanning makes taste exposure *redundant* for fundamental consumption, so it cannot affect equilibrium prices. Fundamental investors arbitrage away any systematic taste premium by constructing taste-neutral portfolios with identical fundamental payoffs.

2.4.3 Constructing the Taste Factor

The standard factor pricing methodology constructs factor-mimicking portfolios as diversified, zero-investment positions with unit exposure to the target factor and minimal exposure to other factors. Following this approach, we define the taste factor-mimicking portfolio $\mathbf{w}_\tau$ satisfying:

$$\mathbf{w}'_\tau \boldsymbol{\beta}_\tau = 1, \quad \mathbf{w}'_\tau \boldsymbol{\beta}_F \approx 0, \quad \mathbf{w}'_\tau \mathbf{1} = 0 \tag{10}$$

The return on this portfolio, $\tilde{r}_\tau = \mathbf{w}_\tau'\tilde{\mathbf{r}}$, approximates the taste factor f_τ. We provide further details in Appendix A.5. This portfolio delivers approximately zero fundamental consumption but non-zero taste output. For large N:

$$\mathbf{w}_\tau'\tilde{\mathbf{y}}^F \approx 0, \quad \mathbf{w}_\tau'\tilde{\mathbf{y}}^\tau \approx \tilde{Y}^\tau \tag{11}$$

Since this portfolio provides fundamental investors zero expected utility gain, Proposition 2.1 implies $E[\tilde{r}_\tau] = \lambda_\tau = 0$.

2.5 Market Clearing and the Role of Noise Traders

Market clearing requires:

$$\omega_a \mathbf{X}_a + \omega_s \mathbf{X}_s + \omega_n \mathbf{X}_n = \mathbf{e} \tag{12}$$

where ω_i denote wealth shares and $\mathbf{e}$ is the vector of market capitalization weights. The taste-driven tilt must be absorbed by either fundamental investors or noise traders. *Without noise traders* ($\omega_n = 0$), as in Pástor et al. (2021), fundamental investors must accommodate the tilt, requiring compensation via a taste risk premium. *With noise traders* ($\omega_n > 0$), markets can clear at $\lambda_\tau = 0$ if noise traders absorb the tilt.

While Proposition 2.1 shows that spanning implies $\lambda_\tau = 0$, market-clearing equilibrium at this price requires noise trader liquidity. Without noise traders ($\omega_n = 0$), the taste tilt from equation (6) creates excess demand proportional to $\mathbf{\Sigma}^{-1}\boldsymbol{\beta}_\tau$. If fundamental investors hold zero taste exposure (as spanning allows), no one absorbs this tilt—market clearing fails unless fundamental investors accommodate by holding taste risk, requiring $\lambda_\tau \neq 0$ as in Pástor et al. (2021).

With noise traders ($\omega_n > 0$), equation (12) can clear at $\lambda_\tau = 0$ because noise trader positions $\mathbf{X}_n$ absorb taste-driven demand. Because noise traders trade for exogenous reasons (periodic rebalancing, tax-loss harvesting, liquidity shocks), they do not require systematic compensation to hold these positions.

Assumption 2 (Noise Trader Liquidity) *Noise traders satisfy: (i) $\omega_n > 0$, (ii) $Var(\mathbf{X}_n'\boldsymbol{\beta}_\tau) > 0$, and (iii) $E[\mathbf{X}_n'\boldsymbol{\beta}_\tau] \approx 0$.*

These conditions ensure noise traders participate, hold dispersed positions across taste exposures, and do not systematically favor or avoid sustainable stocks. Under Assumptions 1 and 2, equilibrium exists where fundamental investors hold taste-neutral portfolios, taste investors tilt toward high-$\beta_{j,\tau}$ stocks, noise traders absorb the tilt, and markets clear at $\lambda_\tau = 0$.

2.6 Comparison to Existing Work

Our framework differs from Pástor et al. (2021) in both market structure and equilibrium mechanism. Pástor et al. (2021) study sustainable investing in a CAPM setting without noise traders, where market clearing forces fundamental investors to absorb taste-driven tilts, implying a priced taste factor. By contrast, our APT-based framework emphasizes cross-sectional spanning. When fundamental investors can replicate any desired exposure to fundamental risk while neutralizing taste exposure, and when noise traders supply liquidity, taste risk becomes redundant for pricing. As a result, tastes affect valuations and return covariation but not expected returns. Table 1 summarizes the key distinctions.

	Pástor et al. (2021)	**Our Model**
Framework	CAPM	APT
Noise traders	No ($\omega_n = 0$)	Yes ($\omega_n > 0$)
Key mechanism	Market clearing	Spanning
Taste premium	$\lambda_\tau < 0$	$\lambda_\tau = 0$
Green (vs brown) expected returns	Lower	Identical
Green (vs brown) valuations	Higher	Higher
Taste affects	Valuations and Expected Returns	Valuations only

Table 1: Comparison to Pástor et al. (2021)

Our contribution is to show that when markets have sufficient liquidity and spanning holds, taste creates systematic covariation without commanding a risk premium. This is a distinct equilibrium arising from a different market structure.

2.7 Empirical Predictions

Our framework generates testable predictions that distinguish it from alternatives.

Prediction 1 (Systematic but Unpriced Taste Risk) *Taste factors create systematic covariation but earn zero premia:*

(a) taste factors explain significant variance in spanning regressions,

(b) taste loadings $\beta_{p,\tau}$ earn zero premia in Fama-MacBeth regressions, and

(c) taste factor-mimicking portfolios exhibit $E[\tilde{r}_\tau] = 0$.

Prediction 2 (Sharpe Ratio Improvement from Taste Neutralization) *Taste-neutral versions of conventional factors improve Sharpe ratios. For factor portfolio $\mathbf{X}_p$ with taste exposure $\beta_{\tau,p}$, the taste-neutral alternative $\mathbf{X}_p^{neutral} = \mathbf{X}_p - \beta_{\tau,p}\mathbf{w}_\tau$ has identical expected return but lower variance.*

Prediction 3 (Factor Contamination) *Conventional factor portfolios inherit taste exposures through Cov(sorting variable, $\beta_{j,\tau}$), appearing even in portfolios formed on characteristics unrelated to sustainability.*

Prediction 4 (State-Dependent Benefits) *Sharpe ratio improvements from taste neutralization are larger when:*

(a) arbitrage constraints bind (recessions, funding illiquidity),

(b) taste salience is elevated (high climate attention), or

(c) taste investor wealth share ω_s is high relative to noise trader wealth ω_n.

All three channels increase Var(f_τ), amplifying contamination.

Prediction 1 directly tests Proposition 2.1. Predictions 2–4 follow from taste creating unpriced covariation: eliminating this exposure reduces variance without sacrificing expected return, with larger benefits when taste shocks are more volatile. Section 4 tests these predictions.

3 Data Description

We assemble a set of global datasets that allow us to measure investor tastes and their impact on asset prices. Our empirical setting is the United Nations' Sustainable

Development Goals (SDG), which provide a comprehensive and policy-relevant framework for non-pecuniary investor preferences. We utilize country-level SDG indicators to capture aggregate variation in tastes. We link these measures to firm-level returns, global factor benchmarks, climate news attention, and corporate controversies. Together, these datasets provide the foundation for testing how systematic but unpriced tastes shape valuations, covariances, and portfolio exposures across global equity markets.

3.1 Sustainable Development Goals Indicators

The construction of *tastes* factors is based on country-level indicators characterized into 17 Sustainable Development Goals (SDG). These data are available from the World Bank Group's Sovereign ESG Data Portal, administered by the Finance, Competitiveness, and Innovation (FCI) Global Practice, the World Bank Treasury, and the Country Credit Risk Group. We further characterize 17 SDGs into three categories: i) sustainability and climate resiliency, ii) human development and social inclusion, and iii) institutional strength and innovation capacity.

The *sustainability and climate resiliency* category includes indicators on emissions and pollution, natural capital endowments, energy use and security, climate risk, and food security, thereby capturing both externalities and long-term resource resilience. The *human development and social inclusion* category encompasses education, employment, demographics, poverty, health outcomes, and access to public services, providing a view of societal development and equity. Lastly, *institutional strength and innovation capacity* is assessed through indicators of human rights, government effectiveness, legal institutions, macroeconomic management, gender equity, and innovation capacity, reflecting institutional quality and political accountability.

The original database includes 67 sub-themes (Table B.1). Where coverage was incomplete, we manually collected additional data from credible external sources, such as the ND-GAIN Index for climate resilience. After data consolidation, the final panel comprises 66 sub-themes across 67 countries from 2000 to 2019. These countries account for over 91 percent of global GDP as of 2023 and represent both advanced and emerging economies, including Argentina, Australia, Austria, Bahrain, Bangladesh, Belgium, Bosnia and Herzegovina, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Germany, Hungary, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Korea, Kuwait, Lithuania, Malaysia, Mauritius, Mexico, Morocco, the Netherlands, New Zealand, Nigeria, Norway, Oman, Pakistan, the Philippines, Poland, Portugal, Qatar, Romania, Russia, Saudi Arabia, Serbia, Singapore, Slovenia, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Trinidad and Tobago, Tunisia, Turkey, the United Arab Emirates, the United Kingdom, the United States, and Vietnam. For each country, we obtain monthly, currency-adjusted total returns for MSCI country indices from Thomson Reuters Datastream, covering the period from January 2001 to December 2020.

3.2 Stock Return Data

The monthly stock returns for 36,475 publicly listed companies across 45 countries from January 2001 to December 2020. The data are sourced from Jensen et al. (2023) via the Wharton Research Data Services (WRDS) platform. All returns are adjusted for dividends and stock splits and denominated in US dollars to ensure comparability across countries. To control for traditional asset pricing risk factors, we use global factor portfolio returns from Ken French's data library. These include the global market factor, size, value, profitability, investment, and momentum factors, along with separate classifications for developed and emerging markets. Firm-country assignments are based on the firms' primary listing locations, ensuring consistency between firm exposures and country-level ESG indicators.

3.3 Other Data Sources

We obtain data on mutual fund characteristics and holdings from the CRSP Survivor-Bias-Free Mutual Fund Database. We also use holdings data from the Thomson Reuters Mutual Fund Holdings database, which we match to CRSP data using the MFLINKS file from the Wharton Research Data Services. The holdings data allows us to link each fund's positions to CRSP equity files. Most funds have multiple share classes, which typically differ in the fee structure and target clientele. Following Doshi et al. (2015), we combine such classes into a single fund and calculate each fund's total net assets (TNA) as the sum of the TNA of its share classes. We use the TNA-weighted average over the share classes for various mutual fund characteristics. We restrict our analysis to diversified domestic actively managed equity mutual funds. We screen for styles and fund names, excluding international, balanced, sector, bond, money market, and index funds. We also exclude funds with TNA less than 15 million dollars, as Elton et al. (2001) show that returns on such small funds tend to be upwardly biased in the CRSP database. To reduce incubation bias (Evans, 2010), we require a fund to be at least 18 months old. Following Kacperczyk et al. (2008), we exclude funds that hold, on average, less than 80 percent net assets in equity because the reported fund objective does not always accurately characterize a fund. We also remove funds with missing names (Cremers and Petajisto, 2009; Amihud and Goyenko, 2013). Finally, we exclude funds with fewer than 11 stock holdings (Kacperczyk et al., 2005) to compute meaningful measures of fund-level exposures to SDG factors. Our final sample spans 14 years, from 2006 to 2019.

We use climate news data from the Media and Climate Change Observatory (MeCCO) to capture variation in public attention to environmental issues. The MeCCO dataset tracks media coverage of climate-related topics across 131 sources in 59 countries, spanning the period from 2004 to 2020. Coverage is disaggregated by volume, content category (such as policy, science, or extreme weather), and sentiment, allowing examination of both the quantity and tone of climate-related news attention. Climate news attention provides an independent measure of time-varying salience of environmental risks, which may influence asset prices through changes in investor perceptions and risk premium.

The analysis of corporate sustainability behavior uses data from RepRisk, which monitors firms' involvement in violations of the United Nations Global Compact (UNGC) principles. RepRisk aggregates information from media outlets, non-governmental organizations, regulatory agencies, and academic institutions to identify corporate controversies related to environmental, social, and governance issues. The ten UNGC principles are grouped into three dimensions: climate (principles 7–9), labor (principles 3–6), and human rights (principles 1, 2, and 10). We map firm-level violations to these categories over the period 2007 to 2020. Firm identifiers are matched to return data using gvkey-ISIN mappings, supplemented by CUSIP-to-ISIN conversions for Canadian and US firms using the Luhn algorithm to calculate check digits. The UNGC violation data provide an external benchmark for assessing the validity of estimated firm-level ESG exposures, offering a real-world measure of sustainability behavior distinct from market-based return data.

3.4 Constructing Taste Factors

We construct three return-based factors, *sustainability and climate resiliency*, *human development and social inclusion*, and *institutional strength and innovation capacity*, which translate country-level differences in these dimensions into long-short portfolio returns. These factors provide the empirical foundation for examining how tastes shape valuations, covariances, and portfolio exposures.

3.4.1 Country-Level Indicators

We begin by calculating standardized scores for each sub-theme within the broader Environment, Social, and Governance categories. For each sub-theme k belonging to theme j within category i, we compute a z-score across the cross-section of countries in each year. These z-scores rank country performance in a given sub-theme relative to other countries that year. We assign each sub-theme a positive or negative tone. For instance, within the sustainability and climate resilience category, carbon emissions per capita are treated as a negative indicator under the *Emissions and Pollution* theme. In contrast, renewable electricity output as a percentage of total electricity is treated as a positive indicator under the *Energy Use and Security* theme. Negative-tone sub-themes are transformed by multiplying the z-score by -1, ensuring that higher values uniformly represent stronger sustainability performance.

After aligning the tones of all sub-themes, scores are aggregated to the category level by equal weighting across themes and sub-themes. Specifically, we define the overall score for category i in country c and year t as:

$$\text{Score}_{ict} = \frac{1}{|j_i|} \sum_{j_i} \frac{1}{|k_{j_i}|} \sum_{k_{j_i}} [\text{z-score}^{+}_{kjict}]. \tag{13}$$

Here, $|j_i|$ denotes the number of themes within category i, $|k_{j_i}|$ denotes the number of sub-themes within theme j of category i, and superscript + represent positively aligned z-score. Table B.2 provides a full breakdown of all sub-themes, their directional tone, and the implied weights used in aggregation. Of the 66 sub-themes, 31 are assigned a negative tone–19 in Sustainability and Climate Resiliency, 11 in Human Development and Social Inclusion, and 1 in Institutional Strength and Innovation Capacity. Equal weighting at both the theme and sub-theme levels ensures that no single metric dominates the overall score. For example, within the Sustainability and Climate Resiliency category, Emissions and Pollution is one of five themes ($|j_i| = 5$), and carbon emissions per capita is one of five sub-themes ($|k_{j_i}| = 5$) under that theme. As a result, this sub-theme carries a weight of 1/25 in the final Sustainability and Climate Resiliency score.

Data availability varies over time and across countries. To ensure comparability, we restrict each cross-section to countries with complete data for all sub-themes within a given category. Table B.3 lists the 67 countries included in our dataset and the years for which complete information is available in each category. For instance, data for the United Arab Emirates become complete for the Sustainability and Climate Resiliency category beginning in 2005, for the Human Development and Social Inclusion category in 2013, and the Institutional Strength and Innovation Capacity category in 2011. As a result, scores for each of these three categories are available for the UAE from the respective starting years. The number of countries with complete Sustainability and Climate Resiliency data increases from 45 in 2000 to 67 in 2019. The corresponding increases for the Human Development and Social Inclusion and the Institutional Strength and Innovation categories are from 38 to 58 and from 40 to 60 countries, respectively.

Table B.4 reports average scores by category over the sample period. From the perspective of investors with preferences for sustainability and climate resiliency, developed economies tend to be more attractive because they tend to have stronger regulatory regimes, better fiscal capacity for environmental management, and legacy investments in pollution control and infrastructure. Developing economies are heterogeneous in their stages of development. Some such economies are undergoing industrialization, and others are relatively agrarian. Hence, developing economies show substantial variation in their sustainability and climate resiliency scores. These patterns in country-level sustainability and climate resiliency scores are consistent with the environmental Kuznets curve, which suggests that environmental degradation initially worsens but improves as income rises.

The high rank of Scandinavian countries and Switzerland in the Human Development and Social Inclusion category reflects public investment in education, healthcare, and social programs. Developing countries, such as Kenya, South Africa, Pakistan, India, and Bangladesh, face fiscal constraints that limit investment in human capital and social infrastructure. In the institutional strength and innovation capacity category, the US and Sweden stand out for high-quality legal institutions, transparent governance, and effective regulation. Persistent challenges such as weak judicial enforcement, corruption, gender imbalances, and high net migration weigh on institutional strength in many developing economies. These issues undermine innovation, particularly when capital and government support are limited, fueling brain drain. For investors motivated by non-pecuniary considerations, these shortcomings reduce the appeal of allocating capital to such markets.

