Sustainability metrics that matter: Analysis of the SASB standards in the cross-section of returns

Ricardo HENRIQUEZ-SALMAN[*]

KEDGE Business School

This version: December 14, 2025

Abstract

This paper investigates the impact of materiality on asset pricing, focusing on the relevance of the Sustainability Accounting Standards Board (SASB) sustainability metrics. As investors place greater emphasis on environmental, social, and governance (ESG) scores, it becomes crucial to identify which sustainability metrics are material and therefore should be used to construct these scores. Using *raw*, granular sustainability data addresses this issue. However, this approach has its drawbacks as many data points are missing. To overcome this, we tackle the challenge of missing ESG data using imputation techniques. The empirical results reveal that *some* SASB metrics are significant in determining exposures with respect to systematic latent factors. In particular, the number of accidents, total waste, CO2 emissions, gender, and recycling metrics play a significant role. However, not all material metrics have the same effect in all sectors. For example, the findings underscore the need for standardized reporting frameworks that prioritize (core) material sustainability metrics, guiding ESG investment strategies.

Keywords: ESG, sustainability reporting, IPCA, missing data, cross-sectional returns.
JEL: G11, G12, G24, M14, Q51, Q56

1. Introduction

In recent years, *sustainable* investors have increasingly focused on materiality; however, identifying which sustainability issues are material to companies, investors, and society remains debated. This paper suggests that analyzing metrics individually is essential for defining materiality. This approach yields a more granular depiction of materiality and insights into which sustainability metrics provide explanatory power in the cross-section of returns. Using the Sustainability Accounting Standards Board (SASB) framework, this article presents evidence on materiality across sectors. For investors, these metrics should encompass core concerns when assessing firms within a sector or industry. [1]

ISSB Background and SASB Framework The International Sustainability Standards Board (ISSB) was established by the IFRS Foundation at COP26 in 2021 to develop global sustainability reporting standards. The ISSB builds on existing sustainability reporting frameworks, with a strong emphasis on the SASB Standards developed by the Value Reporting Foundation (VRF). The SASB Standards have seen rapid growth in adoption in recent years, reflecting their importance in shaping sustainability reporting practices (Petersen et al., 2022).[2] By integrating SASB alongside other frameworks—such as GRI (Global Reporting Initiative), TCFD (Task Force on Climate-related Financial Disclosures), IR (Integrated Reporting), and ISSB (International Sustainability Standards Board), we recognize a set of leading sustainability reporting standards. These frameworks offer guidance on ESG disclosures from varying perspectives, ranging from broad stakeholder impact to financial materiality and integrated value creation, with ISSB aiming to unify standards to enhance comparability and reduce fragmentation across jurisdictions (Giner and Luque-Vílchez, 2022; Busco et al., 2020; Hummel and Jobst, 2024). This initiative has also garnered support from major international bodies, including the G7, G20, and IOSCO, underscoring the global demand for standardized sustainability reporting while aligning with and complementing frameworks such as the European Sustainability Reporting Standards (ESRS). This integration remains a work in progress, as current developments aim to address key challenges related to scope, legitimacy, and

---

1. As of June 2024, 608 companies, representing 72% of the S&P Global 1200, have adopted the SASB Standards to communicate ESG materiality in their investor disclosures. This highlights the growing adoption of industry-specific reporting frameworks to meet investor demands for decision-useful sustainability information. Source: SASB Global Use Data.

2. The number of companies using the SASB Standards grew by 375% between 2019 and 2020, and by 215% between 2020 and 2021. Nearly 1,300 companies now use the SASB Standards globally, and over 50% companies from the S&P Global 1200 index report using the framework.

global applicability (Villiers et al., 2024).

Defining Materiality In the context of sustainability reporting, materiality serves as a critical principle that guides firms in determining which sustainable information to disclose. It is framed through two main approaches: *single* materiality, focusing on information affecting financial decisions (Jørgensen et al., 2022), and *double* materiality, which includes both financial and broader social-environmental impacts (Abhayawansa, 2022). ISSB adopts a *single* materiality approach, defining material information as that which could reasonably influence decisions if omitted, misstated, or obscured.[3] It is important to keep in mind, however, that materiality is not static; as new sustainability issues and material factors emerge, reporting practices must evolve to ensure relevant and timely disclosure (Arias et al., 2024; Kuh et al., 2020).

Materiality is also sector-specific, as sustainability issues vary by sector characteristics, regulatory requirements, and stakeholder expectations (Eccles et al., 2012). Khan et al. (2016), Ioannou and Serafeim (2019), and Grewal et al. (2021) illustrate different ways how materiality varies across sectors. For example, data privacy and cybersecurity are material metrics for the technology sector, but not for the agricultural sector, where water management and soil health are more relevant. The Sustainable Industry Classification System© (SICS), developed by SASB, categorizes companies into 11 sectors and 77 industries.

Inefficient allocation of firm resources to immaterial extra-financial activities can damage shareholders' interests and increase reporting costs (Buallay, 2019). The growing demand for sustainable investments encourages companies to engage in activities that may not directly benefit shareholders in the short term. Although these activities are expected to benefit all stakeholders in the long run, they may be inefficient and potentially harmful to shareholders' interests in the short term. Therefore, identifying core materiality metrics helps investors and corporations prioritize resource allocation and management. Given that multiple standards without widespread market adoption can burden both corporations and investors, we argue that the ISSB should focus on providing clear reporting guidance and prioritizing a reduced set of core material metrics in their standards.

Motivation and Contributions This study analyzes the link between individual sustainability metrics and financial returns, identifying which metrics drive performance,

---

3. While this paper focuses on financial impact on asset prices (single materiality), environmental and social impacts are equally important but outside its scope.

rather than aggregating them into overall ESG scores or SASB categories (Skiadopoulos et al., 2024; Berchicci and King, 2022a, 2022b; Khan et al., 2016), granular studies analyze the impact of specific metrics on pricing (Bams and Kroft, 2022; Lindsey et al., 2023; Guerrero and Viteri, 2025). Related studies, such as Bender et al. (2023), Blank et al. (2016), and Bams and Kroft (2022), examine the determinants of ESG scores and their underlying metrics. Bams and Kroft (2022) focus sustainable performance using a rank-ordering algorithm applied to granular ESG variables, relying on an unsupervised approach. They argue that ESG ratings negatively correlate with companies' sustainable performance, indicating that optimizing portfolios and making divestment decisions based on these ratings results in less sustainable portfolios than the market portfolio.

Rather than relying on composite ESG scores, we analyze individual sustainability metrics, providing insights that are particularly valuable for SASB analysts assessing materiality at the industry level. Our findings also inform investors seeking to identify sustainability metrics that are most strongly linked to both sustainability outcomes and financial performance, thereby encouraging companies to enhance disclosure in the areas that matter most.

A key challenge is the missing sustainability data, as the ISSB framework is new, sustainable disclosure remains voluntary, and international applicability is limited (Kulik and Dobler, 2023; Serafeim, 2011). To address this, we employ imputation techniques that preserve sample size and dataset coverage, outperforming simpler approaches like complete-case analysis (removing missing values) or sector (industry) median imputations (Bryzgalova et al., 2022; Freyberger et al., 2024; Crippa, 2023; Caprioli et al., 2024).

Since we rely on raw reported data, our analysis is free from methodological changes commonly made by rating agencies (Berg et al., 2021). We contribute to the literature by applying imputation and regularization techniques to a wide range of SASB metrics, thereby improving the accuracy of the estimations (Caprioli et al., 2024). Although ESG data can suffer from errors and biases (Berg et al., 2020), including back-filling (Kräussl et al., 2024), arbitrary weightings, and opaque aggregation methods (Berg et al., 2022), such issues are less pronounced when using raw sustainability metrics. Advanced imputation methods help provide a more complete picture of sustainability performance, crucial for decision-making in sustainable finance.

The paper is structured as follows. This section introduces and motivates the paper. Section 2 reviews the literature. Section 3 presents the data. Section 3 introduces the empirical imputation techniques and the latent factor model. Section 4 presents the empirical results. Section 5 discusses the importance of including raw metrics, identifies with metrics as material Section 6 discusses and concludes.

2.   Related Literature

Materiality and Stock Returns Building on SASB's materiality framework the seminal work of Khan et al. (2016) finds that firms with good ratings on material metrics significantly outperform firms with poor ratings. Although their study provided the *first* evidence for this relationship, it sparked extensive research and debate. More recently, Berchicci and King (2022a) revisited these findings, identifying methodological issues that inflated the reported returns of 13% returns over 20 years. They contend that the results may be a statistical artifact influenced by matching, winsorization, data imputation, and industry adjustments. Skiadopoulos et al. (2024) found that the alpha associated with high SASB-based ESG scores disappears when controlling for traditional financial factors, such as profitability and growth risk. This suggests that initial outperformance may be driven by fundamentals, not materiality. In contrast, Xie et al. (2023) found evidence of outperformance specifically associated with a SASB-based environmental dimension, even after taking into account traditional risk factors. This emphasizes the importance of using a more granular approach instead of relying on broad, potentially misleading, aggregated ESG scores.

Building on the implications of using raw sustainable metrics, we employ the latent factor asset pricing model developed by B. T. Kelly et al. (2019, 2020). This model captures hidden factors influencing asset returns, providing a sophisticated framework to examine the relationship between financial and sustainable characteristics. Recent applications of this approach demonstrate its utility in analyzing ESG characteristics: Chini and Rubin (2022) estimates the IPCA sequentially to differentiate between financial and sustainable (green) characteristics, while Lindsey et al. (2023) applies it to distinct ESG dimensions. Following this literature, we model the IPCA using sustainability characteristics to identify the specific factors driving returns, thereby advancing our understanding of how materiality affects asset prices.

Imputations to increase coverage It is well known that ESG data sets often suffer from significant flaws, leading to inconsistencies in ESG ratings due to varying methodological choices: weights, scopes and measurements (Berg et al., 2022), data back-filling (Berg et al., 2020; Kräussl et al., 2024), and missing data (Sahin et al., 2022; Caprioli et al., 2024; Crippa, 2023). More particularly, Sahin et al. (2022) examines the impact of

ESG missingness and its bias on scoring. Caprioli et al. (2024) compares different estimation techniques to account for uncertainty in ESG imputations.[4] Given the high sparsity of ESG data, imputing missing values poses substantial challenges. Kotsantonis and Serafeim (2019) and Berchicci and King (2022a, 2022b) emphasize that different imputation techniques can lead to varying outcomes. For instance, Lindsey et al. (2023) apply median imputation, while others use industry-level averages Li (2024), and some remove observations with missing values. Recent studies have introduced more advanced imputation techniques particularly adapted for financial datasets, though they have yet to be widely applied to ESG data. For example, Bryzgalova et al. (2022) propose a factor model based on firm characteristics that accounts for cross-sectional and temporal dependencies. Crippa (2023) using Bryzgalova et al. (2022) imputes the Environmental dimension scores from Refinitiv and MSCI. Caprioli et al. (2024) employ multiple imputation techniques to correct for selection bias. These methods can increase data coverage, though the choice of imputation technique remains crucial as it can significantly impact subsequent analyses and investment decisions, though further research is needed to establish best practices for ESG investments.

3.   Data

3.1.   Returns and firm characteristics

Return and fundamental data are obtained from CRSP/Compustat North America for US data and from Compustat Global for international data. International returns are expressed in U.S. dollars, calculated using Compustat's exchange rates. The realized returns and characteristics are from Jensen et al. (2023) available through WRDS. We apply specific filters to ensure one observation per security per month, focusing on common stocks and primary exchanges. We include a dummy variable in the data set, where 1 signifies inclusion in the S&P1200 Global index and 0 otherwise.

Table 1 presents the return statistics for each subsample. In particular, there are considerable variations in the number of observations across the different subsamples. Panel A presents the broad market segmentation, revealing distinct patterns in stock returns from 2004 to 2023. The full dataset shows an average monthly return of 0.44%, with US firms (37.19% of the sample) consistently outperforming non-US firms (0.64% versus 0.32%), accompanied by slightly higher volatility (SD of 9.67% vs. 9.24%). Panel

---

4. The results presented in this paper aligns with these studies showing that naive imputations such as sector (industry) medians worsen the explanatory power for asset pricing for some sectors.

Table 1: **Descriptive statistics: stock returns.**
    The table presents summary statistics for returns. Panel A shows the full sample divided into US and non-US firms. Panel B further breaks down the data based on LSEG coverage. Panel C categorizes firms based SASB reporting post-2015. Each panel includes statistics such as the number of observations (N), percentage, mean, standard deviation (SD), and percentiles (5th, 25th, median, 75th, and 95th). The sample period is 2004 to 2023, and 2015 to 2023 for Panel D.

	N.	perc	mean	SD.	5th	25th	median	75th	95th
Panel A: Full, USA and ex-USA sample									
Full Sample	1250435	100	0.44	9.41	-14.69	-5.23	0.43	6.06	15.89
USA	466607	37.19	0.64	9.67	-15.07	-5.19	0.67	6.41	16.50
ex-USA	783828	62.47	0.32	9.24	-14.53	-5.24	0.27	5.84	15.54
Panel B: LSEG coverage									
LSEG	705807	56.25	0.56	9.20	-14.30	-4.99	0.57	6.03	15.69
n/a LSEG	544628	43.40	0.27	9.67	-15.19	-5.55	0.25	6.11	16.11
USA, LSEG	288825	23.02	0.76	9.55	-14.81	-4.95	0.80	6.36	16.58
USA, n/a LSEG	177782	14.17	0.44	9.87	-15.49	-5.58	0.48	6.51	16.39
ex-USA, LSEG	416982	33.23	0.43	8.94	-13.93	-5.01	0.40	5.80	15.06
ex-USA, n/a LSEG	366846	29.24	0.19	9.57	-15.08	-5.53	0.13	5.90	15.97
Panel C: S&P 1200 Constituents									
S&P 1200	137244	10.94	0.62	8.50	-12.96	-4.34	0.65	5.62	14.19
non-S&P 1200	1113191	88.72	0.42	9.51	-14.91	-5.34	0.40	6.12	16.07

B examines ESG data coverage, identifying firms with at least one non-missing SASB metric in the London Stock Exchange Group (LSEG) ESG database. LSEG-covered firms, comprising 56.25% of the sample, report higher average monthly returns (0.56%) compared to 0.27% for non-covered firms. In the USA, non-covered firms account for only 14% of the subsample, compared to 30% in the global sample. Panel C analyzes S&P 1200 constituents, which make up 10.94% of the sample. These large-cap stocks exhibit low volatility, with a standard deviation of 8.50%, and an average return of 0.62%. Panel D focuses on SASB reporting in the post-2015 period, showing that SASB reporters (8.70% of the subsample, 2015-2023) achieve higher cross-sectional returns (0.52%) compared to non-reporters (0.29%). However, these represent only 4% of the full sample, 2004-2023, due to SASB framework launch in 2015. Figure 1 shows the evolution of SASB reporters and the average proportion of reported SASB metrics (available in the LSEG database). In contrast to SASB reports, SASB metrics have a longer history, with reporting rates (proportion of companies with at least one reported variable) increasing significantly since 2004 - from 40% to nearly 100% for S&P1200 companies (red line) and from 20% to 80% for WDF companies (orange line).