3.4.2 Construction of Taste Factors

We use countries' annual standardized scores for each category to construct tastes-based factor portfolios. At the end of each year t, we sort countries into terciles based on their standardized category scores. These terciles are determined independently for each category-year. We then form long-short portfolios by taking an equal-weighted position in the MSCI country indices of the top tercile (long leg) and subtracting an equal-weighted position in the bottom tercile (short leg). The resulting factor portfolio is held throughout year $t + 1$. This procedure is repeated recursively, starting from 2000 to 2019, yielding three time series of monthly factor returns for sustainability and climate resiliency, human development and social inclusion, and institutional strength and innovation capacity, spanning 2001 to 2020. By construction, the factors reflect systematic cross-country differences in non-pecuniary conditions. Our approach enables time-varying country-level performance on the SDGs and aligns with existing factor construction approaches (Fama and French, 1993; Asness et al., 2013), allowing comparison with conventional risk factors.

Panel A of Table 2 shows that, by construction, score spreads between countries in the high and low groups are large across categories, indicating substantial heterogeneity in the cross-section of countries. However, the average returns on the corresponding long–short portfolios are close to zero. Taste-driven demand moves prices, but investors can combine assets so that portfolio payoffs are independent of tastes. As a result, portfolios that load on tastes earn zero average returns. This result corresponds directly to Prediction 1(c).

In Panel B of Table 2, we present descriptive statistics for three SDG factor portfolios whose return averages close to zero but exhibit sizable standard deviation. Panel C of Table 2 reports correlations of three SDG-based factor portfolios with conventional risk factors. Although most correlations are not statistically significant, all three SDG factors correlate positively with market factors in both developed and emerging economies. Correlations among the taste-based factors themselves are strongest between Human Development and Social Inclusion, and Institutional Strength and Innovation Capacity, as social and institutional progress often co-evolve with economic development. In Table B.5, we show that SDG factor portfolios exhibit little persistence. The Human Development and Social Inclusion, and Institutional Strength and Innovation capacity factors also exhibit mean reversion once market returns are controlled for in the specification.

[Insert Table 2 Here]

The near-zero mean returns and weak correlations with standard risk factors suggest that cross-country variation in SDG categories largely moves independently of traditional sources of risk. The lack of persistence in the SDG factors portfolio returns further suggests that taste-related shocks are transitory. This evidence is consistent with a setting in which taste differences exist and are diversifiable across markets. These results thus lend support to the model's Diversifiable Taste Risk assumption.

3.5 Validating Taste Factors

3.5.1 Correlation with Observed Proxies

Next, we relate monthly SDG factor returns to climate attention, economic conditions, and oil price changes across global and regional samples. The results in Table 3 suggest that SDG factors capture genuine shifts in investor tastes. The results suggest that returns on the Human Development and Social Inclusion factor are higher in good economic times and when climate attention increases, with similar patterns across multiple regions. This factor also tends to load positively on changes in oil prices. By contrast, returns on the Institutional Strength and Innovation Capacity factor are lower during periods of economic downturns and declining oil prices, with consistent evidence across regions, including Asia, Oceania, and South America. The Sustainability and Climate Resiliency factor shows weaker associations overall, with coefficients generally small and insignificant in both global and regional samples.

[Insert Table 3 Here]

These results confirm that the SDG factors are not statistical artifacts. Instead, they exhibit systematic co-movement with independent measures of taste shocks. Having established that the return-based factors align with external variation in tastes, we now turn to the firm level to examine how individual companies are exposed to these factors.

3.5.2 Validation: Firm-Level UNGC Violations

We next examine the firm-level sensitivities themselves. We estimate a firm's exposure to taste shocks (γ_j) using 60-month rolling-window regressions. These coefficients quantify the extent to which a firm's return co-moves with shocks to sustainability, social, or institutional tastes. These exposures are useful in their own right as they offer a transparent, market-based measure of firms' alignment with non-pecuniary demand, one that is time-varying, comparable across countries, and independent of disclosure practices or rating agency methodologies. Firm-level exposures are estimated using a rolling-window regression of firm excess returns on global market and SDG factors:

$$\mathrm{r}_{jt} = \gamma_0 + \gamma^d_{jm}\mathrm{r}^d_{mt} + \gamma^e_{jm}\mathrm{r}^e_{mt} + \sum_i \gamma_{ji}\mathrm{r}^i_t + u_{jt}. \tag{14}$$

Here, r_{jt} denotes the monthly excess return of firm j at time t, while r^d_{mt} and r^e_{mt} represent excess returns on the market portfolios of developed and emerging economies, respectively. The variable r^i_t refers to one of the three SDG factor returns constructed from country-level MSCI indices, as described in the previous section. The coefficient γ_{ji} measures firm j's exposure to risk category i, based on a 60-month rolling window. This approach yields time-varying exposures that reflect a firm's evolving sensitivity to SDG factors.

[Insert Figure 1 Here]

Figure 1 shows the increasing breadth of coverage over time: the number of firms with estimated exposures rises from approximately 13,500 in early 2006 to over 23,900 by the end of 2020. Across the full sample, we obtain exposures for 36,077 firms. Table B.6 summarizes the results, based on more than 3.5 million firm-month observations. On average, firms exhibit positive exposures to human development and social inclusion, and institutional strength and innovation capacity factors, and negative exposures to the sustainability and climate resiliency factor. Figure 2 plots the time series of average firm-level exposures. The three series exhibit noticeable shifts around major global events, as all moved sharply during the global financial crisis and the COVID-19 pandemic.

[Insert Figure 2 Here]

These patterns are economically intuitive. Improvements in social infrastructure and governance quality enhance human capital, labor productivity, and the rule of law, and lower policy uncertainty. The climate transition imposes adjustment costs, regulatory compliance, and capital reallocation. As a result, negative average exposure to sustainability and climate resiliency reflects the transitional burden associated with climate adaptation.

We assess the external validity of taste factors using firm-level SDG exposures and firm-level violations of the United Nations Global Compact (UNGC) principles. The ten principles span human rights (Principles 1–2), labor standards (3–6), environmental responsibility (7–9), and anti-corruption (10). Table 4 reports the results. Panel A uses the average firm-level exposure across the three SDG categories as the key explanatory variable. The estimates show a consistent negative relationship between exposures and the number of violations across most principles, indicating that firms with stronger SDG exposures are less likely to engage in practices that contravene internationally recognized standards. This validation is particularly informative because UNGC principles are not part of the construction of the SDG factors, making the test effectively out-of-sample.

[Insert Table 4 Here]

In Panel B, we group the ten principles into three categories: climate (7–9), labor (3–6), and human rights (1–2, 10). This mapping is consistent with the structure described in Table 1. The results show that firms with higher social and governance exposures are significantly less likely to appear in labor or human rights controversies, supporting the interpretation that these exposures capture meaningful variation in corporate conduct. By contrast, the climate-related factor has a weaker and statistically insignificant association with environmental violations, which may reflect heterogeneity in environmental regulation and regulatory arbitrage, or lower salience of environmental controversies in investor perceptions. Overall, the results provide external validation of estimated taste factors as firm-level exposures to these factors align with observed firm conduct.

3.5.3 Validation: Fund Portfolio Tilts

To further validate the SDG factors, we examine whether investors with stronger sustainability orientation hold portfolios with greater exposure to SDG-aligned firms. Because investor tastes are not directly observable, empirical analysis requires a proxy to classify investors by sustainability orientation. We focus on mutual funds and use a fund's status as a signatory to the Principles for Responsible Investment (PRI) for this purpose. PRI signatory status is not seen as a treatment that alters portfolio choice upon adoption. Instead, we assume it reflects a fund's institutional commitment to sustainability principles. Funds that become signatories at any point in the sample are classified as investors with stronger sustainability mandates. To assess whether estimated SDG exposures are reflected in the portfolio holdings of investors with explicit sustainability mandates, this section uses cross-sectional differences across fund types, rather than time-series variation around the signing event.

We estimate fund–quarter panel regressions of the form:

$$\text{Exposure}_{ifqt} = \beta_1 \times \text{PRI Signatory}_f + \Gamma' \mathbb{X}_{fqt} + \gamma_{qt} + u_{ifqt}, \tag{15}$$

In equation (15), the subscripts i, f, q, and t represent SDG category, fund, quarter, and year, respectively. The dependent variable Exposure_{ifqt} is estimated as the value-weighted average SDG exposure of the underlying stocks (estimated in equation (14)) held in the fund's portfolio. The key independent variable, *PRI Signatory*, is a dichotomous variable that equals 1 if a fund is a signatory to the Principles for Responsible Investment. The vector $\mathbb{X}_{fqt}$ includes fund-level controls (fund return and flow), and γ_{qt} denotes time (year-quarter) fixed effects that control for aggregate shocks common to all funds.

[Insert Table 5 Here]

The results in Table 5 show that, across all three SDG dimensions, PRI signatory funds hold portfolios with significantly higher SDG exposures. These patterns indicate that ESG-oriented funds systematically tilt their holdings toward firms with stronger sustainability, social, and institutional characteristics. Importantly, these tilts are present in portfolio composition rather than being driven by return realizations or transitory capital flows. Together, the evidence aligns with the model's implication that taste-motivated investors express their preferences through persistent portfolio tilts toward assets with higher taste exposure.

4 Results

This section evaluates the model's empirical implications. We begin by testing Prediction 1, which formally assesses Proposition 2.1: taste differences generate systematic return covariation but do not command a risk premium. Panel A of Table 2 shows that portfolios mimicking taste differences have average returns near zero. We then formally test whether taste factors are systematic and if their exposures are priced in the cross-section. Next, we test Predictions 2 and 4 by examining whether conventional factor portfolios inherit taste exposures and whether removing these exposures improves risk-adjusted performance, especially when arbitrage constraints are binding or tastes are salient. Finally, we test Prediction 3 by analyzing the pervasiveness of taste exposures across characteristic-sorted portfolios.

4.1 Unpriced Systematic Risks

We follow Pukthuanthong et al. (2019) and proceed in two stages. First, we examine whether the sustainability and climate resiliency, human development and social inclusion, and institutional strength and innovation capacity portfolios explain systematic variation in global stock returns beyond traditional risk factors. Second, we assess whether exposures to these factors are compensated in the cross-section of expected returns. These tests relate to the first testable prediction: if SDG exposures matter for return covariances but do not earn a risk premium, they represent systematic yet unpriced risks.

4.1.1 Canonical Correlation Analysis

Using a global sample of 6,844 stocks with complete monthly return data from 2001 to 2020, we construct a $T \times N$ return panel where T equals 240 months. Following Connor and Korajczyk (1988), we extract latent factors from the stock return matrix. We retain the minimum number of factors necessary to explain at least 80 percent of the total variation. These latent factors serve as a benchmark for systematic risk.

We then conduct canonical correlation analysis between the retained latent return factors and the three SDG-based factor portfolios. This procedure identifies orthogonal linear combinations (canonical variates) that maximize the correlation between the two sets. Panel A of Table 6 presents canonical correlations and z-statistics. All three canonical pairs exhibit statistically significant correlations, suggesting that the SDG-based factor portfolios capture systematic variation in stock returns.

To assess the contribution of each factor individually, we regress the canonical variates on the original sustainability, human development, and institutional strength factors. Panel B of Table 6 reports the average absolute t-statistics from these regressions: 1.7 for sustainability and climate resiliency, 2.3 for human development and social inclusion, and 2.8 for institutional strength and innovation capacity. These results indicate that all three factors are associated with the latent factor space. Thus, these results confirm the relevance of SDG factors for the variance structure of returns, which aligns with the theoretical prediction that exposures to SDG-based factors affect the variance-covariance matrix of stock returns.

[Insert Table 6 Here]

4.1.2 Pricing Analysis

We next test whether exposures to the SDG factors are priced. We estimate Fama–MacBeth regressions of stock returns on exposures to the global market factor, standard asset pricing factors (size, value, profitability, investment, and momentum), and the three SDG factors. This test distinguishes whether SDG exposures matter through first-moment pricing or through their contribution to return co-movements.

Panel C of Table 6 reports the estimated risk premium. Across global markets, exposures to the Environment, Social, and Governance factors are generally not associated with a statistically significant risk premium. The coefficients on SDG factor exposures are economically small and statistically indistinguishable from zero in most regions, except for South American markets. In developed markets, ESG exposures fail to command consistent premiums even when controlling for traditional risk factors such as size, value, profitability, investment, and momentum. Consistent with the first prediction, these findings indicate that SDG factor exposures shape return co-movements and systematic risk, but do not generate consistent differences in returns across firms.

Panel D of Table 6 reports monthly Sharpe ratios for long–short portfolios formed on firm-level exposures to each SDG factor. Sharpe ratios are reasonable (MacKinlay, 1995; Pukthuanthong et al., 2019), indicating that SDG factors contribute to volatility and co-movement in returns but do not generate reliable compensation in the form of higher average returns. In other words, they shape the variance–covariance structure of returns without improving mean–variance trade-offs, consistent with Prediction 1 that taste exposures represent systematic but unpriced risks.

To corroborate the pricing results in Table 6, we test whether return spreads persist in a nonparametric setting. Each month, we sort stocks into 25 Size–BTM portfolios and, within each, further sort them into quintiles based on their SDG-factor exposures. We estimate these exposures using a single time-series simple regression for each stock. We then compute value-weighted high-minus-low (Q5–Q1) return spreads. This design holds firm characteristics constant and isolates whether higher taste exposure is associated with higher average returns.

[Insert Table 7 Here]

The results in Table 7 suggest a lack of a monotonic relationship between taste exposure and average returns, once Size and BTM are held constant. A majority of taste-differenced portfolios' returns lack coherence in sign, magnitude, and most are statistically indistinguishable from zero. These results provide further supporting evidence on the lack of risk premium for investor tastes.

These results support Proposition 2.1 and Prediction 1. The SDG factors load significantly on the latent factor space, confirming that taste-related variation is systematic and affects the covariance structure of returns. At the same time, exposure to these factors does not earn risk premia in cross-sectional tests and does not generate reliable return spreads in portfolio sorts. Consistent with the model, tastes manifest as systematic but unpriced sources of return variation rather than determinants of expected returns.

4.2 Sharpe Ratio Improvement

To understand how tastes affect portfolio performance, Prediction 2 holds that performance should improve once exposures to unpriced taste shocks are removed. The idea is straightforward: taste factors contribute to volatility but are not associated with returns. When stocks with strong taste loadings are included in factor portfolios, they add noise, raising risk without increasing expected reward. Removing such stocks should therefore lower volatility and improve the Sharpe ratio of conventional factors.

To test Prediction 2 , we first estimate firm-level sensitivities to the SDG factors using time-series regressions. A firm is classified as having significant taste exposure if the absolute value of its estimated beta is significant at the 10 percent level or lower. We then reconstruct the conventional Fama–French factors (size, value, profitability, and investment) from the restricted universe that excludes these firms. In Figure B.1, we present a time-series plot of factor returns for original and reconstructed factor portfolios that are agnostic to one or more dimensions of investor tastes. All taste-neutral factor portfolios overlap significantly with their original counterparts. In Table B.7, we present summary statistics of taste-neutral factors, which exhibit high correlations (between 80% and 95%) with the original factor portfolios.

Finally, we compare the squared Sharpe ratios of the Fama–French three- and five-factor models based on the original portfolios and their taste-neutral counterparts. Following Barillas and Shanken (2018) and Fama and French (2018), we compare model performance using the squared Sharpe ratio of the tangency portfolio spanned by each factor set, which provides a direct measure of the attainable risk–return trade-off for an optimally diversified investor.

We follow Fama and French (2018) and compute out-of-sample squared Sharpe ratios for each model specification. Specifically, we partition the monthly return series into adjacent, non-overlapping month-pairs. In each of 10,000 bootstrap replications, we draw month-pairs with replacement and randomly assign one month from each pair to the in-sample (IS) set and the other to the out-of-sample (OS) set. Using the IS data, we estimate the mean vector and covariance matrix of factor returns and compute the tangency portfolio weights. We then apply these weights to the OS data to calculate the realized Sharpe ratio. We square these out-of-sample Sharpe ratios and repeat the process 10,000 times to obtain the bootstrap distribution of squared Sharpe ratios for each model.

Table 8 reports the squared Sharpe ratios for the Fama–French three- and five-factor models, comparing the standard factors to 'taste-neutral' versions that exclude firms with significant exposures to SDG-related factors. For each specification, we report in-sample (IS) and out-of-sample (OS) squared Sharpe ratios, along with the OS difference relative to the benchmark model. As factor construction relies on accounting variables, we implement this test in the US cross-section where Compustat coverage is comprehensive. The theoretical framework in Section 2 implies that taste exposures should depress factor performance by adding volatility without increasing expected returns. The improvements in factor models' performance should occur when all three SDG dimensions are excluded simultaneously. Table 8 therefore evaluates whether squared Sharpe ratios improve when factors are reconstructed under partial or comprehensive exclusion of SDG-exposed firms.