3.2.   Sustainability data

Sustainability data is sourced from LSEG Data & Analytics (formerly Refinitiv, originally Asset4). Available since 2002, it includes aggregated ESG scores and raw metrics. The data is accessible upon the release of companies' sustainability or financial reports, or through LSEG analysts' submissions. However, it is important to note that most sustainability data come from sustainability reports, with only a minor influence from news or ESG-related controversies. Consequently, it exhibits relatively little variation within a financial year. We assume sustainability data are available at the annual financial reporting frequency.[5]

LSEG and SICS mapping   We utilize the mapping provided by LSEG to match SASB metric codes to LSEG indicator codes. The mapping from SASB to LSEG is based on the

---

5. A 18-month period accommodates the varied publishing schedules of companies' sustainability reports. Although many companies release their reports in June, others publish in January, at different months, and sometimes quarterly. This approach ensures that data from all companies are captured, regardless of their specific reporting frequency or timing. Setting a 12-month period would result in missing gaps solely due to these non-standard reporting intervals. Moreover, filling over the entire sample period can be misleading; a company reporting data in 2010 but not thereafter would incorrectly show the same values in 2023. An 18-month window is slightly less conservative than 12 months, but still restricts the forward-filling issue.
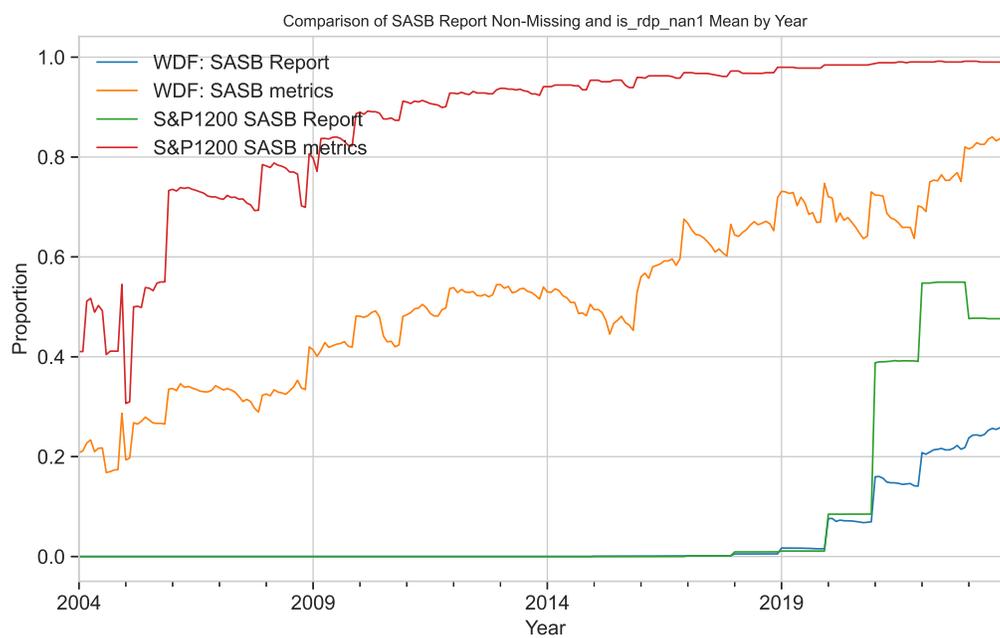
Figure 1: **Evolution of SASB reporting and metrics: WDF and S&P 1200**
Proportion of companies with at least one SASB metric found in LSEG database.
SASB reports are companies that have voluntarily adopted the standards by either
referencing SASB standards as a reporting framework or by specifically including
SASB metrics in their sustainability disclosures.

SASB Standards as of December 19, 2023. During this last update, seven changes were made, including four removals; and two additions related to financed emissions, GHG emissions, and food safety (number of product recalls). Available SASB metrics on the LSEG's ESG content set, can have either a direct match (48%), partial (47%), or can be derived (5%). We use the SASB master file to match firms to SICS classifications. This file maps over 30,000 firms to SICS (11) sectors and (77) industries. We match data using crosswalks to connect identifiers across the datasets.[6] Firms in Compustat are uniquely identified by the GVKEY and Companyid, whereas SICS are attached to firm identifiers—ISIN. We use WRDS Capital IQ Identifiers to create crosswalks between Compustat GVKEY (then Companyid) to ISIN identifiers.

SASB metrics SASB Standards include 656 distinct metrics, totaling 2,540 industry-specific metrics. These are categorized into two types: 1,796 quantitative metrics and 692 discussion metrics. However, about half of these metrics can be matched with the LSEG database, which contains only quantitative metrics. The SASB metrics in LSEG are further classified as 1,320 numerical or 680 binary. Numerical metrics are expressed in various units: 17% are in percentages (e.g. percentage of women managers), 12% in tonnes (e.g., SOx emissions in tonnes), 8% in counts (e.g., total hours of employee training) and 7% in gigajoules (e.g., energy consumption in gigajoules). Binary metrics are represented by yes/no answers. Moreover, discussion metrics, such as *"Discussion of strategies to reduce the environmental impact of packaging throughout its lifecycle,"* enable firms to provide more detailed explanations and improve investor understanding of the company sustainability profile. However, these qualitative metrics are not included in the LSEG database and are difficult to model quantitatively and integrate into traditional ESG scores.

Sample selection This analysis uses the largest dataset of comprehensive financial characteristics to maximize coverage and yield useful observations for imputing missing sustainability data. We incorporate available observations in Jensen et al. (2023) and impute missing values for specific LSEG variables. We retain accordingly the available variables for the regressions. Imputations are performed on the entire dataset, and subsamples are evaluated based on the USA, ex-USA LSEG and S&P 1200 filters. The LSEG database

---

6. While Khan et al. (2016), Berchicci and King (2022a), and Grewal et al. (2021) infer SICS codes from Global Industry Classification Standard (GICS) or Bloomberg Industry Classification Standards (BICS), we directly employ the authoritative SICS mapping from the ISSB to match issuer to SICS.
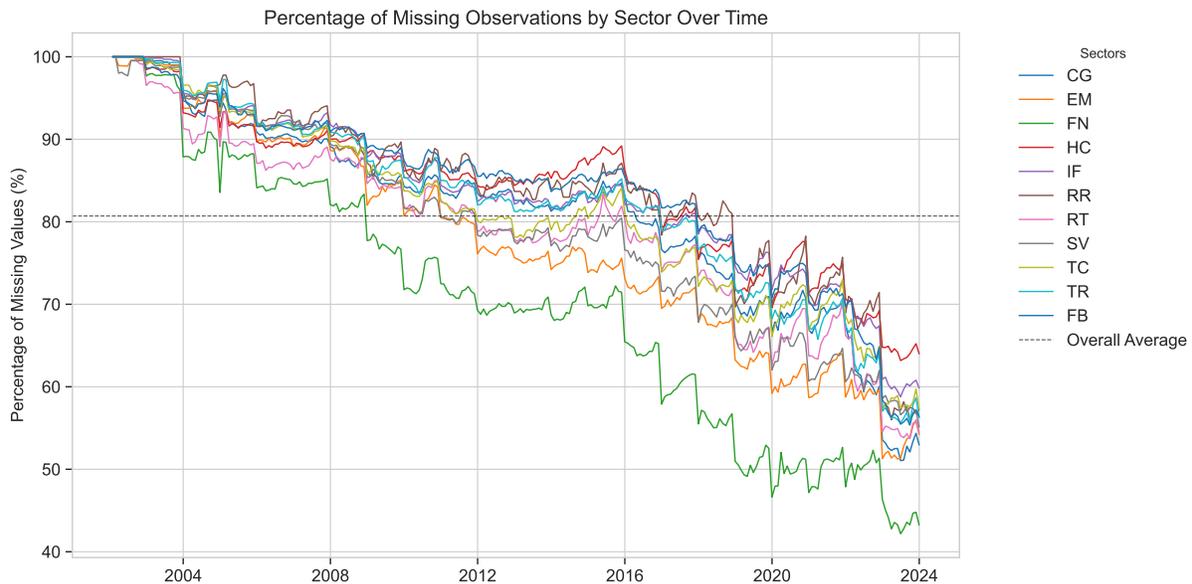
Figure 2: **Missing characteristics over time.**
This figure shows the percentage of missing observations over time by sectors. The SICS sectors and their abbreviations are as follows: 'Technology & Communications' (TC), 'Services' (SV), 'Financials' (FN), 'Resource Transformation' (RT), 'Health Care' (HC), 'Transportation' (TR), 'Consumer Goods' (CG), 'Food & Beverage' (FB), 'Infrastructure' (IF), 'Extractives & Minerals Processing' (EM), and 'Renewable Resources & Alternative Energy' (RR).

covers, on average, 23% of data points across the sample. However, the extent of missing data varies significantly by industry, ranging from 17% to complete absence (100%). Figure 2 illustrates a decline in coverage over time, reflecting the limitations of the LSEG sample.

3.3.   Missing SASB Data

This section starts by presenting the descriptive statistics of the missing sustainability reporting data and the determinants of sustainability disclosure (non-missingness).

LSEG indicates its *large* coverage over "*90% of global market cap with 720 ESG metrics.*" However, this dataset is far from a balanced panel. As we go further back in time, data becomes notably scarce. Although sparse data are expected due to varying material issues in industries, the significant increase in coverage since 2013 aligns with the increasing trend in sustainable reporting (Lindsey et al., 2023).

As shown in Table 2, companies report on sustainability topics with varying levels of coverage. Some firms include all metrics specified in the SASB Standards for their industry, providing full coverage. Others report on all topics but only disclose partial

Table 2: SASB Reporting Scope

Last Report Scope		Last Reporting Year	
Full	4984	2023	2434
Most topics, partial metrics	1477	2022	2196
All topics, partial metrics	1132	2024	1700
Selected Metrics	422	2021	1374
Partial	311	2020	548

metrics for some of them. A third group covers more than 50% of the topics, again with partial metrics. Finally, some firms disclose less than 50% of the topics, providing data on only a few selected metrics. This variation reflects differences in compliance and the level of detail in reporting.

Missing data distributions Figure 3 displays the percentage of missing observations for each characteristic. We categorize missing data into three types: missing at the beginning (Start), missing at the end (End), or missing observations in the middle (Middle). Newer firms tend to have missing data at the beginning, whereas missing data at the end may indicate that a firm stopped reporting that metric. Missing data in the middle suggests that the firm reported the metric at some point but did not report it consistently. The most common form of missingness occurs at the beginning, reflecting the growing adoption of sustainability reporting in recent years.

We note that only 10% of the observations across industries include all SASB metrics. Although many firms miss a few characteristics within their sector, a significant number lack 35 to 45 characteristics by industry. Thus, removing only a few characteristics with many missing values will not effectively resolve the issue of missing data. Figure 2 shows the evolution of missingness over time by sector. Reporting has improved in all sectors, with the financial sector (FN) releasing 50% and the health care sector (HC) the lowest at 35%. On average, 80% of observations are missing values, making a balanced panel nearly impossible.[7]

Mask non-material variables Some companies may report variables that are non-material under SASB standards. For this analysis, we focus solely on the sustainable metrics identified as material by SASB, leaving the exploration of additional material metrics outside the scope of this article.

---

7. Figures in Appendix E further illustrate the missingness structure in the data. Appendix E shows the distribution of missing values by variable type, distinguishing numerical from binary variables.
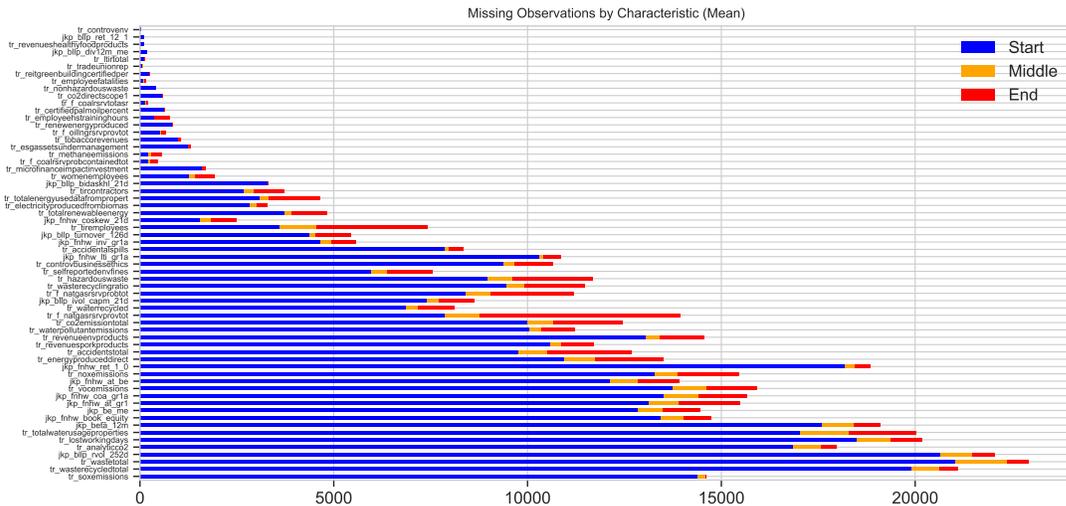
Figure 3: **Missing Observations by Characteristic**
This figure shows the average percentage of missing observations for each characteristic. We decompose the missing values in those missing at the start (no previous observations), the middle (some previous and future observations), the end (no further observations).

Figure 4 shows the fraction of incomplete observations in the market equity (ME) quintiles. Larger firms report more observations, while smaller firms have a lower percentage of observations reported. For example, in the lowest quintile, the most reported sustainable characteristic has around 30% of reporting, while in the largest quintile, the most reported characteristic has more than 80% reported observations. Several reasons explain why sustainability data may be missing in relation to the size of the firm. First, smaller or younger firms may be less likely to report comprehensive sustainability metrics due to resource constraints, even if their sustainability performance is not systematically worse than that of larger firms. Second, companies in certain industries or geographic regions may face varying reporting requirements or norms about sustainability disclosure, leading to differential missingness patterns. Third, firms with lower analyst coverage or market visibility may have less external pressure to disclose detailed sustainability information, regardless of their true sustainability profile. [8]

8. Appendix Table 7 presents the top 10 most and least frequently reported SASB sub-metrics within LSEG, categorized by data type (numerical and binary).
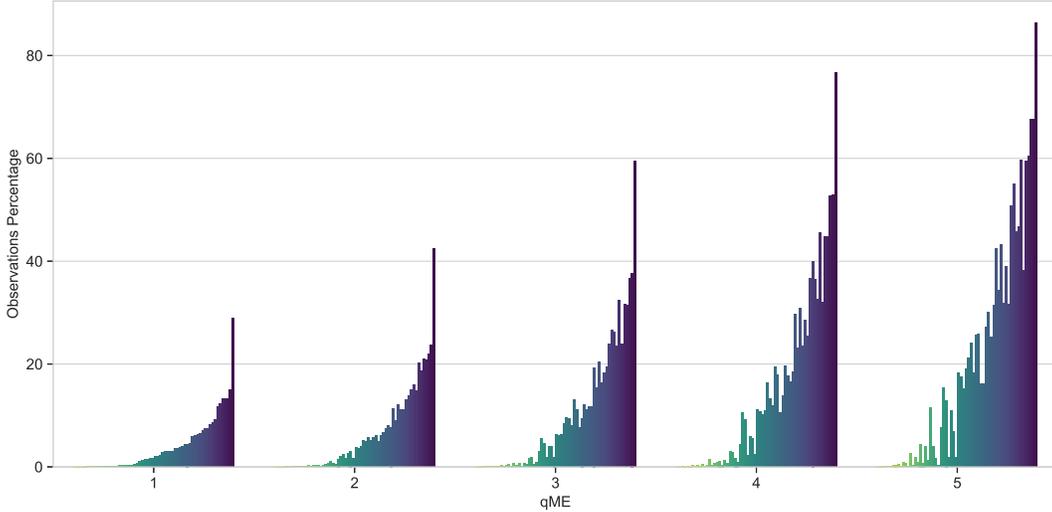
Figure 4: **Non-Missing Observations by Characteristic over ME quintiles**
This figure shows the percentage of missing observations by size quintiles. Each bar represents a characteristic, with taller bars indicating a higher level of available observations.

4.   Imputation and Asset Pricing Model

To impute data, certain algorithms require consistent characteristics across the sample. We select characteristics that closely align with those used by Bryzgalova et al. (2022) and Freyberger et al. (2024). From Bryzgalova et al. (2022), we use market equity (`me`), dividend yield (`div12m_me`), idiosyncratic volatility (`ivol_capm_252d`), return reversal (`ret_12_1`), bid-ask spread (`bidaskhl_21d`), turnover (`turnover_126d`), return volatility (`rvol_252d`). From Freyberger et al. (2024), we use asset growth (`at_gr1`), market beta (`beta_252d`), book-to-market equity (`be_me`), book leverage (`at_be`), inventory change (`inv_gr1a`), coskewness (`coskew_21d`), change in current operating assets (`coa_gr1a`), change in long term investments (`lti_gr1a`), highest daily closing price during month (`prc_high`), maximum daily return (`rmax1_21d`), and short-term reversal (`ret_1_0`).

As the main estimation, we use both sets of characteristics to impute missing values.[9] Table 6 presents descriptive statistics for financial characteristics. Most financial variables have high coverage, with missing values ranging from 1% to 16%. Notably, inv_gr1a, lti_gr1a, and coa_gr1a exhibit the lowest coverage (92% to 84%).