The first eight rows of Table 8 correspond to the Fama-French three-factor model. The benchmark model (row 1) delivers an OS squared Sharpe ratio of 0.0224. When we reconstruct size and value factors while excluding firms highly exposed to individual SDG categories, results are mixed. Excluding firms with strong climate exposures has little effect (row 2), while excluding those with high human development exposures slightly raises OS performance (row 3). In contrast, excluding firms exposed to institutional strength lowers OS performance (row 4). Pairwise exclusions (rows 5–7) yield squared Sharpe ratios close to the benchmark. In row 8, the reconstructed factors are agnostic to all SDG factors. This specification raises the OS squared Sharpe ratio to 0.0232, an improvement of 0.0008 that is statistically significant at the 1 percent level. Given the correlation between the SDG exposures, excluding all three categories provides the most comprehensive adjustment, and the gains are consistent with the prediction that removing taste exposures reduces noise in factor construction and improves the attainable risk–return trade-off.

[Insert Table 8 Here]

The following eight rows of Table 8 correspond to the Fama-French five-factor model. The benchmark five-factor model (row 9) achieves a much higher OS squared Sharpe ratio of 0.0707. Results differ when factors are reconstructed. Excluding climate-exposed firms (row 10), social-exposed firms (row 11), or governance-exposed firms (row 12) all reduce OS performance, in some cases substantially. For example, excluding institutional strength exposures lowers the OS squared Sharpe ratio to 0.0510, a decline of nearly 30 percent. Pairwise exclusions produce mixed effects: eliminating both climate and social exposures raises OS performance above the benchmark (row 13), while removing social and governance exposures lowers it (row 15). In row 16, where all three SDG categories are excluded, the OS squared Sharpe ratio rises to 0.0847, an increase of 0.0140 that is statistically significant at the 5 percent level. This result reinforces the notion that a comprehensive adjustment to tastes improves model performance by stripping out exposures that add volatility but do not contribute to expected returns.[1]

Investor preferences and perceived risks may vary over time. Prediction 4 states that the impact of taste-driven demand depends on the context and varies with the salience of sustainability concerns, economic conditions affecting arbitrage, and the wealth share of taste-motivated investors. Periods of heightened climate attention make sustainability-linked tastes more prominent, while high-valuation states, measured by the CAPE ratio, highlight the influence of non-pecuniary motives. When a larger share of market capitalization is tied to taste-related factors, taste-driven demand has broader effects on equilibrium. If these channels are significant, removing taste exposures should lead to greater improvements in factor performance during these periods.

We next examine whether the performance gains from taste-neutral factors vary systematically with the state of the economy and with climate salience. To capture variation in taste-investor activity, we use the cyclically adjusted price-to-earnings (CAPE) ratio as a proxy for market sentiment (Shiller, 2000), defining "good times" as months in which CAPE is above the prior decade's median. High sentiment periods likely coincide with greater appetite for non-pecuniary investment. This classification provides a forward-looking, valuation-based measure of regimes that maps directly into investor sentiment and risk-taking capacity. In good times, when valuations are high, investors may be more willing to allocate capital toward non-pecuniary benefits, consistent with the argument in Bansal et al. (2022) that non-pecuniary demand strengthens in expansions. Conversely, in times of economic distress, tighter financial conditions and

[1]We repeat the factor reconstruction using Refinitiv ESG scores, and present results in Table B.8. Excluding firms with extreme ESG attributes raises the squared Sharpe ratio of the three-factor model but has little effect on the five-factor model. These results roughly align with our SDG-based results. The ESG data has narrower coverage (number of firms and years), and is prone to measurement error and selection bias, as most data are collected via disclosures in public filings and surveys. In contrast, we construct SDF factors from country-level data to estimate exposures across a broader cross-section and over a longer time period. Due to this reason, we treat the results in Table B.8 as supportive but not directly comparable.

heightened risk aversion may reduce the willingness to pay for tastes. Still, they could also constrain arbitrage capital, thereby amplifying the price impact of taste-driven flows.

Panel A of Table 9 shows that Sharpe ratio gains vary by factor model and market conditions. Specifically, in the three-factor model, removing SDG-exposed firms yields greater improvements during bad times, supporting Prediction 4(a): taste-driven price distortions increase when arbitrage capital is scarce. By contrast, in the five-factor model, gains occur mainly in good times, with little or no improvement during downturns. This pattern suggests that, in downturns, firms with strong taste exposure also undergo major changes in profitability and investment, which the five-factor model captures. As a result, neutralizing taste exposure during bad times removes meaningful economic variation, thereby reducing the benefits of taste neutralization. Taken together, these results align with Shleifer and Vishny (1997), who note that arbitrage is most constrained when correcting mispricing exposes investors to fundamental risk, especially in downturns.

To test Prediction 4(b), we measure climate salience using the Media and Climate Change Observatory (MeCCO) dataset. We define periods of high climate attention as those in which the log number of climate-related news articles published in North America exceeds its sample average, and low climate attention as all other periods. This measure captures the extent to which sustainability issues are salient in public discourse, which should directly affect the prominence of non-pecuniary investor demand. When climate attention is high, investors with strong sustainability preferences are more likely to trade on those tastes, and financial markets are more likely to reflect such demand.

[Insert Table 9 Here]

Panel B of Table 9 shows that the five-factor model with taste-neutral factors performs better in high-attention periods. Removing all three SDG dimensions increases (decreases) the squared Sharpe ratio by 0.047 (-0.016) in high-attention states (low-attention states). These findings align with Prediction 4(b): when sustainability issues are salient, taste-driven demand exerts a stronger influence on prices, and purging taste exposure improves risk-adjusted performance. The three-factor model, by contrast, exhibits an opposite effect with neutralization reducing performance in high-attention states.

The analysis next considers Prediction 4(c) and tests whether the gains from taste-neutral factor construction vary with the wealth share of taste-exposed stocks, which serves as a market-based proxy for the strength of taste-motivated demand. A key challenge is that we observe neither investor types (arbitrageurs, taste, and noise) nor investors' complete holdings. Our proxy, thus, is a coarse measure of investor wealth tilted towards firms more exposed to taste shocks. We construct a proxy for the wealth share of taste investors as follows. Each month, stocks are classified as taste-exposed if their excess returns display statistically significant loadings (t-statistics > 1.65) on at least one of the three SDG factors in a simple time-series regression. The fraction of total market capitalization represented by these stocks is then calculated, using lagged market capitalization to mitigate look-ahead bias. Figure 3 illustrates the evolution of this measure over time. Periods of high or low taste wealth share are defined as months in which this fraction is above or below its sample median, respectively. This measure reflects the extent of the market whose prices are systematically influenced by sustainability-related tastes. When taste factors drive a larger share of market capitalization, taste-motivated demand has greater potential to influence prices.

[Insert Figure 3 Here]

The results in Panel C of Table 9 support Prediction 4(c). The performance effects of taste-neutral factor construction differ markedly across wealth-share regimes. In the three-factor model, removing SDG exposures improves out-of-sample performance when taste-exposed stocks constitute a large share of the market but reduces performance when their market presence is limited, generating large and significant regime differences in squared Sharpe Ratios. In the five-factor model, taste neutralization improves performance in both regimes, but the gains are significantly larger when the wealth share of taste-exposed assets is high. Together, these results indicate that taste-driven demand has broader equilibrium effects when it represents a larger fraction of market capitalization, making taste neutralization more valuable in such states.

The results support Prediction 2 and the state-dependent implications in Prediction 4, with notable differences between models. Removing taste exposure improves risk-adjusted performance in all models, confirming that conventional factor portfolios include uncompensated taste-related risk. For Prediction 4(a), only the three-factor model achieves larger gains during downturns. For Prediction 4(b), the five-factor model shows clear improvements during periods of high climate attention. Prediction 4(c) is consistently supported as both models show greater gains from taste-neutralization when the wealth share of taste-exposed assets is high. Overall, these findings indicate that taste effects are state-dependent and depend on the extent to which each factor structure captures priced fundamentals.

4.3 Pervasive Portfolio Exposures

In this section, we test Prediction 3 and examine whether portfolios exhibit systematic exposures to SDG factors. We use the monthly returns of 185 characteristic-sorted portfolios (25 Size-Accruals, 25 Size-Book-to-Market, 25 Size-Beta, 25 Size-Investment, 25 Size-Momentum, 35 Size-New Issuance, and 25 Size-Operating Profitability) and estimate their factor loadings from a time-series regression featuring three SDG portfolios and two market benchmarks (one for developed and one for emerging markets).

[Insert Figure 4 Here]

Figure 4 reports the distribution of estimated exposures to the three SDG factors and their correlation with value-weighted average returns across portfolios. The distributions show that exposures are not concentrated around zero. Instead, they span a wide range of positive and negative values across portfolios, confirming that taste shocks pervade even diversified, characteristic-sorted portfolios. The right-hand panels further illustrate that exposures to Sustainability and Climate Resiliency and to Institutional Strength and Innovation Capacity are negatively correlated with average portfolio returns, while exposures to Human Development and Social Inclusion are positively correlated. This evidence is consistent with our Prediction 3 that broad portfolio strategies unintentionally load on taste factors, reflecting their systematic role in return co-movement.

5 Conclusion

This paper examines how investor preferences for non-pecuniary attributes affect asset prices. We develop an APT-based framework that shows that when fundamental investors can span their desired consumption using portfolios with zero taste exposure, systematic taste risk is not priced despite generating substantial return covariation. This spanning property emerges from cross-sectional heterogeneity in firms' taste characteristics relative to their fundamental exposures, with noise traders providing the liquidity that enables fundamental investors to maintain taste-neutral positions.

Our empirical analysis supports this framework. We construct three taste factors from United Nations Sustainable Development Goals indicators across 67 countries. External validation confirms our taste interpretation: return-based factor loadings correlate significantly with UN Global Compact violations, and taste factor returns exhibit negative autocorrelation consistent with temporary price pressure rather than permanent return differences. Taste factors explain substantial systematic variation in the cross-section of returns, yet earn zero risk premia in Fama-MacBeth regressions. Neutralizing taste exposure in Fama-French factors improves squared Sharpe ratios by 20%. These improvements concentrate during periods when arbitrage constraints bind, sustainability is salient, or the taste investors' wealth share is high.

Our results clarify how sustainability preferences affect asset prices. When sustainability-related demand operates at a broad, market-wide level, it introduces a common component in returns that increases volatility but not expected returns. Portfolios exposed to this systematic taste risk show weaker risk-adjusted performance. In contrast, firm-specific sustainability improvements, which are not yet widespread, can increase valuations without introducing systematic risk. Notably, taste investors do not sacrifice expected returns and only accept higher volatility from taste factor exposure. Removing systematic taste exposure from standard factor portfolios improves Sharpe ratios, especially when arbitrage constraints bind. When spanning holds, systematic taste exposure carries no premium: sustainability affects valuations through firm-specific differentiation, not market-wide tilts.

Several questions remain for future research. First, our model treats noise traders as a reduced-form source of liquidity and does not specify their microfoundations. Distinguishing whether liquidity comes from market makers, institutions with exogenous flows, or retail traders would clarify when spanning operates and when taste-driven demand overwhelms available liquidity and becomes priced, as in Pástor et al. (2021). It also remains open whether noise-trader activity is random or systematically correlated with taste-driven demand; high-frequency order flow around sustainability-related events could shed light on this channel. Second, the relative wealth shares of taste investors, fundamental investors, and noise traders likely vary across markets and over time, potentially leading to different pricing regimes. Third, exploring alternative ways to measure and construct taste factors could provide complementary evidence, test robustness, and identify additional dimensions of non-pecuniary demand beyond the SDG-based factors considered here.

A Proofs

This appendix provides proofs and technical details omitted from the main text. We work with excess returns throughout and assume readers are familiar with standard mean-variance portfolio optimization and factor-mimicking portfolio construction.

A.1 Portfolio Choice

A.1.1 Fundamental Investor Optimization

From equation (2), the fundamental investor maximizes expected utility over fundamental consumption. Using the factor structure $\tilde{y}_j^F = \beta_{j,F}\tilde{Y}^F + \tilde{\epsilon}_j^F$ from equation (1), portfolio fundamental consumption is:

$$\mathbf{X}_a'\tilde{\mathbf{y}}^F = (\mathbf{X}_a'\boldsymbol{\beta}_F)\tilde{Y}^F + \sum_j X_{a,j}\tilde{\epsilon}_j^F \tag{A.1}$$

Standard mean-variance optimization with covariance matrix $\boldsymbol{\Sigma} = \mathrm{Cov}(\tilde{\mathbf{y}}^F)$ yields equation (4).

A.1.2 Taste Investor Optimization

Taste investors additionally value taste consumption $\mathbf{X}_s'\tilde{\mathbf{y}}^\tau = (\mathbf{X}_s'\boldsymbol{\beta}_\tau)\tilde{Y}^\tau + \sum_j X_{s,j}\tilde{\epsilon}_j^\tau$ from equation (3). Since taste risk does not enter the variance term (taste output has no financial value), the first-order condition includes the additional term $\delta E[\tilde{\mathbf{y}}^\tau]$, yielding equation (5). The difference between taste and fundamental investor portfolios is equation (6):

$$\mathbf{X}_s - \mathbf{X}_a = \frac{\delta E[\tilde{Y}^\tau]}{A}\boldsymbol{\Sigma}^{-1}\boldsymbol{\beta}_\tau \propto \boldsymbol{\Sigma}^{-1}\boldsymbol{\beta}_\tau \tag{A.2}$$

Taste investors overweight stocks with high taste exposure $\beta_{j,\tau}$.

A.2 Fundamental Spanning and Redundancy of Taste Exposure

A.2.1 Definition of Fundamental Spanning

We formalize the notion that fundamental investors can replicate any desired exposure to fundamental risk while neutralizing exposure to tastes. The Definition 1 requires that fundamental and taste exposures can be independently controlled via portfolio weights. As discussed in Assumption 1, this property holds when:

(i) Dispersion: $\text{Var}(\beta_{j,\tau}) > 0$ ensures firms have heterogeneous taste characteristics, making it possible to construct portfolios with different taste exposures. The normalization $E[\beta_{j,\tau}] \approx 0$ is without loss of generality.

(ii) Orthogonality: $\text{Cov}(\beta_{j,F}, \beta_{j,\tau}) \approx 0$ ensures fundamental and taste exposures are approximately uncorrelated cross-sectionally. Without this, if $\beta_{j,\tau} = c \cdot \beta_{j,F}$, any portfolio with fundamental exposure would automatically inherit proportional taste exposure, thereby violating the spanning property.

(iii) Full rank: $[\boldsymbol{\beta}_F \; \boldsymbol{\beta}_\tau]$ having full column rank ensures the system of equations in Definition 1 has a solution.

Fundamental spanning implies that taste exposure is not technologically linked to fundamental consumption: portfolios with identical fundamental risk characteristics can be constructed with arbitrarily different taste exposure.

A.2.2 Taste Exposure Is Redundant for Fundamental Consumption

Lemma A.1 (Redundancy of Taste Exposure) *Suppose returns and outputs follow the factor structure in equation (1), and the spanning conditions in Definition 1 holds. Then for any well-diversified portfolios p and p' satisfying:*

$$\beta_{p,F} = \beta_{p'F}, \tag{A.3}$$

the expected value and variance of fundamental consumption are identical, regardless of differences in taste exposure $\beta_{p,\tau}$.

Proof. Fundamental consumption from portfolio p is:

$$\mathbf{X}_p' \tilde{\mathbf{y}}^F = (\mathbf{X}_p' \boldsymbol{\beta}_F)\tilde{Y}^F + \sum_j X_{p,j} \tilde{\epsilon}_j^F. \tag{A.4}$$

Taking expectations yields:

$$E[\mathbf{X}_p'\tilde{\mathbf{y}}^F] = \beta_{p,F}E[\tilde{Y}^F] \tag{A.5}$$

which depends only on fundamental exposure and not on taste exposure. The variance of fundamental consumption is:

$$\text{Var}(\mathbf{X}_p'\tilde{\mathbf{y}}^F) = \beta_{p,F}^2\text{Var}(\tilde{Y}^F) + \sum_j X_{p,j}^2\text{Var}(\tilde{\epsilon}_j^F). \tag{A.6}$$

For well-diversified portfolios, the idiosyncratic term vanishes as $N \to \infty$. Hence:

$$\text{Var}(\mathbf{X}_p'\tilde{\mathbf{y}}^F) \to \beta_{p,F}^2\text{Var}(\tilde{Y}^F). \tag{A.7}$$

Consider any portfolio p' satisfying $\beta_{p',F} = \beta_{p,F}$. Then:

$$E[\mathbf{X}_p'\tilde{\mathbf{y}}^F] = E[\mathbf{X}_{p'}'\tilde{\mathbf{y}}^F], \quad \text{Var}(\mathbf{X}_p'\tilde{\mathbf{y}}^F) = \text{Var}(\mathbf{X}_{p'}'\tilde{\mathbf{y}}^F) \tag{A.8}$$

Thus, taste exposure does not affect the mean or variance of fundamental consumption for diversified portfolios. □

A.3 Proof of Proposition 2.1

From the factor structure in equation (7), the Arbitrage Pricing Theory implies expected returns on well-diversified portfolios satisfy:

$$E[\tilde{r}_p] = \beta_{p,F}\lambda_F + \beta_{p,\tau}\lambda_\tau \tag{A.9}$$

where $\beta_{p,F} = \mathbf{X}_p'\boldsymbol{\beta}_F$ and $\beta_{p,\tau} = \mathbf{X}_p'\boldsymbol{\beta}_\tau$. We prove $\lambda_\tau = 0$ by contradiction.