---

9. As a robustness check, we estimate the models using each set individually, yielding similar results.

Set of characteristics Let $C_{i,t,l}$ represent the characteristics in a 3-dimensional tensor, where:

$$C_{i,t,l} \quad \text{for} \quad i = 1, \dots, N_t, \quad l = 1, \dots, L, \quad t = 1, \dots, T. \tag{1}$$

This tensor C has dimensions $N_t \times T \times L$, where N_t is the number of firms observed at time t, T is the total number of time periods, and L is the total number of characteristics. At time t, $C_{i,l}^t$ corresponds to the matrix of characteristics $N_t \times L$.

To standardize characteristics like financial ratios, monetary values, or estimates, we apply a cross-sectional rank transformation followed by normal inversion (Freyberger et al., 2024; Goyal and Saretto, 2024). This method reduces the influence of measures and ensures comparability. For each characteristic l, we apply its rank transformation, denoted $\widetilde{C}_{i,l}^{t-1}$, mapping the cross-sectional distribution to the unit interval with mean 0; that is, $\widetilde{C}_{i,l}^{t-1} \in [-0.5, 0.5]$. The transformation is defined as follows:

$$\widetilde{C}_{i,l}^{t-1} = \frac{\text{rank}(C_{i,l}^{t-1})}{N_t} - 0.5 \tag{2}$$

Then, to convert this rank transformation to z-scores, apply the inverse cumulative distribution function (CDF) of the normal distribution:

$$\check{C}_{i,l}^{t-1} = \Phi^{-1}\left(\widetilde{C}_{i,l}^{t-1}\right) \tag{3}$$

where Φ^{-1} represents the inverse CDF of the standard normal distribution, and its interval $\check{C}_{i,l}^{t-1} \in [-3; 3]$. The advantage is that, relative to the ranks, it enforces normal distributions (Goyal and Saretto, 2024). This will be important for purely convenience and facilitates a placebo test in which we will select random values from the normal distribution $\mathcal{N}(0, 1)$ to impute the data.

4.1.   Imputation Methodology

To tackle the problem of missing data, various imputation methods exist, depending on whether the data is continuous or binary. Cutting-edge developments in imputation strategies for financial data are primarily concerned with continuous data (Freyberger et al., 2024; Bryzgalova et al., 2022; Chen and McCoy, 2024).[10]

---

10. For binary variables the multiple imputations by chained equations (MICE) approach can be applied, see example, Caprioli et al. (2024) with regard to ESG scores, however, the IPCA factor-latent model does not apply to binary data, which necessitates concentrating solely on numerical metrics.

Numerical Variables   For numerical variables, we implement the Bryzgalova et al. (2022) and Xiong and Pelger (2023) imputation algorithm due to its efficiency and accuracy in the handling of financial data. This approach utilizes partially observed characteristics rather than depending solely on a limited subset of observations. For example, in unreported results, we imputed the data set using the Freyberger et al. (2024) algorithm, which imputes on the subset of stocks with fully observed financial characteristics, which imply *single* materiality. We perform imputations at both the global and sector levels for all variables, capturing industry-specific trends and correlations. Consequently, we utilize the complete set of financial and sustainability metrics by industry to impute missing values. The ranking transformation described in Eq. 2 is also applied to sustainability characteristics.

Bryzgalova et al. (2022) method works for small T and large C. In this analysis, the dimensions for the full sample are $N = 6,000$, $T = 228$ and $L = 64$, and for the S&P1200 sample $N = 900$, $T = 228$, and $L = 64$. The model employed exploits two dimensions: the data cross-sectional dependency and their time series (B-XS). That is, the prediction of $C_{i,l}^t$ may derive from past or contemporaneous cross-sectional information. Moreover, the model allows for local estimation, hence preserving the dependency of factor and loadings over time. This simulates the information set available to investors at time t. This setup allows for a different factor model at each time t and, hence, is a local model. Appendix C provides more details.

Sector (industry) median   After the imputation process, we mask the variables irrelevant to the specific industries for each sector. To benchmark and evaluate our imputation methods, we compare against industry (MED-Ind) and median imputation (MED-Sect). RMSEs for local B-XS and median imputations are presented in table 3. The models are tested against removing 30% of all observations for each sustainability metric and removing 60 months randomly from the sample for all characteristics. The table shows that the B-XS model performs best in terms of RMSE, with values of 0.19 for the random mask and 0.20 for the time mask. This suggests that B-XS is the most effective in imputing missing values, probably because of its ability to use cross-sectional and historical data. In contrast, the median imputation methods show worse performance, with MED-Sect performing the worst (0.35 for random mask and 0.41 for time mask). This is expected, as imputing values using a sector-wide median likely fails to capture the nuanced relationships within a specific industry, highlighting that relying on broader sector data can degrade imputation accuracy.

Model	Random Mask	Time Mask
B-XS	0.19	0.20
MED-Sect	0.35	0.41
MED-Ind	0.25	0.27

Table 3: RMSE for local BXS from (Bryzgalova et al., 2022) and median imputations: on random mask (removing 10% of each characteristic), and time mask (removing 60 months from the sample).

4.2. Asset Pricing Implications

This section outlines the conditional asset price model, including estimates and inference details.

Empirical Model: IPCA The asset pricing model derives from the latent factor model of B. T. Kelly et al. (2020, 2019) and Bybee et al. (2023). This model extends PCA by incorporating time-varying parameters to explain stock returns, extracting common factors from characteristics that may represent both financial and sustainable characteristics.

The cross-section of excess stock returns adheres to a latent factor structure:

$$r_{i,t+1} = \alpha_{i,t} + \boldsymbol{\beta}'_{i,t}\mathbf{f}_{t+1} + \epsilon_{i,t+1}, \ \forall i = 1, \cdots, N \text{ and } t = 1, \cdots, T \tag{4}$$

the alphas $\alpha_{i,t}$ and the factor loadings $\boldsymbol{\beta}'_{i,t} \in \mathbb{R}^{(K \times 1)}$ are time-dependent. The IPCA models

$$\alpha_{i,t} = \mathbf{c}'_{i,t}\boldsymbol{\Gamma}_\alpha + \upsilon_{\alpha,i,t} \tag{5}$$

$$\beta_{i,t} = \mathbf{c}'_{i,t}\boldsymbol{\Gamma}_\beta + \mathbf{v}_{\beta,i,t}, \tag{6}$$

where $\mathbf{c} \in \mathbb{R}^{(1 \times L)}$ denotes observed asset-specific characteristics, and $\boldsymbol{\Gamma}_\alpha \in \mathbb{R}^{(L \times 1)}$ and $\boldsymbol{\Gamma}_\alpha \in \mathbb{R}^{(L \times K)}$ are matrices of parameters estimated from the data. $\boldsymbol{\Gamma} = [\boldsymbol{\Gamma}_\alpha, \boldsymbol{\Gamma}_\beta]$ are estimated by panel regressions of stock returns on the interaction of factor realizations and lagged firm (financial and sustainable) characteristics. Given that ICAPM theory assumes a zero intercept and that $\epsilon_{i,t}$ is orthogonal to f_t (Merton, 1973), the estimation of the restricted IPCA, where $\boldsymbol{\Gamma}\alpha = \mathbf{0}_{(L \times 1)}$, is denoted:

$$r_{i,t+1} = \mathbf{c}'_{i,t}\boldsymbol{\Gamma}_\beta\mathbf{f}_{t+1} + \epsilon^*_{i,t+1} \tag{7}$$

In matrix form for N_t firms at time t it becomes:

$$\boldsymbol{r}_{t+1} = \mathbf{C}'_t\boldsymbol{\Gamma}_\beta\mathbf{f}_{t+1} + \epsilon^*_{t+1} \tag{8}$$

The model is estimated by minimizing:

$$\min_{\boldsymbol{\Gamma}_\beta,\mathbf{f}} \sum_{t=1}^{T} (\boldsymbol{r}_{t+1} - \mathbf{C}'_t\boldsymbol{\Gamma}_\beta\mathbf{f}_{t+1})'(\boldsymbol{r}_{t+1} - \mathbf{C}'_t\boldsymbol{\Gamma}_\beta\mathbf{f}_{t+1}) \tag{9}$$

with first-order condition $\hat{\mathbf{f}}_{t+1} = (\hat{\boldsymbol{\Gamma}}'_\beta\hat{\mathbf{C}}'_t\hat{\boldsymbol{\Gamma}}_\beta\hat{\mathbf{C}}_t)^{-1}\hat{\boldsymbol{\Gamma}}'_\beta\hat{\mathbf{C}}'_t\boldsymbol{r}_{t+1}$, $\forall t$.[11]

Some advantages using this model include the estimation of large N cross-section of stocks, large characteristics L with relatively small T, it is able to handle missing data information (given some conditions), conditional betas, and an estimated factor space that has been shown to be closer to the mean variance-efficient frontier (B. T. Kelly et al., 2019; Deng et al., 2024). We will assess its performance by comparing the Sharpe ratios of the tangency portfolios across different specifications. This analysis will evaluate the role of sustainable characteristics and the impact of their imputations on the models.

Given the latent nature of the model, it identifies which instruments drive returns without imposing the fact that the factor structure is known beforehand. Unlike studies on ESG materiality reporting either significant or insignificant returns to sustainability portfolios—often raw or adjusted using traditional factor models—this approach assesses whether sustainability adds incremental information beyond the pre-specified factors already considered by investors.

Characteristic-Managed Portfolios We rely on the interpretation behind the characteristics managed portfolios, constructed as follows:

$$\boldsymbol{x}_{t+1} := \frac{\mathbf{C}'_t\boldsymbol{r}_{t+1}}{N_t} \tag{10}$$

where $\boldsymbol{x}_{t+1} \in \mathbb{R}^{(L\times1)}$, N_t, $\mathbf{C}'_t \in \mathbb{R}^{(L\times N_t)}$, and $\boldsymbol{r}_{t+1} \in \mathbb{R}^{(N_t\times1)}$ are respectively the return on a characteristic-managed portfolio at time $t+1$, the number of firm at time t, all financial and sustainable characteristics at time t and the individual returns at time $t+1$. The characteristic-managed portfolio return is the return on a portfolio weighted by characteristics and normalized by $\frac{1}{N_t}$ so that the volatility of the portfolio is not affected by the number of firms available at time t. This results in a $(T\times L)$ matrix X, where each column represents a series of time periods of returns for a portfolio managed according to a particular characteristic, facilitating the examination of how sustainable characteristics affect portfolio performance.

11. For further details please refer to the appendix D and B. T. Kelly et al. (2019, 2020).

Estimation and inference: Which characteristics matter ? Following Goyal and Saretto (2024), we test which characteristics are most important. We compute the Wald statistics $W_\alpha = \hat{\Gamma}'_\alpha \hat{\Gamma}_\alpha$ from the actual data and $W_\alpha^b = \hat{\Gamma}_\alpha^b{}' \hat{\Gamma}_\alpha^b$ from the bth bootstrap sample. Inferences are made by calculating the p-value as the fraction of bootstrapped W_α^b statistics that exceed the value of W_α from the observed data. We use $B = 1,000$ bootstrap simulations.

5.   Results

Long-Short Portfolios: Quintiles We begin by presenting the results on long-short (LS) portfolios. For each sustainability variable l that is material (according to SASB) within a sector s, we sort monthly returns into portfolio quintiles.[12] Form LS portfolios for each material variable l within each sector s.[13] This method ensures that the materiality at the sector level is preserved. Figure 5 shows the performance of the LS portfolios for the observed sample, the median industry imputed sample, and the BXS imputed sample. Raw returns and alphas are either close to zero or significantly different from zero but relatively close to each other. After accounting for traditional factors (CAPM, FF5 and Q-factors),[14] `waste_recycled_total` for the three samples and `litigation_expenses` for med-ind and BXS show significant returns different from 0.

If we restrict the sample from 2015-2023, more sustainable characteristics become significantly different from 0. For example, `co2emissionstotal` (Bolton and Kacperczyk, 2023; Aswani et al., 2024; Zhang, 2024),[15] `water_recycled` (Eubank, 1991), and `accidents_total` (Lanza et al., 2020). Furthermore, positive performance from water

---

12. Portfolio sorts are useful but limited. They can only analyze a small set of characteristics; the curse of dimensionality is a well-known drawback in asset pricing. See Fama and French (2015) for a discussion.

13. Two other approaches were considered but ultimately discarded to maintain the materiality-driven impact of these metrics. The first involved forming portfolios using all available observations for a metric l at time t, irrespective of materiality. This method neglects SASB-defined materiality, incorporating metrics reported by firms that may not be sector-relevant. The second approach aggregated all sectors where a given metric l was deemed material. Although this captures the overall metric impact, it fails to address sector-specific variations.

14. We calculate the alphas of these prespecified factors models for each characteristic l. Using the classical factor modeling, as presented by Fama and French (1993, 2015), we assume that returns adhere to the linear model:

$$r_{i,t} = \alpha_i + \boldsymbol{\beta'}_{i,t} \mathbf{f}_t + \epsilon_{i,t}. \tag{11}$$

We compute Newey and West (1987) standard errors with 12 lags.

15. Although there is well-known mixed evidence regarding the sign of the relationship between CO2 emissions and stock returns, Lioui and Misra (2023) appears to reconcile these findings.

recycling suggests that companies investing in water recycling are increasingly being rewarded, highlighting that sustainability initiatives, especially in resource conservation, can lead to improved financial performance over time. These trends suggest that the market may be starting to price in the benefits of sustainability, and certain practices are becoming more aligned with positive financial return. This is corroborated by Chen and Huang (2024), and more particularly in the chemical industry by Zhang et al. (2018).

LS portfolios with positive significant results can represent a "green premium," where firms with better sustainability traits are rewarded for lower risk or greater investor confidence. In contrast, negative relationships reflect a "risk premium," where firms with weaker sustainability characteristics face higher risks, such as regulatory penalties or reputational damage, leading investors to demand higher returns as compensation. This difference highlights the risk-return trade-off in sustainable investing (Zerbib, 2022; Pástor et al., 2020; Pedersen et al., 2021). However, two challenges arise with long-short (LS) portfolios based on sustainable characteristics. First, certain material characteristics behave as anomalies within standard asset pricing models. As Skiadopoulos et al. (2024) argue, the performance of these materiality-based portfolios stems from the economic relevance of the metrics, though their returns often reflect correlations with other firm characteristics, complicating interpretation. Second, the use of imputation techniques, where missing values are replaced cross-sectionally using industry or sector medians, has minimal influence on the overall results. This occurs because firms with imputed metrics are typically assigned to middle quintiles, leaving the extreme portfolios—those driving LS returns—largely unaffected

Sustainability-Managed Portfolios Sustainability-managed portfolios represent a better alternative compared to LS portfolios. Since the characteristics most of the time are cross-sectionally correlated, it is important to understand how much independent information they provide. Therefore, as a first step, we check the correlation between the managed portfolio returns.