A.3.1 Proof by Contradiction

Fix any well-diversified portfolio p with exposures $(\beta_{p,F}, \beta_{p,\tau})$. By Definition 1, for the same $\beta_{p,F}$ there exists another well-diversified portfolio p' satisfying

$$\mathbf{X}_{p'}'\boldsymbol{\beta}_F = \beta_{p,F}, \quad \mathbf{X}_{p'}'\boldsymbol{\beta}_\tau = 0, \quad \sum_{j=1}^{N} X_{p',j} = 1. \tag{A.10}$$

By Lemma A.1, portfolios p and p' deliver the same fundamental consumption up to diversifiable idiosyncratic terms. In particular, as $N \to \infty$, both portfolios have the same mean and variance of fundamental consumption:

$$E[\mathbf{X}_p'\tilde{\mathbf{y}}^F] = E[\mathbf{X}_{p'}'\tilde{\mathbf{y}}^F], \quad \mathrm{Var}(\mathbf{X}_p'\tilde{\mathbf{y}}^F) = \mathrm{Var}(\mathbf{X}_{p'}'\tilde{\mathbf{y}}^F). \tag{A.11}$$

Hence, fundamental investors (who care only about fundamental consumption) are indifferent between p and p'. In other words, $U_a(\mathbf{X}_p) = U_a(\mathbf{X}_{p'})$.

Now, suppose that portfolio p with fundamental exposure $\beta_{p,F}$ and taste exposure $\beta_{p,\tau} \neq 0$. Without loss of generality, assume that $\beta_{p,\tau} > 0$. Then, by equation (A.9) and $\beta_{p',\tau} = 0$, we have

$$E[\tilde{r}_p] - E[\tilde{r}_{p'}] = \beta_{p,\tau}\lambda_\tau > 0. \tag{A.12}$$

This creates an arbitrage opportunity. Consider $\mathbf{X}_{arb} = \mathbf{X}_p - \mathbf{X}_{p'}$. This portfolio has:

- Zero fundamental exposure: $\mathbf{X}_{arb}'\boldsymbol{\beta}_F = 0$ (systematic risk cancels)
- Zero fundamental consumption: $\mathbf{X}_{arb}'\tilde{\mathbf{y}}^F \to 0$ as $N \to \infty$ (idiosyncratic risk diversifies)
- Positive expected return: $E[\tilde{r}_{arb}] = \beta_{p,\tau}\lambda_\tau > 0$

All fundamental investors would take infinite positions in this zero-risk, positive-return arbitrage. This creates unbounded excess demand inconsistent with market clearing (equation (12)). The assumed $\lambda_\tau > 0$ leads to a contradiction. The same argument applies for $\lambda_\tau < 0$. Therefore, $\lambda_\tau = 0$. $\square$

A.4 Equilibrium and Market Clearing

A.4.1 Noise Traders

Without noise traders ($\omega_n = 0$), market clearing (12) becomes:

$$\omega_a \mathbf{X}_a + \omega_s \mathbf{X}_s = \mathbf{e} \tag{A.13}$$

The taste tilt in equation (A.2) creates excess demand proportional to $\mathbf{\Sigma}^{-1}\boldsymbol{\beta}_\tau$. If fundamental investors hold zero taste exposure (as spanning allows), this tilt cannot be absorbed, and markets cannot clear at $\lambda_\tau = 0$. Fundamental investors must accommodate the tilt, requiring compensation $\lambda_\tau \neq 0$ as in Pástor et al. (2021).

With noise traders ($\omega_n > 0$), their exogenous positions $\mathbf{X}_n$ can absorb the taste tilt:

$$\omega_n \mathbf{X}_n' \boldsymbol{\beta}_\tau \approx -\omega_s (\mathbf{X}_s - \mathbf{X}_a)' \boldsymbol{\beta}_\tau \tag{A.14}$$

Assumption 2 ensures this is possible. Noise traders provide liquidity without requiring systematic compensation because their trades are driven by exogenous factors (e.g., pension rebalancing, tax-loss harvesting, index tracking, redemptions). In Pástor et al. (2021), fundamental investors are the only counterparty to taste investors and must be induced to hold brown stocks via higher returns. In our model, noise traders break this link, allowing equilibrium at $\lambda_\tau = 0$.

A.5 Factor Construction

The taste factor-mimicking portfolio $\mathbf{w}_\tau$ is constructed via standard constrained optimization: minimize $\mathbf{w}_\tau' \mathbf{w}_\tau$ subject to constraints in equation (10). Under Assumption 1, the solution is approximately:

$$w_{\tau,j} \propto \beta_{j,\tau} \tag{A.15}$$

normalized to satisfy the constraints. This goes long high-$\beta_{j,\tau}$ stocks and short low-$\beta_{j,\tau}$ stocks. The factor return satisfies:

$$\tilde{r}_\tau = \mathbf{w}'_\tau \tilde{\mathbf{r}} \approx f_\tau \tag{A.16}$$

for large N, since $\mathbf{w}'_\tau \boldsymbol{\beta}_F \approx 0$ and idiosyncratic returns diversify away. From equation (1), this portfolio delivers:

$$\mathbf{w}'_\tau \tilde{\mathbf{y}}^F \approx 0 \tag{A.17}$$

$$\mathbf{w}'_\tau \tilde{\mathbf{y}}^\tau \approx \tilde{Y}^\tau \tag{A.18}$$

Since fundamental investors derive zero utility from this (equation (A.17)), Proposition 2.1 implies $E[\tilde{r}_\tau] = 0$.

A.6 Cross-Sectional Pricing Implications

For well-diversified portfolios, expected returns satisfy equation (A.9) with $\lambda_\tau = 0$:

$$E[\tilde{r}_p] = \beta_{p,F}\lambda_F \tag{A.19}$$

This predicts that in Fama-MacBeth regressions:

$$E[\tilde{r}_j] = \lambda_0 + \lambda_F \beta_{j,F} + \lambda_\tau \beta_{j,\tau} + \epsilon_j \tag{A.20}$$

the estimate $\hat{\lambda}_\tau$ should be statistically indistinguishable from zero.

A.6.1 Sharpe Ratio Improvement

Portfolio variance decomposes as:

$$\mathrm{Var}(\tilde{r}_p) = \beta_{p,F}^2\sigma_F^2 + \beta_{p,\tau}^2\sigma_\tau^2 + \sigma_{\varepsilon,p}^2 \tag{A.21}$$

where $\sigma_F^2 = \text{Var}(f_F)$, $\sigma_\tau^2 = \text{Var}(f_\tau)$, and $\sigma_{\varepsilon,p}^2$ is diversifiable variance. The taste-neutral portfolio $\mathbf{X}_p^{neutral} = \mathbf{X}_p - \beta_{p,\tau}\mathbf{w}_\tau$ satisfies:

$$\beta_{p^{neutral},F} = \beta_{p,F} \quad \text{(fundamental exposure unchanged)} \tag{A.22}$$

$$\beta_{p^{neutral},\tau} = 0 \quad \text{(taste exposure eliminated)} \tag{A.23}$$

$$E[\tilde{r}_{p^{neutral}}] = \beta_{p,F}\lambda_F = E[\tilde{r}_p] \quad \text{(expected return unchanged)} \tag{A.24}$$

$$\text{Var}(\tilde{r}_{p^{neutral}}) = \beta_{p,F}^2\sigma_F^2 + \sigma_{\varepsilon,p^{neutral}}^2 < \text{Var}(\tilde{r}_p) \quad \text{(variance reduced)} \tag{A.25}$$

Therefore, $\text{SR}(p^{neutral}) > \text{SR}(p)$. The squared Sharpe ratio improvement is:

$$\text{SR}(p^{neutral})^2 - \text{SR}(p)^2 \propto \beta_{p,\tau}^2\sigma_\tau^2 \tag{A.26}$$

This improvement increases with portfolio taste exposure $\beta_{p,\tau}^2$ and taste factor volatility σ_τ^2.

A.7 State-Dependent Benefits

Suppose taste factor variance varies over time: $\sigma_{\tau,t}^2 = \text{Var}_t(f_{\tau,t+1})$. From equation (A.26), Sharpe ratio improvements are larger when $\sigma_{\tau,t}^2$ is high.

When is $\sigma_{\tau,t}^2$ high?

(i) High taste salience: After major ESG events (COP conferences, climate disasters, ESG regulation), investor attention to sustainability increases, raising volatility in taste investor demand and aggregate taste characteristics.

(ii) Binding arbitrage constraints: During recessions or funding liquidity crises, fundamental investors and noise traders face tighter leverage constraints and cannot fully offset taste-driven price pressure, amplifying the impact of taste shocks on prices.

(iii) Wealth distribution: From equation (12), total taste-driven demand scales as $\omega_s(\mathbf{X}_s - \mathbf{X}_a)$. When ω_s rises or ω_n falls, the price impact of taste shocks increases, raising $\sigma_{\tau,t}^2$.

Together, conditions (i)-(iii) yield Prediction 4: Sharpe ratio improvements $\Delta\text{SR}_{p,t}$ should be positively related to (a) ESG salience, (b) arbitrage constraints, and (c) the wealth share of taste investors relative to noise traders (ω_s/ω_n).

A.8 Extensions

A.8.1 Multiple Fundamental Factors

With K fundamental factors, returns follow:

$$\tilde{r}_j - E[\tilde{r}_j] = \sum_{k=1}^{K} \beta_{j,k} f_k + \beta_{j,\tau} f_\tau + \varepsilon_j \tag{A.27}$$

Spanning requires $[\boldsymbol{\beta}_1 \ \cdots \ \boldsymbol{\beta}_K \ \boldsymbol{\beta}_\tau]$ to have full column rank. The proof that $\lambda_\tau = 0$ is identical: portfolios with identical fundamental exposures $(\beta_{p,1}, \ldots, \beta_{p,K})$ but different $\beta_{p,\tau}$ deliver identical fundamental consumption.

A.8.2 Heterogeneous Risk Aversion

With heterogeneous risk aversion A_i, portfolio tilts scale as $\frac{1}{A_i}$:

$$\mathbf{X}_{s,i} - \mathbf{X}_{a,i} = \frac{\delta_i E[\tilde{Y}^\tau]}{A_i} \boldsymbol{\Sigma}^{-1} \boldsymbol{\beta}_\tau \tag{A.28}$$

The spanning argument remains unchanged: taste exposure is redundant for fundamental consumption regardless of individual risk aversion.

References

Alves, R., Krüger, P., and van Dijk, M. A. (2023). Drawing up the bill: Is ESG related to stock returns around the world? *Available at: https://ssrn.com/abstract=4674146*.

Amihud, Y. and Goyenko, R. (2013). Mutual fund's R^2 as predictor of performance. *Review of Financial Studies*, 26(3):667–694.

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and momentum everywhere. *Journal of Finance*, 68(3):929–985.

Bansal, R., Wu, D., and Yaron, A. (2022). Socially responsible investing in good and bad times. *Review of Financial Studies*, 35(4):2067–2099.

Barillas, F. and Shanken, J. (2018). Comparing asset pricing models. *Journal of Finance*, 73(2):715–754.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549.

Bolton, P. and Kacperczyk, M. (2023). Global pricing of carbon-transition risk. *Journal of Finance*, 78(6):3677–3754.

Bolton, P. and Kacperczyk, M. T. (2022). Firm commitments. *Available at SSRN: https://ssrn.com/abstract=3840813*.

Chowdhry, B., Davies, S. W., and Waters, B. (2019). Investing for impact. *Review of Financial Studies*, 32(3):864–904.

Connor, G. and Korajczyk, R. A. (1988). Risk and return in an equilibrium APT: Application of a new test methodology. *Journal of Financial Economics*, 21(2):255–289.

Cremers, K. J. M. and Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies*, 22(9):3329–3365.

Daniel, K., Mota, L., Rottke, S., and Santos, T. (2020). The cross-section of risk and returns. *The Review of Financial Studies*, 33(5):1927–1979.

Darolles, S., Faverjon, A., and Lambert, M. (2025). Can us equity funds time esg score updates? *Available at SSRN:*.

Doshi, H., Elkamhi, R., and Simutin, M. (2015). Managerial activeness and mutual fund performance. *Review of Asset Pricing Studies*, 5(2):156–184.

Elton, E. J., Gruber, M. J., and Blake, C. R. (2001). A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and Morningstar mutual fund databases. *Journal of Finance*, 56(6):2415–2430.

Eskildsen, M., Ibert, M., Jensen, T. I., and Pedersen, L. H. (2024). In search of the true greenium. *Available at SSRN: https://ssrn.com/abstract=4744608*.

Evans, R. B. (2010). Mutual fund incubation. *Journal of Finance*, 65(4):1581–1611.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (1996). The CAPM is wanted, dead or alive. *Journal of Finance*, 51(5):1947–1958.

Fama, E. F. and French, K. R. (2007). Disagreement, tastes, and asset prices. *Journal of Financial Economics*, 83(3):667–689.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Grinblatt, M. and Saxena, K. (2018). When factors do not span their basis portfolios. *Journal of Financial and Quantitative Analysis*, 53(6):2335–2354.

Hartzmark, S. M. and Sussman, A. B. (2019). Do investors value sustainability? A natural experiment examining ranking and fund flows. *Journal of Finance*, 74(6):2789–2837.

He, Z., Kelly, B., and Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, 126(1):1–35.

Heinkel, R., Kraus, A., and Zechner, J. (2001). The effect of green investment on corporate behavior. *Journal of Financial and Quantitative Analysis*, 36(4):431–449.

Hong, H. and Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1):15–36.

Jensen, T. I., Kelly, B., and Pedersen, L. H. (2023). Is there a replication crisis in finance? *Journal of Finance*, 78(5):2465–2518.

Kacperczyk, M., Sialm, C., and Zheng, L. (2005). On the industry concentration of actively managed equity mutual funds. *Journal of Finance*, 60(4):1983–2011.

Kacperczyk, M., Sialm, C., and Zheng, L. (2008). Unobserved actions of mutual funds. *Review of Financial Studies*, 21(6):2379–2416.

Larcker, D. F. and Watts, E. M. (2020). Where's the greenium? *Journal of Accounting and Economics*, 69(2–3):101312.

Ledoit, O. and Wolf, M. (2008). Robust performance hypothesis testing with the sharpe ratio. *Journal of Empirical Finance*, 15(5):850–859.

MacKinlay, A. C. (1995). Multifactor models do not explain deviations from the CAPM. *Journal of Financial Economics*, 38(1):3–28.

Mitchell, M., Pedersen, L. H., and Pulvino, T. (2007). Slow moving capital. *American Economic Review*, 97(2):215–220.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2):550–571.

Pedersen, L. H., Fitzgibbons, S., and Pomorski, L. (2021). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*, 142(2):572–597.

Pukthuanthong, K., Roll, R., and Subrahmanyam, A. (2019). A protocol for factor identification. *Review of Financial Studies*, 32(4):1573–1607.

Shiller, R. J. (2000). *Irrational Exuberance*. Princeton University Press, Princeton, NJ.

Shleifer, A. and Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, 52(1):35–55.

Zhang, S. (2025). Carbon returns across the globe. *Journal of Finance*, 80(1):615–645.