We present the heatmap of the 64×64 correlations in Figure 7. While some clusters exhibit high correlations—most notably among variables associated with board composition and gender characteristics (e.g., the proportion of women in executive management, managerial roles, and general employment)—portfolios in the lower-left corner display a broader range of correlation magnitudes. On average, the correlations in the observed sample are 4.1%, which is lower than those derived from the median imputations, at 6.5% and 6.7%, respectively. Notably, the BXS-imputed sample achieves the lowest average correlation of 3.7%. This enhances the potential for portfolio diversification by reducing
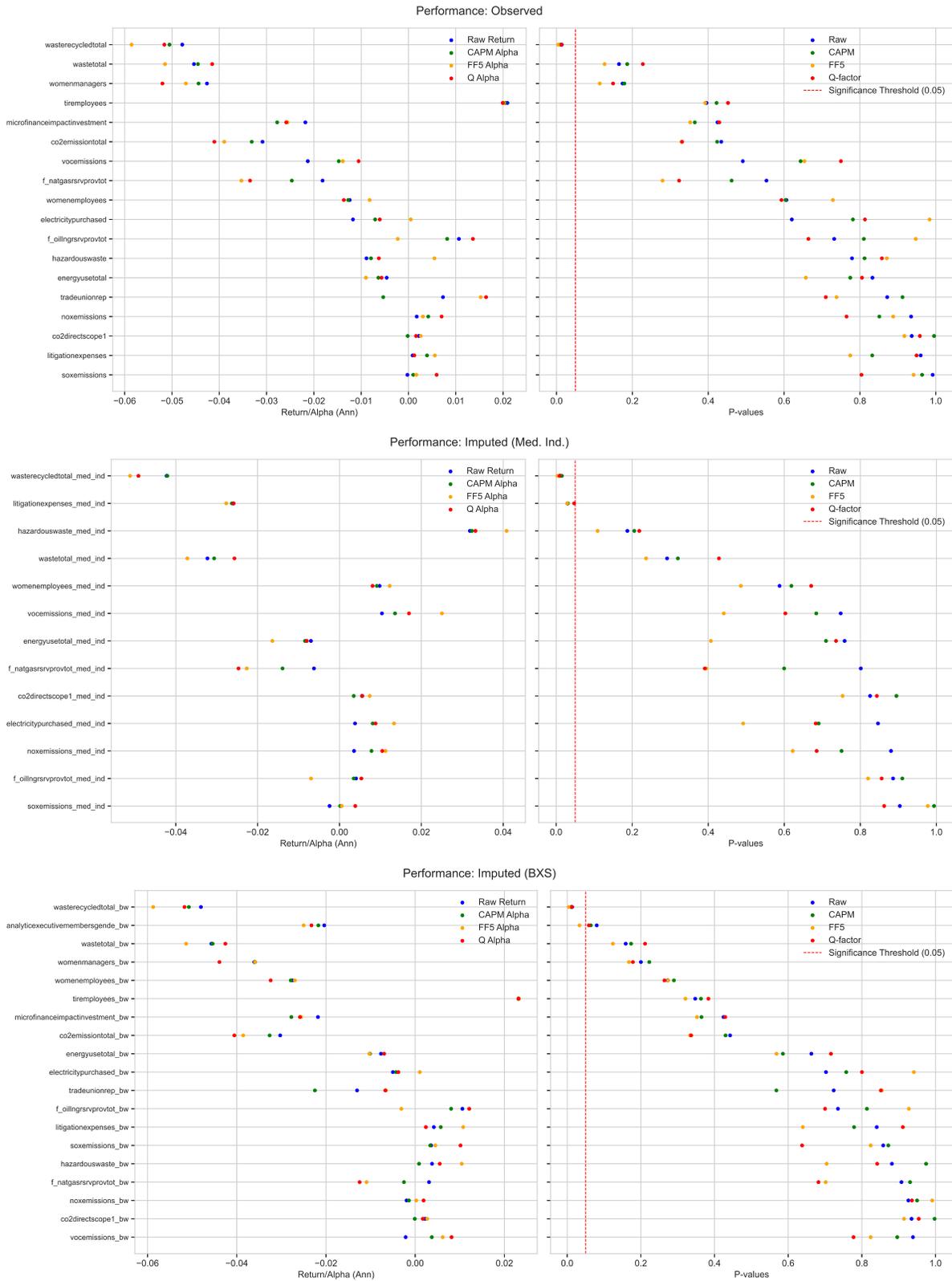
Figure 5: **Long-Short Portfolios Sorted on Sustainability characteristics: full sample**
Top (Observed), Middle (Med-Ind), and Bottom (B-XS)

Figure 6: **Long-Short Portfolios Sorted on Sustainability characteristics: 2015-2023 sample**
Top (Observed), Middle (Med-Ind), and Bottom (BXS)

systematic co-movements. Additionally, correlation clusters do not align with established sustainability dimensions (Environment, Social Capital, Human Capital, Leadership & Governance, or Business Model & Innovation).
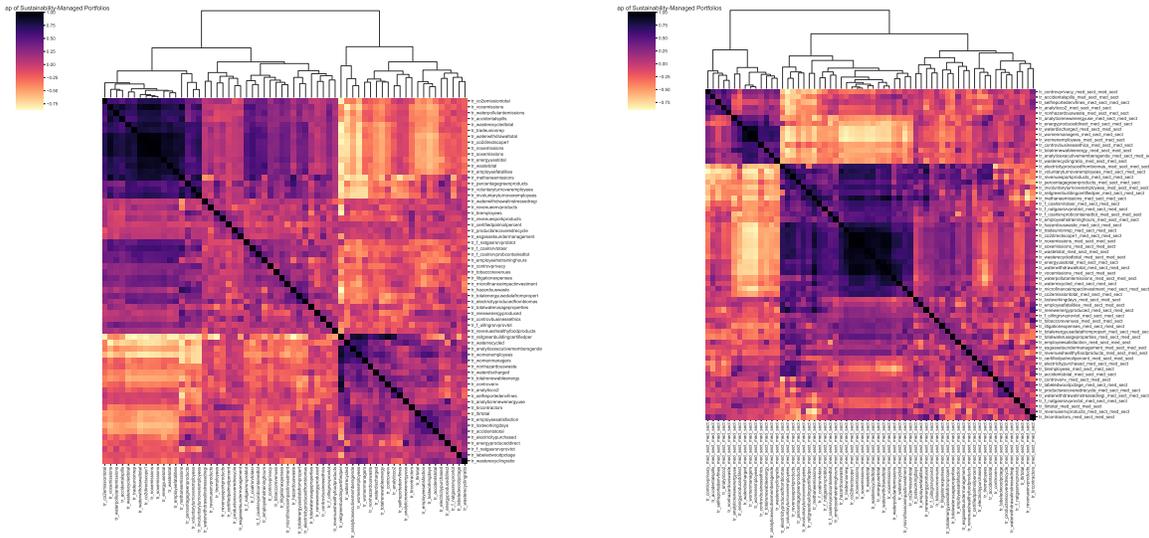
(a) Observed Sample (Avg. corr: 4.1%)

(b) Median Sector (Avg. corr: 6.5%)
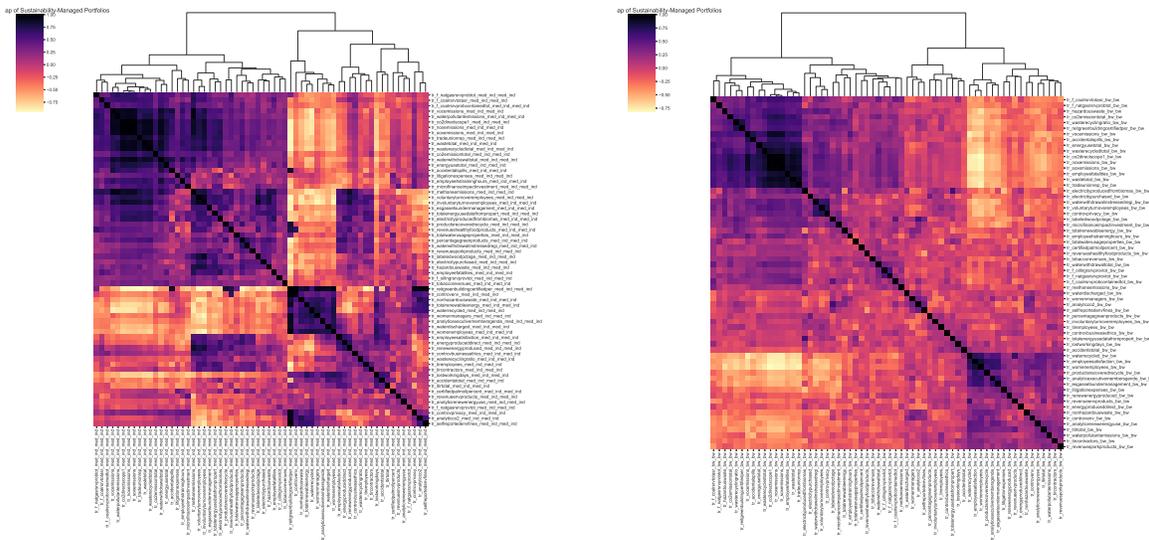
(c) Median Industry (Avg. corr: 6.7%)

(d) BXS (Avg. corr: 3.7%)

Figure 7: **Clustermap of Sustainability-Managed Portfolios**

IPCA performance   Now, we examine the constrained IPCA model by setting α to zero ($\mathbf{\Gamma}_\alpha = 0$). Our objective is to estimate the IPCA model across various specifications using different data imputations: observed (Obs.), median imputation by sector (sect.)