Table 2: **Descriptive Statistics for SDG Factor Portfolios**
This table presents descriptive statistics and correlations for portfolios constructed based on the United Nations Sustainable Development Goals aligned factors across multiple panels. Panel A reports average scores and returns for portfolios sorted into low (bottom tercile) and high (top tercile) groups, along with high-minus-low differences, with t-statistics based on Newey-West corrected standard errors (12 lags) in parentheses. Panel B summarizes key statistics for portfolio returns across the three categories. Panel C displays correlations between these portfolio returns and traditional risk factors separately for developed and emerging economies, with statistically significant correlation coefficients in **bold**. The standard errors are Newey-West corrected for 12 lags, and t-statistics are in parentheses. The sample spans 240 months, from January 2001 to December 2020. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Country Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)
	Average (-) Scores			Average MSCI Index Return		
	Low Group	High Group	High-Low	Low Group	High Group	High-Low
Sustainability and climate resiliency	-0.317***	0.271***	0.589***	0.577	0.584	0.007
	(-41.057)	(120.482)	(61.124)	(1.448)	(1.320)	(0.055)
Human development and social inclusion	-0.515***	0.406***	0.922***	0.772*	0.417	-0.355*
	(-69.800)	(100.041)	(81.575)	(1.721)	(0.964)	(-1.690)
Institutional strength and innovation capacity	-0.781***	0.777***	1.559***	0.755*	0.540	-0.215
	(-71.800)	(194.251)	(112.061)	(1.674)	(1.305)	(-1.035)
N	240	240	240	240	240	240

Panel B: Summary Statistics

	Mean	SD	p10	p25	p50	p75	p90
Sustainability and climate resiliency	0.007	2.177	-2.492	-1.387	-0.191	1.410	2.846
Human development and social inclusion	-0.355	3.190	-4.031	-2.099	-0.284	1.553	3.622
Institutional strength and innovation capacity	-0.215	2.968	-4.258	-2.016	-0.057	1.611	3.492

Panel C: Correlation with Traditional Factors

	(1)	(2)	(3)	(4)	(5)	(6)
	Sustainability and climate resiliency	Human development and social inclusion	Institutional strength and innovation capacity	Sustainability and climate resiliency	Human development and social inclusion	Institutional strength and innovation capacity
	Traditional Factors: Developed Economies			Traditional Factors: Emerging Economies		
Market	0.090	0.106	0.063	**0.154**	0.061	0.001
Size	0.003	**0.145**	0.094	-0.085	-0.045	-0.081
Value	-0.019	**-0.180**	**-0.197**	0.007	-0.008	-0.035
Profitability	**-0.140**	0.002	0.013	-0.015	0.004	0.029
Investment	**-0.146**	**-0.267**	**-0.235**	**-0.179**	**-0.146**	-0.073
Momentum	**-0.130**	-0.070	-0.026	-0.099	-0.052	-0.004
Human development and social inclusion	**0.217**					
Institutional strength and innovation capacity	**0.141**	**0.868**				

Table 3: **Time Variation in SDG Portfolios**
This table reports regression results that examine time variation in the pricing of risk associated with the three SDG across different regions. The sample spans 181 months, from December 2005 to December 2020. Risk prices are estimated using Fama-MacBeth regressions based on a factor model that includes the three SDG factors and market factors for both developed and emerging economies. Climate Attention is measured as the logarithm of the number of newspaper articles mentioning climate change, with sources matched to each region. Economic conditions are classified as good or bad based on the cyclically adjusted price-to-earnings (CAPE) ratio: months in which the CAPE exceeds its 10-year median are labeled good times, and all others are labeled bad times. ΔOil Price denotes the monthly percentage change in the global, seasonally unadjusted price of WTI crude oil (in US dollars per barrel). The sample period spans 181 months, from December 2005 to December 2020. Standard errors are Newey-West corrected using 12 lags, and t-statistics are shown in parentheses. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Region	SDG Factor	Climate Attention	Good Economic Times	ΔOil Price	Intercept	N	R^2
World	Sustainability and climate resiliency	0.073	0.066	-0.001	-0.460	181	0.000
		(0.203)	(0.194)	(-0.047)	(-0.213)		
	Human development and social inclusion	-0.087	1.758**	0.177**	-0.134	181	0.111
		(-0.131)	(2.303)	(2.417)	(-0.034)		
	Institutional strength and innovation capacity	-0.073	-1.967***	-0.118**	1.599	181	0.070
		(-0.116)	(-2.763)	(-2.152)	(0.429)		
North America	Sustainability and climate resiliency	0.320	0.185	-0.002	-2.057	181	0.005
		(0.828)	(0.522)	(-0.044)	(-0.903)		
	Human development and social inclusion	1.000	1.216	0.218**	-6.312	181	0.127
		(1.111)	(1.271)	(2.485)	(-1.182)		
	Institutional strength and innovation capacity	-0.507	-1.634*	-0.158**	3.814	181	0.079
		(-0.678)	(-1.804)	(-2.446)	(0.867)		
Europe	Sustainability and climate resiliency	0.002	0.339	-0.014	-0.257	181	0.007
		(0.004)	(0.866)	(-0.452)	(-0.093)		
	Human development and social inclusion	0.193	1.203	0.199**	-1.845	181	0.105
		(0.284)	(1.442)	(2.277)	(-0.388)		
	Institutional strength and innovation capacity	-0.181	-1.167	-0.163**	2.094	181	0.080
		(-0.271)	(-1.437)	(-2.464)	(0.452)		
Asia	Sustainability and climate resiliency	-0.533	-0.075	0.009	3.856	181	0.010
		(-0.801)	(-0.185)	(0.379)	(0.827)		
	Human development and social inclusion	1.131	1.894**	0.137**	-8.685	181	0.086
		(1.433)	(2.332)	(2.429)	(-1.610)		
	Institutional strength and innovation capacity	-1.313*	-2.188***	-0.071	10.612*	181	0.058
		(-1.665)	(-2.692)	(-1.525)	(1.953)		
Oceania	Sustainability and climate resiliency	-0.766	-0.347	-0.000	4.848	181	0.013
		(-1.387)	(-0.796)	(-0.003)	(1.350)		
	Human development and social inclusion	1.761*	2.431**	0.201***	-11.816*	181	0.120
		(1.739)	(2.478)	(2.709)	(-1.758)		
	Institutional strength and innovation capacity	-1.371	-2.125**	-0.146***	9.289	181	0.082
		(-1.608)	(-2.593)	(-2.917)	(1.631)		
South America	Sustainability and climate resiliency	-0.121	-0.522	-0.042	0.750	181	0.028
		(-0.268)	(-1.445)	(-1.627)	(0.320)		
	Human development and social inclusion	0.962	1.781	0.185***	-5.565	181	0.070
		(0.838)	(1.477)	(2.778)	(-0.937)		
	Institutional strength and innovation capacity	-0.255	-2.211*	-0.114**	2.298	181	0.041
		(-0.267)	(-1.766)	(-2.456)	(0.458)		
Africa	Sustainability and climate resiliency	-0.013	-0.022	0.019	0.298	181	0.005
		(-0.044)	(-0.049)	(0.589)	(0.278)		
	Human development and social inclusion	-0.481	2.923*	0.108	1.542	181	0.031
		(-0.594)	(1.968)	(1.163)	(0.488)		
	Institutional strength and innovation capacity	-0.188	-1.876	-0.034	0.851	181	0.016
		(-0.393)	(-1.536)	(-0.570)	(0.452)		

Table 4: **Violations of UNGC Principles and Exposures to SDG Factors**
This table reports Fama-MacBeth regression results examining the cross-sectional relationship between exposures to SDG factors and violations of United Nations Global Compact (UNGC) principles. A higher estimated exposure indicates an improved firm profile in the respective category, implying a lower risk of violations. The dependent variable is the logarithm of one plus the total number of UNGC violations for a given firm-year. The exposures are annualized by computing the average of monthly exposures over the calendar year. The sample covers 14 years (2007–2020) and has 21,258 observations. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Average exposure to SDG factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: Ln(1+Number of violations of UNGC Principle)									
	Principle 1	Principle 2	Principle 3	Principle 4	Principle 5	Principle 6	Principle 7	Principle 8	Principle 9	Principle 10
Average Exposure Across Categories	-0.036**	-0.037***	-0.019***	-0.018***	-0.017***	-0.016**	-0.003	-0.003	-0.003	-0.028***
	(-2.477)	(-3.057)	(-4.842)	(-4.316)	(-3.137)	(-3.051)	(-0.168)	(-0.138)	(-0.138)	(-4.214)
N	21,258	21,258	21,258	21,258	21,258	21,258	21,258	21,258	21,258	21,258
T	14	14	14	14	14	14	14	14	14	14

Panel B: Results by SDG category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: Ln(1+Number of violations of UNGC Principle)									
	Principle 7	Principle 8	Principle 9	Principle 3	Principle 4	Principle 5	Principle 6	Principle 1	Principle 2	Principle 10
	Climate			Labor				Human Rights		
Sustainability and climate resiliency	-0.013	-0.012	-0.012							
	(-1.065)	(-1.062)	(-1.062)							
Human development and social inclusion				-0.016***	-0.015***	-0.013**	-0.013***			
				(-4.935)	(-5.144)	(-3.039)	(-4.129)			
Institutional strength and innovation capacity								-0.013	-0.014	-0.019***
								(-1.255)	(-1.646)	(-3.339)
N	21,258	21,258	21,258	21,258	21,258	21,258	21,258	21,258	21,258	21,258
T	14	14	14	14	14	14	14	14	14	14

Table 5: **SDG Preferences and Portfolio Exposures**

This table examines whether funds with a stronger sustainability orientation hold portfolios with higher exposure to Sustainable Development Goal (SDG) characteristics. The dependent variable is fund–quarter exposure to a given SDG dimension, calculated as the value-weighted average SDG exposure of stocks in the fund's portfolio. The key independent variable, PRI Signatory, is a dichotomous variable equal to 1 if a fund is a signatory to the Principles for Responsible Investment (PRI), 0 otherwise. Fund Return is the compounded quarterly return from monthly returns. Fund Flow is quarterly net flow scaled by beginning-of-quarter assets. The sample covers 2006:Q1–2019:Q4. Standard errors are clustered at the fund level, and t-statistics are in parentheses.Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: $(\cdot)$ Exposure$_{fqt}$					
	Sustainability and Climate Resiliency	Human Development and Social Inclusion	Institutional strength and innovation capacity	Sustainability and Climate Resiliency	Human Development and Social Inclusion	Institutional strength and innovation capacity
PRI Signatory	0.0053***	0.0034*	0.0049**	0.0050***	0.0034*	0.0045**
	-2.8745	-1.7411	-2.2994	-2.6558	-1.6629	-2.0647
Fund Return				-0.0241**	0.1005***	0.1135***
				(-1.9771)	-8.0058	-8.5757
Fund Flow				-0.0018	0.0006	0.0006
				(-1.2652)	-0.4217	-0.4777
N	66,576	66,576	66,576	58,906	58,906	58,906
R^2	0.4573	0.2957	0.3236	0.4357	0.2934	0.314
Year × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Fund	Fund	Fund	Fund	Fund	Fund

Table 6: **SDG Factor Portfolios**

This table presents descriptive statistics and correlations for portfolios constructed based on UN-SDG factors across multiple panels. Panels A and B present canonical correlations between factors extracted using the cross-sectional method of Connor and Korajczyk (1988) and the SDG factors. Panel A reports canonical correlation coefficients and z-statistics for the first three canonical variates. Panel B presents the average absolute t-statistics for the SDG factors. Panel C reports risk premia estimated from Fama-MacBeth regressions extending the Carhart four-factor model with SDG factors. Panel D presents Sharpe ratios and related statistics for long-short hedge portfolios based on SDG factors. The sample comprises 6,844 securities spanning 240 months from January 2001 to December 2020. Standard errors are Newey-West corrected for 12 lags, and t-statistics are reported in parentheses. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Canonical correlations

	Canonical variate 1	Canonical variate 2	Canonical variate 3
Value	0.613	0.540	0.483
z-statistics	19.416	16.715	14.917

Panel B: Significance level for SDG Factors

	Sustainability and climate resiliency	Human development and social inclusion	Institutional strength and innovation capacity
Average |t-statistics|	1.719	2.345	2.788

Panel C: Pricing Results – Carhart 4-factors augmented with SDG factors

	World	NA	Europe	Asia	SA	Oceania	Africa
Sustainability and climate resiliency	0.066	0.160	0.067	0.074	-0.403	-0.034	-0.167
	(0.448)	(1.137)	(0.294)	(0.418)	(-0.992)	(-0.114)	(-0.476)
Human development and social inclusion	0.153	-0.029	-0.021	0.132	-1.099*	-0.163	-0.729
	(0.633)	(-0.126)	(-0.065)	(0.675)	(-1.819)	(-0.345)	(-1.516)
Institutional strength and innovation capacity	-0.210	-0.187	-0.181	-0.002	-1.216**	-0.522	-0.838**
	(-1.025)	(-0.957)	(-0.583)	(-0.012)	(-2.025)	(-1.241)	(-2.086)
R^2	0.319	0.225	0.086	0.288	0.623	0.919	0.418
N	6,844	1,607	1,418	3,544	61	158	56

Panel D: Performance statistics of long-top-decile short-bottom-decile of $(\cdot)$ exposure portfolios

Measure	Sustainability and climate resiliency	Human development and social inclusion	Institutional strength and innovation capacity
Average monthly return	0.003	0.005	-0.005
Monthly standard deviation	0.054	0.050	0.046
Monthly Sharpe ratio	0.063	0.093	-0.113
Standard error of Sharpe ratio	0.065	0.065	0.065
t-statistic: H_0: |Annualized Sharpe| ≥ 0.6	-1.700	-1.230	-0.926

Table 7: **Portfolio Sorts**

This table reports average monthly High–Minus–Low taste-exposure return spreads (in percent). Each month, stocks are independently sorted into five Size quintiles and five Book-to-Market (BTM) quintiles. The intersection of these independent sorts produces 25 Size–BTM portfolios. Within each of the 25 portfolios, stocks are further sorted into five groups based on their exposure (beta) to one dimension of the Sustainable Development Goal (SDG) taste factors–sustainability and climate resiliency, social inclusion and human development, and institutional strength and innovation capacity–estimated from a time-series regression of each stock's returns on the SDG factor. For each Size–BTM portfolio and month, we compute the value-weighted return spread between the highest and lowest SDG-exposure quintiles (Q5–Q1). The table reports the time-series average and its t-statistic based on Newey-West standard errors corrected for 12 lags. The sample covers US stocks from 2001:M1 to 2020:M12.

Panel A: Sustainability and Climate Resiliency

	Book-to-Market				
Size ↓	Low	2	3	4	High
Small	-0.133	-0.318	0.947*	0.534	-0.729
	(-0.152)	(-0.340)	(1.739)	(0.895)	(-1.321)
2	0.854	0.089	0.646	0.023	0.433
	(1.100)	(0.175)	(1.180)	(0.063)	(0.895)
3	0.654	-0.172	0.261	0.325	0.395
	(1.048)	(-0.439)	(0.720)	(0.748)	(0.783)
4	0.492	0.244	0.330	0.447	1.024**
	(1.073)	(0.731)	(1.019)	(1.271)	(2.046)
Large	0.130	0.044	0.288	-0.090	0.347
	(0.424)	(0.158)	(0.941)	(-0.278)	(0.751)

Panel B: Human Development and Social Inclusion

	Book-to-Market				
Size ↓	Low	2	3	4	High
Small	0.271	0.255	1.117*	0.317	0.271
	(0.254)	(0.309)	(1.679)	(0.512)	(0.522)
2	0.206	0.778	1.189***	0.648*	1.112
	(0.316)	(1.354)	(2.612)	(1.832)	(1.605)
3	1.095*	0.401	0.503	0.638	0.426
	(1.769)	(0.879)	(1.446)	(1.614)	(0.701)
4	1.073**	0.370	0.369	0.918**	0.953**
	(2.402)	(1.223)	(1.469)	(2.127)	(2.011)
Large	0.792*	0.591**	0.600**	0.428	0.826**
	(1.762)	(2.081)	(2.240)	(1.092)	(2.136)

Panel C: Institutional Strength and Innovation Capacity

	Book-to-Market				
Size ↓	Low	2	3	4	High
Small	-0.308	0.557	0.761	0.625	0.694
	(-0.294)	(0.545)	(1.219)	(1.331)	(1.452)
2	-0.060	1.428**	1.047**	0.752**	0.461
	(-0.100)	(2.443)	(2.402)	(2.305)	(0.806)
3	1.146**	0.416	0.705*	0.338	0.597
	(2.038)	(1.121)	(1.775)	(1.043)	(1.084)
4	0.438	0.046	0.335	0.607*	0.720*
	(1.486)	(0.147)	(1.576)	(1.674)	(1.696)
Large	0.556*	0.508*	-0.047	0.049	1.070**
	(1.923)	(1.969)	(-0.133)	(0.151)	(2.429)

Table 8: **Comparing Performance of Standard and SDG-Agnostic Fama-French Models**
This table compares the out-of-sample squared Sharpe ratios of Fama-French factor models under two alternative constructions of non-market factors. In each comparison, *agnostic* models exclude securities with high exposure to three SDG factors (*Sustainability and climate resiliency*, *Human development and social inclusion*, and *Institutional strength and innovation capacity*) when estimating SMB, HML, CMA, and RMW, while the original model uses factors' data from the Kenneth French data library. The market factor is held constant across all specifications, and the sample is a cross-section of US firms. Panel A evaluates the three-factor model. Panel B extends the analysis to the five-factor model. The final column reports the difference in squared Sharpe ratios between the agnostic and original models, calculated out-of-sample using a bootstrap procedure based on the methodology of Fama and French (2018). In this approach, the time series is partitioned into adjacent monthly pairs. For each bootstrap replication, one month from each pair is randomly assigned to the in-sample set and the other to the out-of-sample (OS) set. Factor model weights are estimated using IS data, then applied to OS data to compute the OS Sharpe ratio. This procedure is repeated 10,000 times to generate the distribution of OS squared Sharpe ratios for each model. The reported differences in squared Sharpe ratios reflect out-of-sample performance, and the accompanying t-statistics are calculated using the standard error of the difference in squared Sharpe ratios across the bootstrap replications. The sample period spans from January 2001 to December 2020. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Row	Model	Factor construction agnostic to (·)	In-Sample Squared Sharpe Ratio	Out-of-sample Squared Sharpe Ratio	Difference Out-of-sample Squared Sharpe Ratio
1	Market, SMB, HML	·	0.0279	0.0224	
2	Market, SMB, HML	(i) Sustainability and Climate Resiliency	0.0273	0.0221	-0.0003
3	Market, SMB, HML	(ii) Human Development and Social Inclusion	0.0286	0.0220	0.0004*
4	Market, SMB, HML	(iii) Institutional Strength and Innovation Capacity	0.0281	0.0219	-0.0005**
5	Market, SMB, HML	(i) and (ii)	0.0284	0.0226	0.0002
6	Market, SMB, HML	(i) and (iii)	0.0275	0.0223	-0.0001
7	Market, SMB, HML	(ii) and (iii)	0.0291	0.0223	-0.0001
8	Market, SMB, HML	Sustainable Development Goals [(i), (ii), and (iii)]	0.0294	0.0232	0.0008***
9	Market, SMB, HML, CMA, RMW	·	0.1207	0.0707	
10	Market, SMB, HML, CMA, RMW	(i) Sustainability and Climate Resiliency	0.1102	0.0658	-0.0049***
11	Market, SMB, HML, CMA, RMW	(ii) Human Development and Social Inclusion	0.1001	0.0584	-0.0123***
12	Market, SMB, HML, CMA, RMW	(iii) Institutional Strength and Innovation Capacity	0.0912	0.0510	-0.0197***
13	Market, SMB, HML, CMA, RMW	(i) and (ii)	0.1195	0.0754	0.0047***
14	Market, SMB, HML, CMA, RMW	(i) and (iii)	0.1170	0.0718	0.0011
15	Market, SMB, HML, CMA, RMW	(ii) and (iii)	0.1046	0.0623	-0.0084***
16	Market, SMB, HML, CMA, RMW	Sustainable Development Goals [(i), (ii), and (iii)]	0.1299	0.0847	0.0140**

Table 9: **Comparing Performance of SDG-Agnostic Factor Models Across Regimes**
This table compares the out-of-sample squared Sharpe ratios of SDG-agnostic Fama-French factor models to the standard specification across different regimes. Panel A focuses on economic cycles, where good times are defined as months in which the cyclically adjusted price-to-earnings (CAPE) ratio exceeds the median over the prior decade, while all other months are classified as bad times. Panel B considers variation in climate attention, measured by the number of climate-related news articles published in North America. Periods of high climate attention are those in which the log number of articles exceeds the sample average; all other periods are classified as low climate attention. In Panel C, the wealth share of taste investors is defined as the fraction of total market capitalization accounted for by stocks whose returns exhibit statistically significant exposure to at least one of the three SDG factors. This share is lagged by one period. In each panel, the reported differences in squared Sharpe ratios reflect the performance gap between the agnostic and original models within each regime. Squared Sharpe ratios are estimated using the paired-sample bootstrap procedure proposed by Ledoit and Wolf (2008), which constructs in-sample and out-of-sample splits by randomly selecting adjacent time pairs and assigning one observation from each pair to the in-sample set and the other to the out-of-sample set. Portfolio weights are optimized in-sample and then applied to the out-of-sample data to compute Sharpe ratios. This procedure is repeated 10,000 times to generate a distribution of out-of-sample squared Sharpe ratios for each model. The statistical significance is based on t-statistics computed using the bootstrap standard errors of the squared Sharpe ratio differences. The sample covers the period from January 2001 to December 2020. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Good and Bad Times based on Cyclically-Adjusted Price-to-Earnings Ratio

Row	Model	Factor construction agnostic to (·)	Good Time	Δ_G	Bad time	Δ_B	$\Delta_G - \Delta_B$
			OOS Squared Sharpe Ratio		OOS Squared Sharpe Ratio		
1	Market, SMB, HML	·	0.0440		0.0288		
2	Market, SMB, HML	(i) Sustainability and Climate Resiliency	0.0448	0.0007*	0.0336	0.0047***	-0.004***
3	Market, SMB, HML	(ii) Human Development and Social Inclusion	0.0438	-0.0002	0.0344	0.0055***	-0.0057***
4	Market, SMB, HML	(iii) Institutional Strength and Innovation Capacity	0.0438	-0.0002	0.0359	0.0071***	-0.0073***
5	Market, SMB, HML	(i) and (ii)	0.0453	0.0013***	0.0326	0.0037***	-0.0024***
6	Market, SMB, HML	(i) and (iii)	0.0449	0.0009**	0.0335	0.0047***	-0.0038***
7	Market, SMB, HML	(ii) and (iii)	0.0442	0.0001	0.0347	0.0058***	-0.0057***
8	Market, SMB, HML	Sustainable Development Goals [(i), (ii), and (iii)]	0.0459	0.0019***	0.0334	0.0046***	-0.0027***
9	Market, SMB, HML, CMA, RMW	·	0.0711		0.0799		
10	Market, SMB, HML, CMA, RMW	(i) Sustainability and Climate Resiliency	0.0532	-0.0179***	0.0812	0.0013	-0.0192***
11	Market, SMB, HML, CMA, RMW	(ii) Human Development and Social Inclusion	0.0706	-0.0005	0.0555	-0.0245***	0.0240***
12	Market, SMB, HML, CMA, RMW	(iii) Institutional Strength and Innovation Capacity	0.0639	-0.0071***	0.0536	-0.0263***	0.0192***
13	Market, SMB, HML, CMA, RMW	(i) and (ii)	0.0687	-0.0023**	0.0729	-0.0071***	0.0047***
14	Market, SMB, HML, CMA, RMW	(i) and (iii)	0.0660	-0.0050***	0.0748	-0.0051***	0.0001
15	Market, SMB, HML, CMA, RMW	(ii) and (iii)	0.0806	0.0096***	0.0553	-0.0246***	0.0342***
16	Market, SMB, HML, CMA, RMW	Sustainable Development Goals [(i), (ii), and (iii)]	0.0771	0.0061***	0.0792	-0.0007	0.0068***

Panel B: High and Low Climate Attention

Row	Model	Factor construction agnostic to (·)	High Climate Attention	Δ_H	Low Climate Attention	Δ_L	$\Delta_H - \Delta_L$
			OOS Squared Sharpe Ratio		OOS Squared Sharpe Ratio		
1	Market, SMB, HML	·	0.0718		0.0448		
2	Market, SMB, HML	(i) Sustainability and Climate Resiliency	0.0485	-0.0233	0.0599	0.0151***	-0.0383***
3	Market, SMB, HML	(ii) Human Development and Social Inclusion	0.0458	-0.0261	0.0609	0.0160***	-0.0421***
4	Market, SMB, HML	(iii) Institutional Strength and Innovation Capacity	0.0485	-0.0233	0.0648	0.0199***	-0.0432***
5	Market, SMB, HML	(i) and (ii)	0.0469	-0.0249	0.0588	0.0140***	-0.0389***
6	Market, SMB, HML	(i) and (iii)	0.0487	-0.0231	0.0610	0.0161***	-0.0392***
7	Market, SMB, HML	(ii) and (iii)	0.0450	-0.0268	0.0641	0.0192***	-0.0460***
8	Market, SMB, HML	Sustainable Development Goals [(i), (ii), and (iii)]	0.0461	-0.0257	0.0629	0.0181***	-0.0438***
9	Market, SMB, HML, CMA, RMW	·	0.1127		0.0766		
10	Market, SMB, HML, CMA, RMW	(i) Sustainability and Climate Resiliency	0.1019	-0.0108***	0.0611	-0.0155***	0.0047***
11	Market, SMB, HML, CMA, RMW	(ii) Human Development and Social Inclusion	0.1295	0.0168***	0.0551	-0.0215***	0.0382***
12	Market, SMB, HML, CMA, RMW	(iii) Institutional Strength and Innovation Capacity	0.1243	0.0115***	0.0559	-0.0207***	0.0322***
13	Market, SMB, HML, CMA, RMW	(i) and (ii)	0.1439	0.0312***	0.0552	-0.0214***	0.0526***
14	Market, SMB, HML, CMA, RMW	(i) and (iii)	0.1256	0.0129***	0.0612	-0.0153***	0.0283***
15	Market, SMB, HML, CMA, RMW	(ii) and (iii)	0.1446	0.0319***	0.0571	-0.0195***	0.0513***
16	Market, SMB, HML, CMA, RMW	Sustainable Development Goals [(i), (ii), and (iii)]	0.1600	0.0473***	0.0609	-0.0157***	0.0630***

Panel C: Relative Wealth Share of Taste Investors

Row	Model	Factor construction agnostic to (·)	High Wealth Share OOS Squared Sharpe Ratio	Δ_H	Low Wealth Share OOS Squared Sharpe Ratio	Δ_L	$\Delta_H - \Delta_L$
1	Market, SMB, HML	·	0.0668		0.0725		
2	Market, SMB, HML	(i) Sustainability and Climate Resiliency	0.0374	0.0054***	0.0621	-0.0104***	0.0158***
3	Market, SMB, HML	(ii) Human Development and Social Inclusion	0.0384	0.0064***	0.0573	-0.0152***	0.0216***
4	Market, SMB, HML	(iii) Institutional Strength and Innovation Capacity	0.0374	0.0054***	0.0619	-0.0106***	0.0160***
5	Market, SMB, HML	(i) and (ii)	0.0393	0.0073***	0.0589	-0.0136***	0.0209***
6	Market, SMB, HML	(i) and (iii)	0.0368	0.0048***	0.0632	-0.0093***	0.0142***
7	Market, SMB, HML	(ii) and (iii)	0.0384	0.0064***	0.057	-0.0155***	0.0219***
8	Market, SMB, HML	Sustainable Development Goals [(i), (ii), and (iii)]	0.0401	0.0081***	0.0584	-0.0141***	0.0222***
9	Market, SMB, HML, CMA, RMW	·	0.0668		0.0696		
10	Market, SMB, HML, CMA, RMW	(i) Sustainability and Climate Resiliency	0.0722	0.0054***	0.0955	0.0258***	-0.0205***
11	Market, SMB, HML, CMA, RMW	(ii) Human Development and Social Inclusion	0.0661	-0.0007***	0.0975	0.0278***	-0.0285***
12	Market, SMB, HML, CMA, RMW	(iii) Institutional Strength and Innovation Capacity	0.0562	-0.0106***	0.1003	0.0307***	-0.0413***
13	Market, SMB, HML, CMA, RMW	(i) and (ii)	0.0904	0.0236***	0.0984	0.0288***	-0.0051***
14	Market, SMB, HML, CMA, RMW	(i) and (iii)	0.0792	0.0124***	0.0995	0.0298***	-0.0174***
15	Market, SMB, HML, CMA, RMW	(ii) and (iii)	0.0708	0.0040***	0.0947	0.0251***	-0.0211***
16	Market, SMB, HML, CMA, RMW	Sustainable Development Goals [(i), (ii), and (iii)]	0.1032	0.0364***	0.1005	0.0309***	0.0056***

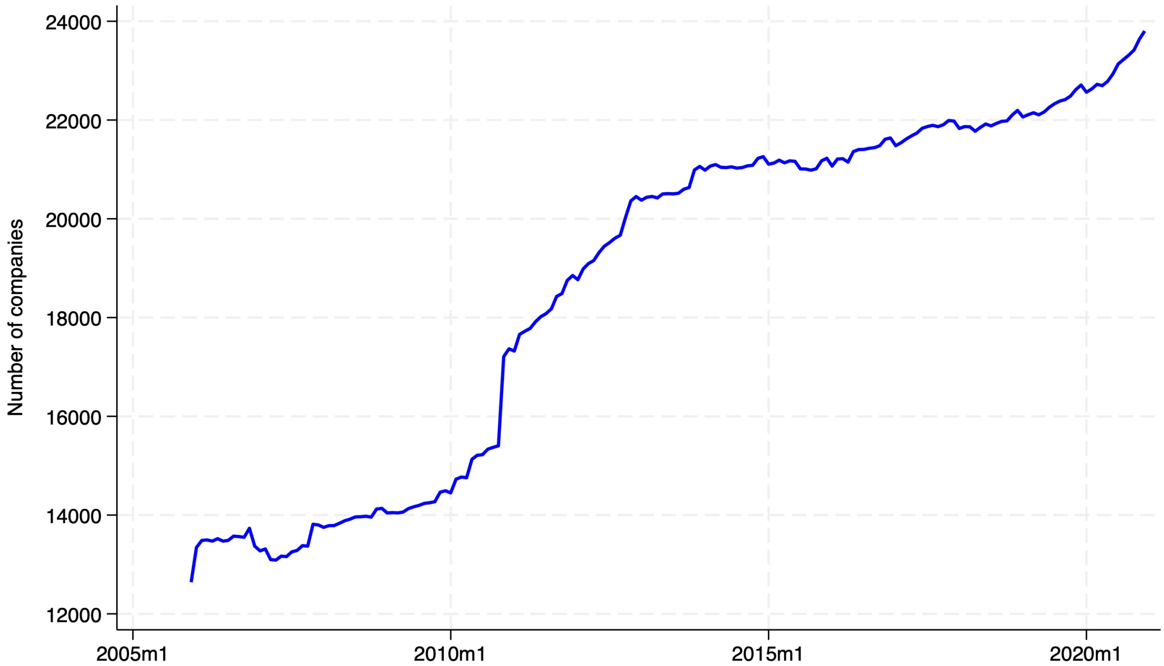

Figure 1: This figure displays a time series of the number of companies for which SDG factors' exposures are calculated using rolling-window regression. The analysis employs a 60-month rolling window regression, with data spanning 240 months from January 2006 to December 2020.

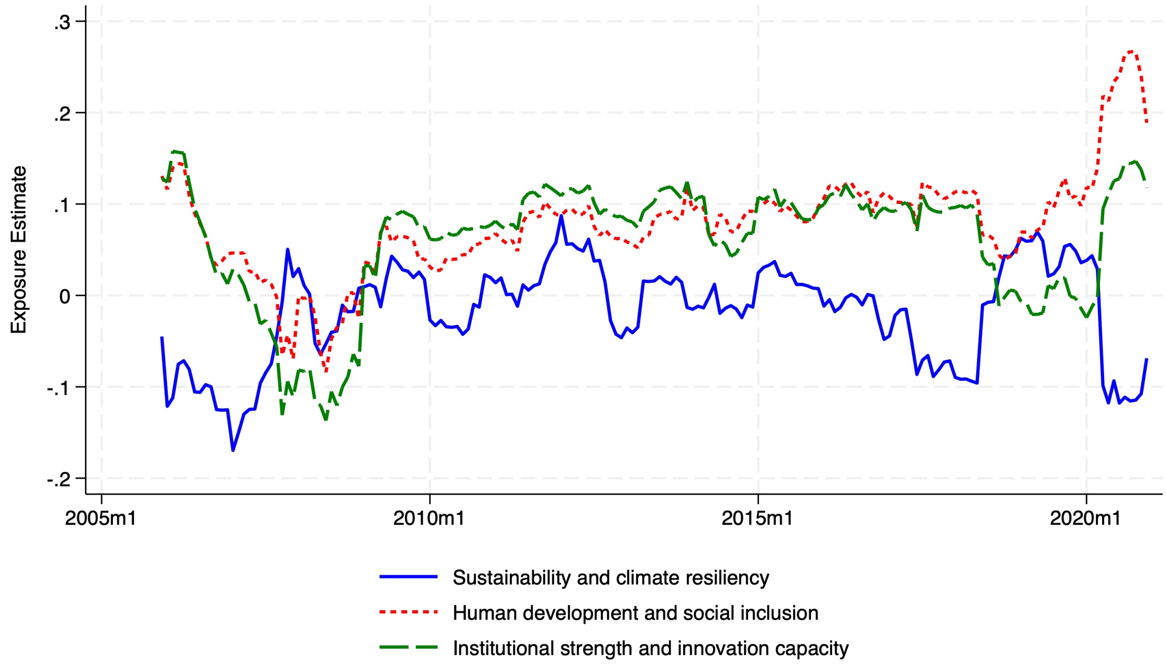

Figure 2: This figure presents a time-series average of firm-level exposures to SDG factors. The sample period spans from January 2006 to December 2020.

Figure 3: This figure presents the monthly share of total US equity market capitalization attributable to stocks whose returns exhibit statistically significant exposure to at least one of the three SDG factors. Exposures to these factors are estimated using simple time-series regression, and a stock is classified as exposed if the absolute t-statistic for any SDG factor exceeds 1.65. The plotted series uses lagged market capitalization to mitigate look-ahead bias and is computed for the period 2001:M1–2020:M12.

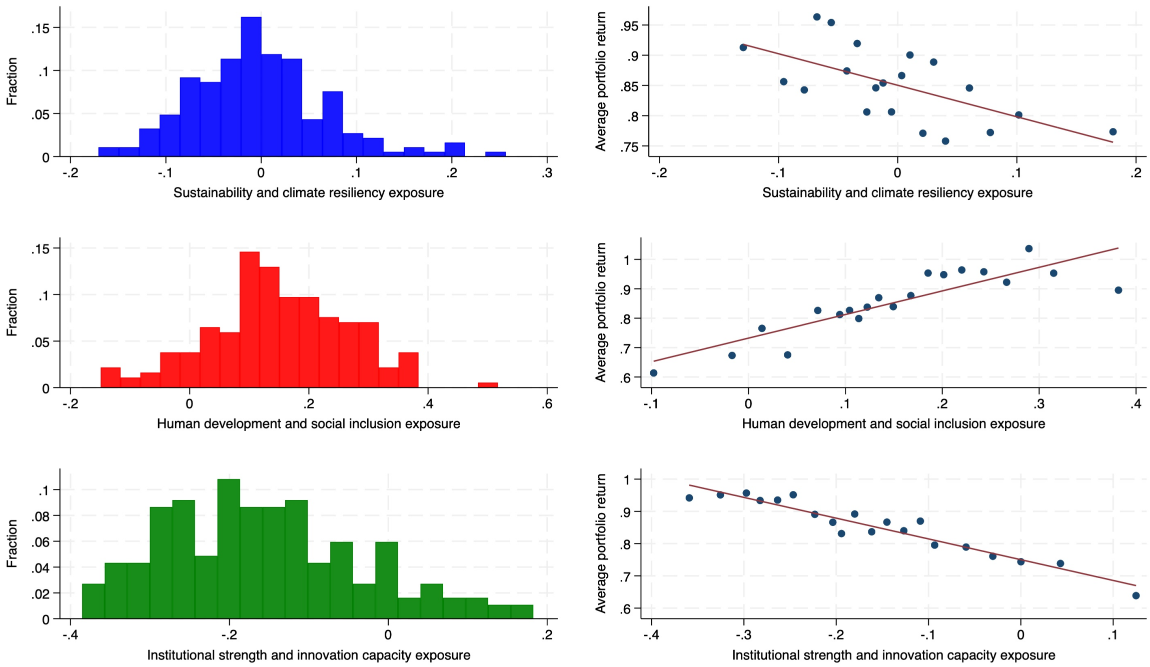

Figure 4: This figure presents histograms (left) and binned scatter plots (right) of the exposures of 185 portfolios to three SDG factors. The analysis employs a single time-series regression for each portfolio, with data spanning 240 months from January 2001 to December 2020.

Online Appendix

When Tastes Affect Asset Prices But Not Expected Returns

Table B.1: **Categories, Themes, and Sub-Themes in the World Bank's Country-Level ESG Dataset**

The table provides information on the original themes and sub-themes within the *Environment*, *Social*, and *Governance* categories.

1. ENVIRONMENT
1.1 Emissions and Pollution
1.1.1 CO2 emissions (metric tons per capita)
1.1.2 GHG net emissions/removals by LUCF (Mt of CO2 equivalent)
1.1.3 Methane emissions (metric tons of CO2 equivalent per capita)
1.1.4 Nitrous oxide emissions (metric tons of CO2 equivalent per capita)
1.1.5 PM2.5 air pollution, mean annual exposure (micrograms per cubic meter)
1.2 Natural Capital Endowment and Management
1.2.1 Adjusted savings: natural resources depletion (% of GNI)
1.2.2 Adjusted savings: net forest depletion (% of GNI)
1.2.3 Annual freshwater withdrawals, total (% of internal resources)
1.2.4 Forest area (% of land area)
1.2.5 Mammal species, threatened
1.2.6 Terrestrial and marine protected areas (% of total territorial area)
1.3 Energy Use and Security
1.3.1 Electricity production from coal sources (% of total)
1.3.2 Energy imports, net (% of energy use)
1.3.3 Energy intensity level of primary energy (MJ/$2011 PPP GDP)
1.3.4 Energy use (kg of oil equivalent per capita)
1.3.5 Fossil fuel energy consumption (% of total)
1.3.6 Renewable electricity output (% of total electricity output)
1.3.7 Renewable energy consumption (% of total final energy consumption)
1.4 Environment/Climate Risk and Resilience
1.4.1 Cooling Degree Days (projected change in number of degree Celsius)
1.4.2 Droughts, floods, extreme temperatures (% of population, average 1990-2009)
1.4.3 Heat Index 35 (projected change in days)
1.4.4 Maximum 5-day Rainfall, 25-year Return Level (projected change in mm)
1.4.5 Mean Drought Index (projected change, unitless)
1.4.6 Population density (people per sq. km of land area)
1.5 Food Security
1.5.1 Agricultural land (% of land area)
1.5.2 Agriculture, forestry, and fishing, value added (% of GDP)
1.5.3 Food production index (2004-2006 = 100)

2. SOCIAL
2.1 Education and Skills
2.1.1 Government expenditure on education, total (% of government expenditure)
2.1.2 Literacy rate, adult total (% of people ages 15 and above)
2.1.3 School enrollment, primary (% gross)
2.2 Employment
2.2.1 Children in employment, total (% of children ages 7-14)
2.2.2 Labor force participation rate, total (% of total population ages 15-64) (modeled ILO estimate)
2.2.3 Unemployment, total (% of total labor force) (modeled ILO estimate)
2.3 Demography
2.3.1 Fertility rate, total (births per woman)
2.3.2 Life expectancy at birth, total (years)
2.3.3 Population ages 65 and above (% of total population)
2.4 Poverty and Inequality
2.3.1 Annualized average growth rate in per capita real survey mean consumption or income, total population (%)
2.3.2 GINI index (World Bank estimate)
2.3.3 Income share held by lowest 20%
2.3.4 Poverty headcount ratio at national poverty lines (% of population)

Continued on next page

2.5 Health and Nutrition
2.5.1 Cause of death, by communicable diseases and maternal, prenatal, and nutrition conditions (% of total)
2.5.2 Hospital beds (per 1,000 people)
2.5.3 Mortality rate, under-5 (per 1,000 live births)
2.5.4 Prevalence of overweight (% of adults)
2.5.5 Prevalence of undernourishment (% of population)
2.6 Access to Services
2.6.1 Access to clean fuels and technologies for cooking (% of population)
2.6.2 Access to electricity (% of population)
2.6.3 People using safely managed drinking water services (% of population)
2.6.4 People using safely managed sanitation services (% of population)

3. GOVERNANCE
3.1 Human Rights
3.1.1 Strength of legal rights index (0=weak to 12=strong)
3.1.2 Voice and Accountability: Estimate
3.2 Government Effectiveness
3.2.1 Government Effectiveness: Estimate
3.2.2 Regulatory Quality: Estimate
3.3 Stability and Rule of Law
3.3.1 Control of Corruption: Estimate
3.3.2 Net migration
3.3.3 Political Stability and Absence of Violence/Terrorism: Estimate
3.3.4 Rule of Law: Estimate
3.4 Economic Environment
3.4.1 Ease of doing business index (1=most business-friendly regulations)
3.4.2 GDP growth (annual %)
3.4.3 Individuals using the Internet (% of population)
3.5 Gender
3.5.1 Proportion of seats held by women in national parliaments (%)
3.5.2 Ratio of female to male labor force participation rate (%) (modeled ILO estimate)
3.5.3 School enrollment, primary and secondary (gross), gender parity index (GPI)
3.5.4 Unmet need for contraception (% of married women ages 15-49)
3.6 Innovation
3.6.1 Patent applications, residents
3.6.2 Research and development expenditure (% of GDP)
3.6.3 Scientific and technical journal articles

Table B.2: **Themes and Sub-Themes within Sustainable Development Goals**
This table provides a detailed classification of themes and sub-themes within the United Nations Sustainable Development Goals. Each sub-theme is accompanied by its associated tone (positive or negative) and relative weight within its broader theme. The weights reflect the relative importance of sub-themes within their respective themes, as well as the relative importance of themes within their corresponding categories.

1. SUSTAINABILITY AND CLIMATE RESILIENCE	**Tone**	**Weight**
1.1 Emissions and Pollution		**1/5**
1.1.1 CO2 Emissions (Tonnes Per Capita)	Negative	1/5
1.1.2 CH4 Emissions (CO2 Equivalent) (Tonnes Per Capita)	Negative	1/5
1.1.3 N2O Emissions (CO2 Equivalent) (Tonnes Per Capita)	Negative	1/5
1.1.4 PM2.5 Air Pollution (Tonnes)	Negative	1/5
1.1.5 PM10 Air Pollution (Tonnes)	Negative	1/5
1.2 Natural Capital Endowment and Management		**1/5**
1.2.1 Adjusted Savings: Natural Resources Depletion (% of GNI)	Negative	1/5
1.2.2 Adjusted Savings: Net Forest Depletion (% of GNI)	Negative	1/5
1.2.3 Annual Freshwater Withdrawals, Total (% of Internal Resources)	Negative	1/5
1.2.4 Forest Area (% of Land Area)	Positive	1/5
1.2.5 Average Proportion of Terrestrial Key Biodiversity Areas Covered	Positive	1/5
1.3 Energy Use and Security		**1/5**
1.3.1 Electricity Production from Coal (% of Total)	Negative	1/7
1.3.2 Energy Imports, Net (% of Energy Use)	Negative	1/7
1.3.3 Energy Intensity Level of Primary Energy (MJ/$ 2011 PPP GDP)	Negative	1/7
1.3.4 Energy Use (kg of Oil Equivalent Per Capita)	Negative	1/7
1.3.5 Fossil Fuel Energy Consumption (% of Total)	Negative	1/7
1.3.6 Renewable Energy Output (% of Total Electricity Output)	Positive	1/7
1.3.7 Renewable Energy Consumption (% of Total Final Energy Consumption)	Positive	1/7
1.4 Environment/Climate Risk and Resilience		**1/5**
1.4.1 Projected Change in Warm Periods	Negative	1/6
1.4.2 Projected Change in Deaths from Climate Change Induced Diseases	Negative	1/6
1.4.3 Projected Change of Sea Level Rise Impacts	Negative	1/6
1.4.4 Projected Change of Flood Hazards	Negative	1/6
1.4.5 Population Living Under 5m Above Sea Level	Negative	1/6
1.4.6 Population Density (People Per Square Kilometer of Land Area)	Negative	1/6
1.5 Food Security		**1/5**
1.5.1 Agricultural Land (% of Land Area)	Positive	1/3
1.5.2 Agriculture, Forestry, and Fishing, Value Added (% of GDP)	Positive	1/3
1.5.3 Food Production Index (2004-2006 = 100)	Positive	1/3
2. HUMAN DEVELOPMENT AND SOCIAL INCLUSION		
2.1 Education and Skills		**1/6**
2.1.1 Government Expenditure on Education, Total (% of Government Expenditure)	Positive	1/3
2.1.2 Literacy Rate, Adult Total (% of People Ages 15 and Above)	Positive	1/3
2.1.3 School Enrollment, Primary (% Gross)	Positive	1/3
2.2 Employment		**1/6**
2.2.1 Children in Employment, Total (% of Children Ages 7-14)	Negative	1/3
2.2.2 Labor Force Participation Rate, Total (% of Total Population Ages 15-64)	Positive	1/3
2.2.3 Unemployment Rate, Total (% of Total Labor Force)	Negative	1/3
2.3 Demography		**1/6**
2.3.1 Fertility Rate, Total (Births Per Woman)	Positive	1/3
2.3.2 Life Expectancy at Birth, Total (Years)	Positive	1/3
2.3.3 Population Aged 65 and Above (% of Total Population)	Negative	1/3
2.4 Poverty and Inequality		**1/6**
2.4.1 Poverty Headcount	Negative	1/5
2.4.2 Poverty Gap	Negative	1/5
2.4.3 Watts Index	Negative	1/5
2.4.4 GINI Index	Negative	1/5
2.4.5 MLD Index	Negative	1/5
2.5 Health and Nutrition		**1/6**
2.5.1 Cause of Death, By Communicable Diseases and Maternal, Prenatal and Nutrition Conditions (% Total)	Negative	1/4
2.5.2 Hospital Beds (Per 1000 People)	Positive	1/4
2.5.3 Mortality Rate, Under-5 (Per 1000 Live Births)	Negative	1/4
2.5.4 Prevalence of Undernourishment (% of Population)	Negative	1/4
2.6 Access to Services		**1/6**
2.6.1 Access to Clean Fuels and Technologies for Cooking (% of Population)	Positive	1/4
2.6.2 Access to Electricity (% of Population)	Positive	1/4
2.6.3 People Using Improved Sanitation Facilities (% of Population with Access)	Positive	1/4
2.6.4 People Using Improved Water Facilities (% of Population with Access)	Positive	1/4

Continued on the next page

3. INSTITUTIONAL STRENGTH AND INNOVATION CAPACITY		
3.1 Human Rights		**1/6**
3.1.1 Strength of Legal Rights Index (0 = Weak, 12 = Strong)	Positive	1/3
3.1.2 Voice and Accountability	Positive	1/3
3.1.3 Human Rights Index	Positive	1/3
3.2 Government Effectiveness		**1/6**
3.2.1 Government Effectiveness	Positive	1/2
3.2.2 Regulatory Quality	Positive	1/2
3.3 Stability and Rule of Law		**1/6**
3.3.1 Control of Corruption	Positive	1/4
3.3.2 Net Migration	Positive	1/4
3.3.3 Political Stability and Absence of Violence/Terrorism	Positive	1/4
3.3.4 Rule of Law	Positive	1/4
3.4 Economic Environment		**1/6**
3.4.1 Ease of Doing Business Index	Positive	1/3
3.4.2 GDP Growth (% Annual)	Positive	1/3
3.4.3 Individuals Using Internet (% of Population)	Positive	1/3
3.5 Gender		**1/6**
3.5.1 Proportion of Seats Held by Women in National Parliament (%)	Positive	1/3
3.5.2 Ratio of Female to Male Labor Force Participation Rate (%)	Positive	1/3
3.5.3 Gender Inequality Index	Negative	1/3
3.6 Innovation		**1/6**
3.6.1 Patent Applications, Residents	Positive	1/3
3.6.2 Research and Development Expenditure (% of GDP)	Positive	1/3
3.6.3 Scientific and Technical Journal Articles	Positive	1/3

Table B.3: **Temporal and Categorical Coverage of Countries**
This table provides an overview of temporal and categorical coverage for 67 countries across the three categories of the 17 United National Sustainable Development Goals. The temporal coverage specifies the time range for which complete data is available in each category for each country. A '·' symbol indicates missing data for the respective category within the specified time frame.

Country	Temporal Coverage:		
	Sustainability and climate resiliency	Human development and social inclusion	Institutional strength and innovation capacity
Argentina	2000-2018	2000-2018	2000-2018
Australia	2000-2018	2000-2018	2000-2018
Austria	2000-2018	2000-2018	2000-2018
Bahrain	2005-2018	·	2014-2018
Bangladesh	2009-2018	2009-2018	·
Belgium	2000-2018	2000-2018	2000-2018
Bosnia and Herzegovina	2010-2018	2011-2018	2010-2018
Brazil	2000-2018	2000-2018	2000-2018
Bulgaria	2002-2018	2002-2018	2002-2018
Canada	2000-2018	2000-2018	2000-2018
Chile	2000-2018	2000-2018	2007-2018
China	2000-2018	2000-2018	2000-2018
Colombia	2000-2018	2000-2018	2000-2018
Croatia	2002-2018	2002-2018	2002-2018
Czech Republic	2000-2018	2000-2018	2000-2018
Denmark	2000-2018	2000-2018	2000-2018
Egypt	2000-2018	2000-2018	·
Estonia	2002-2018	2002-2018	2002-2018
Finland	2000-2018	2000-2018	2000-2018
France	2000-2018	2000-2018	2000-2018
Germany	2000-2018	2000-2018	2000-2018
Hungary	2000-2018	2000-2018	2000-2018
India	2000-2018	2000-2018	2000-2018
Indonesia	2000-2018	2000-2018	2000-2018
Ireland	2000-2018	2000-2018	2000-2018
Israel	2000-2018	2000-2018	2000-2018
Italy	2000-2018	2000-2018	2000-2018
Jamaica	2008-2018	2008-2018	2008-2018
Japan	2000-2018	2008-2018	2000-2018
Jordan	2000-2018	2000-2018	2002-2018
Kenya	2002-2018	2002-2018	2007-2018
Korea	2000-2018	2006-2018	·
Kuwait	2005-2018	·	2016-2018
Lithuania	2008-2018	2008-2018	2008-2018
Malaysia	2000-2018	2000-2018	2000-2018
Mauritius	2002-2018	2006-2018	2002-2018
Mexico	2000-2018	2000-2018	2000-2018
Morocco	2000-2018	2000-2018	2000-2018
Netherlands	2000-2018	2000-2018	2000-2018
New Zealand	2000-2018	·	2000-2018
Nigeria	2002-2018	·	·
Norway	2000-2018	2000-2018	2000-2018
Oman	2005-2018	·	2015-2018
Pakistan	2000-2018	2000-2018	2000-2018
Philippines	2000-2018	2000-2018	2002-2018
Poland	2000-2018	2000-2018	2000-2018
Portugal	2000-2018	2003-2018	2000-2018
Qatar	2005-2018	·	2012-2018
Romania	2005-2018	2005-2018	·
Russia	2000-2018	2000-2018	2000-2018
Saudi Arabia	2014-2018	·	2014-2018
Serbia	2008-2018	2008-2018	·
Singapore	2000-2018	·	2000-2018
Slovenia	2002-2018	2002-2018	2002-2018
South Africa	2000-2018	2002-2018	2000-2018
Spain	2000-2018	2000-2018	2000-2018
Sri Lanka	2000-2018	2000-2018	2000-2018
Sweden	2000-2018	2000-2018	2000-2018
Switzerland	2000-2018	2000-2018	2000-2018
Thailand	2000-2018	2000-2018	2000-2018
Trinidad and Tobago	2008-2018	2008-2018	2008-2018
Tunisia	2004-2018	2004-2018	2004-2018
Turkey	2000-2018	·	2000-2018
UAE	2005-2018	2013-2018	2011-2018
UK	2000-2018	2000-2018	2000-2018
USA	2000-2018	2000-2018	2000-2018
Vietnam	2006-2018	2008-2018	·

Table B.4: **Time Series Average of Categorical Scores by Country**
This table presents the time series average scores for the Environment, Social, and Governance categories across countries. Rankings are based on the average scores, with higher values indicating better performance.

Rank	Sustainability and climate resiliency		Human development and social inclusion		Institutional strength and innovation capacity	
	Country	Scores	Country	Scores	Country	Scores
1	Nigeria	0.379	Norway	0.520	USA	1.091
2	Pakistan	0.341	Denmark	0.506	Sweden	1.002
3	Switzerland	0.340	Sweden	0.494	Finland	0.986
4	Austria	0.320	Switzerland	0.451	Denmark	0.945
5	Portugal	0.301	Netherlands	0.446	Norway	0.900
6	Morocco	0.301	Israel	0.436	New Zealand	0.814
7	Romania	0.301	Finland	0.416	Germany	0.809
8	Sri Lanka	0.299	Austria	0.407	Netherlands	0.804
9	Spain	0.294	Australia	0.389	Switzerland	0.793
10	Slovenia	0.290	France	0.380	Canada	0.757
11	France	0.284	Germany	0.359	Australia	0.730
12	Hungary	0.255	Slovenia	0.345	Japan	0.683
13	Italy	0.251	Japan	0.343	UK	0.649
14	Colombia	0.245	Czech Republic	0.338	Singapore	0.640
15	Kenya	0.227	Belgium	0.338	Austria	0.605
16	Philippines	0.222	Canada	0.332	Belgium	0.519
17	Sweden	0.189	UK	0.320	Ireland	0.505
18	Bulgaria	0.184	Korea	0.313	France	0.410
19	Tunisia	0.168	Ireland	0.313	Estonia	0.399
20	Turkey	0.166	UAE	0.284	Spain	0.303
21	Bangladesh	0.159	USA	0.283	Slovenia	0.260
22	Bosnia and Herzegovina	0.149	Hungary	0.223	Lithuania	0.205
23	UK	0.140	Estonia	0.215	Portugal	0.179
24	Czech Republic	0.134	Portugal	0.187	Czech Republic	0.159
25	Mauritius	0.132	Malaysia	0.158	Israel	0.135
26	Jamaica	0.120	Poland	0.150	Chile	0.060
27	Croatia	0.118	Spain	0.126	Poland	0.037
28	Norway	0.113	Lithuania	0.113	UAE	-0.020
29	Lithuania	0.109	Russia	0.108	Hungary	-0.026
30	Germany	0.102	Italy	0.101	Italy	-0.040
31	Brazil	0.095	Argentina	0.080	Croatia	-0.121
32	Poland	0.068	Croatia	0.073	Mauritius	-0.164
33	Estonia	0.068	Mauritius	0.004	Malaysia	-0.215
34	Serbia	0.065	Chile	0.003	China	-0.219
35	Thailand	0.061	Bulgaria	-0.001	Bulgaria	-0.235
36	Finland	0.058	Tunisia	-0.007	South Africa	-0.303
37	Mexico	0.048	Brazil	-0.008	Qatar	-0.323
38	Ireland	0.019	Vietnam	-0.026	Trinidad and Tobago	-0.409
39	Argentina	-0.002	Trinidad and Tobago	-0.033	Bahrain	-0.520
40	Vietnam	-0.009	Romania	-0.044	Oman	-0.523
41	Chile	-0.016	Mexico	-0.089	Thailand	-0.572
42	Jordan	-0.030	Jordan	-0.100	Jamaica	-0.583
43	Denmark	-0.037	Thailand	-0.105	Argentina	-0.598
44	Israel	-0.041	Egypt	-0.178	Saudi Arabia	-0.628
45	Japan	-0.043	China	-0.207	Bosnia and Herzegovina	-0.630
46	Indonesia	-0.044	Serbia	-0.231	Mexico	-0.651
47	Belgium	-0.049	Bosnia and Herzegovina	-0.232	Russia	-0.652
48	New Zealand	-0.057	Colombia	-0.252	Tunisia	-0.655
49	Korea	-0.079	Jamaica	-0.299	Brazil	-0.685
50	South Africa	-0.091	Sri Lanka	-0.387	Turkey	-0.692
51	Malaysia	-0.131	Morocco	-0.417	Kuwait	-0.746
52	Egypt	-0.144	Philippines	-0.508	Colombia	-0.788
53	USA	-0.179	Indonesia	-0.526	Jordan	-0.831
54	Netherlands	-0.184	Bangladesh	-1.084	Philippines	-0.844
55	India	-0.191	India	-1.093	Morocco	-0.875
56	Saudi Arabia	-0.191	Pakistan	-1.154	Kenya	-0.896
57	Canada	-0.209	South Africa	-1.356	Sri Lanka	-0.948
58	Australia	-0.271	Kenya	-1.885	Indonesia	-0.961
59	Russia	-0.299			India	-1.019
60	UAE	-0.400			Pakistan	-1.382
61	China	-0.519				
62	Trinidad and Tobago	-0.604				
63	Singapore	-0.654				
64	Kuwait	-0.693				
65	Oman	-0.782				
66	Bahrain	-1.022				
67	Qatar	-1.037				

Table B.5: **Persistence in SDG Factors**

This table reports AR(1) regressions of monthly SDG factor returns from January 2001 to December 2020 (240 months). Specifications include (i) baseline AR(1), (ii) AR(1) with global market excess returns for developed and emerging markets, and (iii) AR(1) with extended value and size factors for both developed and emerging markets. Standard errors are Newey-West corrected for 12 lags, and t-statistics are reported in parentheses. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
Panel A: Sustainability and climate resiliency			
Lag sustainability and climate resiliency	0.034 (0.501)	0.032 (0.480)	0.041 (0.578)
Market - Emerging		0.110*** (2.753)	0.125** (2.482)
Market - Developed		-0.086 (-1.565)	-0.100* (-1.731)
SMB - Emerging			-0.052 (-0.630)
HML - Emerging			-0.075 (-0.670)
SMB - Developed			-0.046 (-0.457)
HML - Developed			0.022 (0.251)
Panel B: Human development and social inclusion			
Lag human development and social inclusion	-0.044 (-0.751)	-0.165*** (-2.836)	-0.125** (-2.024)
Market - Emerging		-0.132* (-1.888)	-0.202** (-2.565)
Market - Developed		0.268*** (3.076)	0.297*** (3.073)
SMB - Emerging			-0.102 (-0.806)
HML - Emerging			0.176 (1.515)
SMB - Developed			0.398*** (3.269)
HML - Developed			-0.411*** (-3.583)
Panel C: Institutional strength and innovation capacity			
Lag institutional strength and innovation capacity	-0.038 (-0.647)	-0.198*** (-3.200)	-0.188*** (-3.031)
Market - Emerging		-0.208*** (-3.367)	-0.282*** (-4.233)
Market - Developed		0.318*** (4.156)	0.358*** (4.316)
SMB - Emerging			-0.162 (-1.356)
HML - Emerging			0.166 (1.434)
SMB - Developed			0.339*** (2.870)
HML - Developed			-0.388*** (-4.129)

Table B.6: **Summary Statistics of Estimated Exposures**

This table presents detailed summary statistics of firm-level exposures, estimated via rolling window regressions, to SDG factors. The sample period spans 181 months, from December 2005 to December 2020.

	N	n	T	Mean	Standard Deviation			Min	p1	p5	p10	p25	p50	p75	p90	p95	p99	Max	Correlation	
					Overall	Between	Within												(2)	(3)
Excess Return (in \%)	3,413,573	36,649	93.142	1.009	16.303	4.598	16.199	-100.156	-33.658	-19.105	-13.339	-5.955	0.001	6.243	15.041	23.149	50.857	1689.395		
(1) Sustainability and climate resilience	3,413,573	36,649	93.142	-0.016	0.969	0.879	0.718	-30.194	-2.634	-1.407	-0.981	-0.455	-0.019	0.420	0.960	1.389	2.584	31.318		
(2) Human development and social inclusion	3,413,573	36,649	93.142	0.085	0.782	0.705	0.589	-23.612	-1.914	-0.992	-0.677	-0.289	0.057	0.429	0.887	1.261	2.300	32.676	0.1033	
(3) Institutional strength and innovation capacity	3,413,573	36,649	93.142	0.065	0.791	0.705	0.596	-27.236	-1.979	-1.046	-0.717	-0.312	0.048	0.424	0.874	1.236	2.239	30.995	0.1066	0.8462

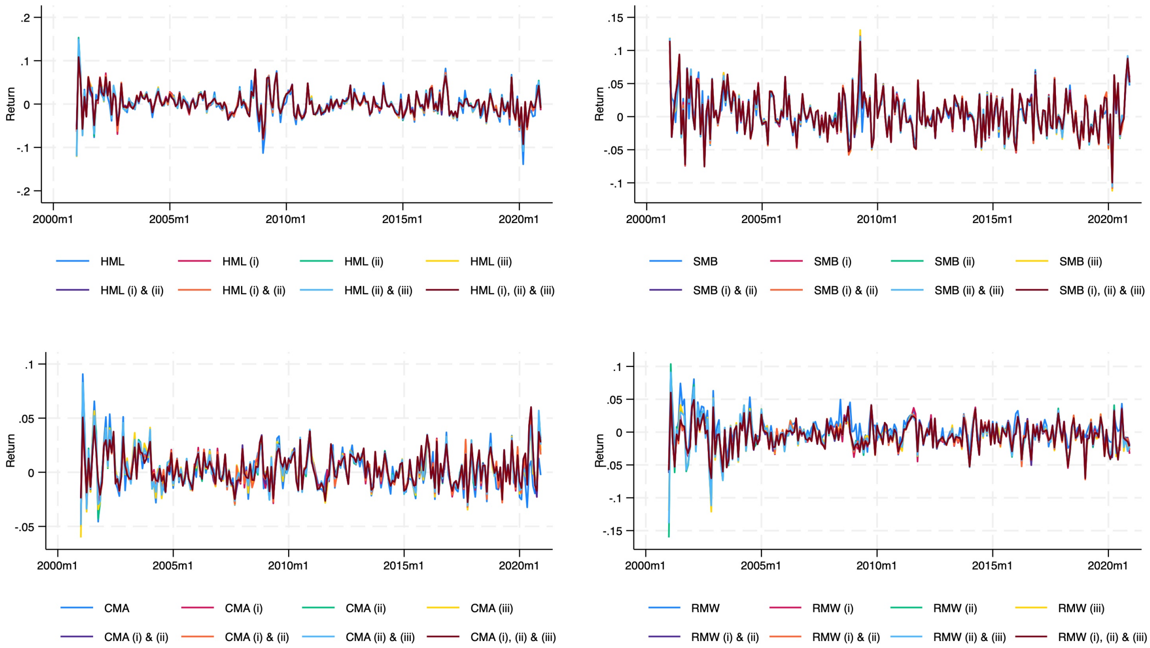

Figure B.1: This figure presents time-series plots for the portfolio returns for the original Fama-French factors and their reconstructions that are agnostic to: (i) Sustainability and Climate Resiliency, (ii) Human Development and Social Inclusion, and (iii) Institutional Strength and Innovation Capacity. The sample period spans 240 months from January 2001 to December 2020.

Table B.7: **Summary Statistics of Fama-French Factors**
This table presents the descriptive statistics of the original and reconstructed Fama-French factors. In Panel A, we present summary statistics for the returns of the original factor portfolios and their SDG-agnostic reconstructions. In Panel B, we present the correlation between original factors and their versions agnostic to SDG factors. The sample period spans 240 months, starting from 2001:M1 to 2020:M12.

Panel A: Summary Statistics

Factor Construction Agnostic to	HML		SMB		CMA		RMW	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Original	-0.001	0.029	0.003	0.027	0.001	0.018	0.003	0.022
(i) Sustainability and Climate Resiliency	0.001	0.027	0.005	0.032	0.003	0.016	-0.005	0.021
(ii) Human Development and Social Inclusion	0.001	0.029	0.004	0.031	0.003	0.017	-0.005	0.026
(iii) Institutional Strength and Innovation Capacity	0.001	0.029	0.005	0.032	0.003	0.018	-0.005	0.024
(i) & (ii)	0.001	0.026	0.005	0.031	0.003	0.015	-0.005	0.021
(i) & (iii)	0.001	0.027	0.005	0.032	0.003	0.016	-0.005	0.021
(ii) & (iii)	0.001	0.029	0.005	0.031	0.004	0.017	-0.005	0.025
(i), (ii), & (iii)	0.001	0.026	0.005	0.032	0.004	0.015	-0.005	0.021

Panel B: Correlation Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Correlations with original factor of reconstructed factors agnostic to: (i) Sustainability and Climate Resiliency, (ii) Social Inclusion and Human Development, or (iii) Institutional Strength and Innovation Capacity						
	(i)	(ii)	(iii)	(i) & (ii)	(i) & (iii)	(ii) & (iii)	(i), (ii), & (iii)
HML	0.932	0.925	0.927	0.929	0.927	0.926	0.926
SMB	0.943	0.946	0.945	0.935	0.940	0.944	0.931
CMA	0.875	0.910	0.917	0.815	0.853	0.905	0.806
RMW	0.835	0.857	0.871	0.821	0.819	0.860	0.817

Table B.8: **Comparing Performance of Standard and ESG-Agnostic Fama-French Models**

This table compares the out-of-sample squared Sharpe ratios of Fama-French factor models under two alternative constructions of non-market factors. In each comparison, *agnostic* models exclude securities with extreme *Environment*, *Social*, *Governance*, and *ESG* scores when estimating SMB, HML, CMA, and RMW, while the original model uses factors' data from the Kenneth French data library. Specifically, we remove stocks in the bottom and top deciles of each score category. The ESG scores data are from Refinitiv. The market factor is held constant across all specifications, and the sample is a cross-section of US firms. In Rows 1–8, we evaluate the three-factor model. In Rows 9–16, we extends the analysis to the five-factor model. The final column reports the difference in squared Sharpe ratios between the agnostic and original models, calculated out-of-sample using a bootstrap procedure based on the methodology of Fama and French (2018). In this approach, the time series is partitioned into adjacent monthly pairs. For each bootstrap replication, one month from each pair is randomly assigned to the in-sample set and the other to the out-of-sample (OS) set. Factor model weights are estimated using IS data, then applied to OS data to compute the OS Sharpe ratio. This procedure is repeated 10,000 times to generate the distribution of OS squared Sharpe ratios for each model. The reported differences in squared Sharpe ratios reflect out-of-sample performance, and the accompanying t-statistics are calculated using the standard error of the difference in squared Sharpe ratios across the bootstrap replications. The sample period spans from January 2001 to December 2020. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Row	Model	Factor construction agnostic to $(\cdot)$	In-Sample Squared Sharpe Ratio	Out-of-sample Squared Sharpe Ratio	Difference Out-of-sample Squared Sharpe Ratio
1	Market, SMB, HML	·	0.0279	0.0224	
2	Market, SMB, HML	(i) Environment	0.0278	0.0217	-0.0007***
3	Market, SMB, HML	(ii) Social	0.0262	0.0212	-0.0012***
4	Market, SMB, HML	(iii) Governance	0.0282	0.0219	-0.0005**
5	Market, SMB, HML	(i) and (ii)	0.0286	0.0223	0.0001
6	Market, SMB, HML	(i) and (iii)	0.0303	0.0229	0.0005**
7	Market, SMB, HML	(ii) and (iii)	0.0271	0.0214	-0.0010***
8	Market, SMB, HML	ESG	0.0300	0.0229	0.0005*
9	Market, SMB, HML, CMA, RMW	·	0.1207	0.0707	
10	Market, SMB, HML, CMA, RMW	(i) Environment	0.0847	0.0456	-0.0251***
11	Market, SMB, HML, CMA, RMW	(ii) Social	0.0890	0.0499	-0.0208***
12	Market, SMB, HML, CMA, RMW	(iii) Governance	0.0897	0.0486	-0.0221***
13	Market, SMB, HML, CMA, RMW	(i) and (ii)	0.0986	0.0573	-0.0134***
14	Market, SMB, HML, CMA, RMW	(i) and (iii)	0.0988	0.0560	-0.0147***
15	Market, SMB, HML, CMA, RMW	(ii) and (iii)	0.0959	0.0543	-0.0164***
16	Market, SMB, HML, CMA, RMW	ESG	0.1138	0.0696	-0.0011