or industry (ind.) and B-XS. We set a threshold of 70%, corresponding on average the 30 variables with the least number of missing observations. Otherwise, if the percentage of missing observations exceeds this threshold, the IPCA model fails to converge.We assess IPCA factor performance by calculating Sharpe ratios of their optimal portfolios. These portfolios are constructed by mean-variance optimization of the latent factors, with results reported for factor counts (K) ranging from 3 to 6. Figure 8 presents the Sharpe ratios for the full sample and the S&P 1200 sub-sample. The figure reveals that the JKP+SUS (BXS.) imputation (in red) consistently yields the highest Sharpe ratios, suggesting it delivers superior risk-adjusted returns across both samples. For example, with $K = 3$, the Sharpe ratio is 0.15 for B-XS. Using only financial data (in blue) yields a Sharpe ratio of 0.10, while using only observable sustainable characteristics (in orange) gives a ratio of 0.12. The imputation based on industry median (in green) results in a Sharpe ratio of 0.11, outperforming the use of financial data alone but falling short of the observed sustainable characteristics. Conversely, the "JKP+SUS (ind.)" strategy, relying on industry-level imputations, generally produces lower Sharpe ratios, indicating that this imputation method may be less effective in enhancing portfolio performance. The last column, in purple, presents the results of the placebo test, where the characteristics are filled based on a random distribution. This shows that increases in performance are not purely due to chance.
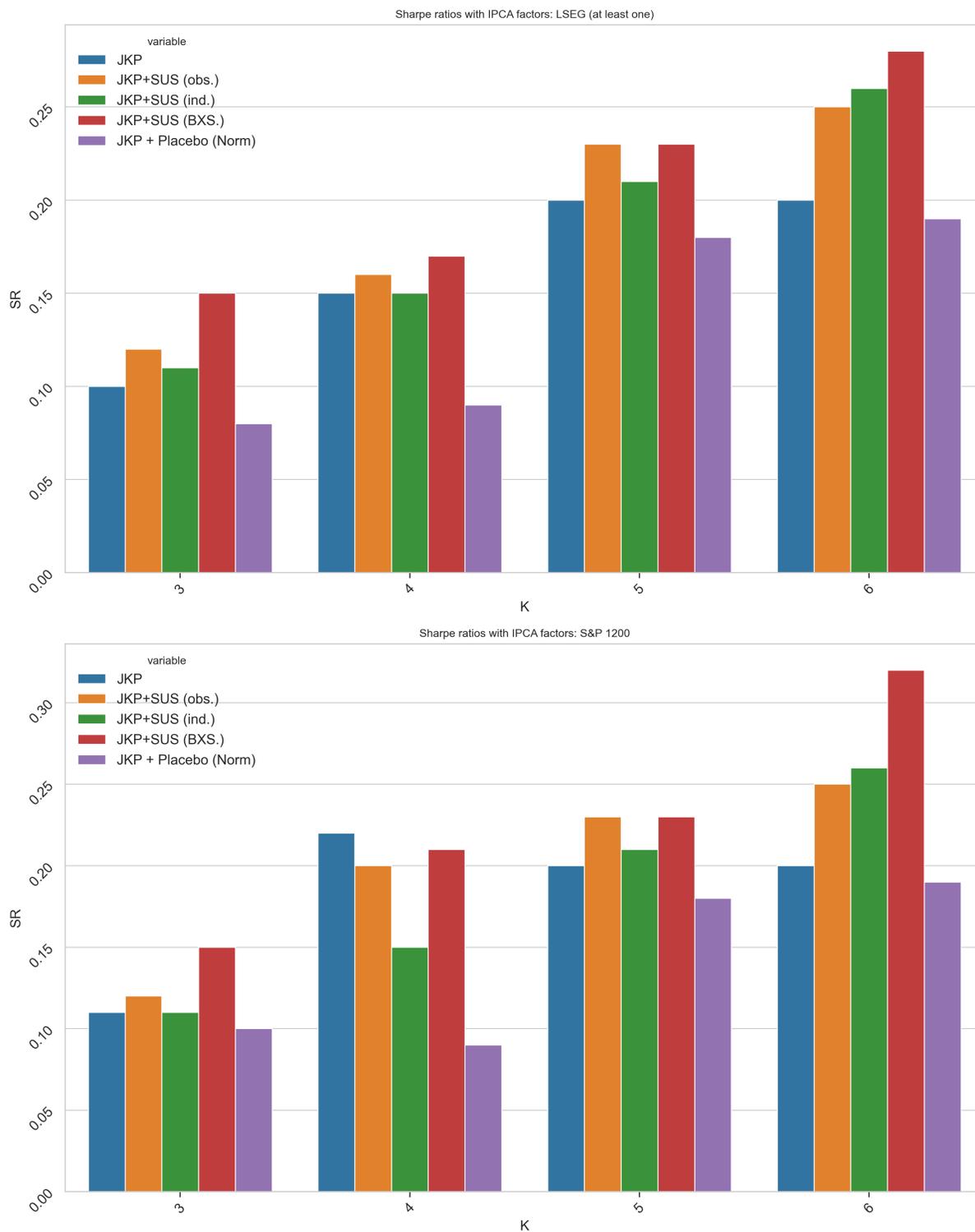
Figure 8: Sharpe ratios with IPCA factors: WDF (above) and S&P 1200 (below).

Table 4: **IPCA performance**

The table presents performance measures of IPCA models for different latent factors (K) returns. We report Total, Time Series, and Cross Section R2, as well as the Relative Pricing Error (all in percent) from equation for individual stocks and managed portfolios for the constrained ($\Gamma_\alpha = 0$) model. The last row of the top panel reports number of unpriced factors calculated as the number of estimated IPCA factors whose returns are statistically indistinguishable from zero. In Panel B, we report out-of-sample performance measures, obtained by splitting the sample in half and using the first half to estimate the model. We then roll the estimation procedure forward one month at a time, until the end of the sample. Results are reported for IPCA models with K=1 to 5. The sample period is 2004 to 2023.

	Number of Factors				
	1	2	3	4	5
Stock-Level:					
Total R^2	35.77	36.07	36.35	36.61	36.85
Time Series R^2	31.60	31.90	32.14	32.36	32.62
Cross Section R^2	23.28	23.60	23.86	24.09	24.35
Relative Pricing Error	73.85	73.80	73.72	73.71	73.66
Managed Portfolios:					
Total R^2	95.92	96.11	96.31	96.46	96.59
Time Series R^2	20.30	25.43	29.53	32.56	36.11
Cross Section R^2	76.79	77.57	77.93	78.56	78.96
Relative Pricing Error	1.53	1.03	1.10	1.08	1.00
# Unpriced Factors	0	0	0	1	3
Stock Level OOS:					
Total R^2	30.16	30.37	30.39	30.62	30.74
Time Series R^2	−62.17	−58.38	−59.55	−58.56	−55.05
Cross Section R^2	23.24	23.46	23.51	23.71	23.85
Relative Pricing Error	76.43	75.19	74.95	74.54	74.55
Managed Portfolios OOS:					
Total R^2	36.08	34.31	35.46	33.67	36.54
Time Series R^2	6.48	10.27	11.47	14.20	15.26
Cross Section R^2	29.58	27.72	28.77	27.59	30.47
Relative Pricing Error	64.07	59.26	54.28	54.01	50.90

Table 5: **IPCA across different models:** $K = 5$

The table presents performance measures of IPCA models ($K = 5$) for different set of characteristics. JKP includes observed financial characteristics, JKP+SUS includes observed financial and sustainability characteristics, JKP + SUS (Med-Sect) imputes missing sustainability data at the sector median, JKP + SUS (Med-Sect) imputes at the industry median, JKP + SUS (B-XS) imputes sustainability data using Bryzgalova et al. (2022), JKP + SUS (Norms) fills missing data from a random normal distribution. We report Total, Time Series, and Cross Section R2, as well as the Relative Pricing Error (all in percent) from equation for individual stocks and managed portfolios for the constrained ($\Gamma_\alpha = 0$) model. The last row of the top panel reports number of unpriced factors calculated as the number of estimated IPCA factors whose returns are statistically indistinguishable from zero. In Panel B, we report out-of-sample performance measures, obtained by splitting the sample in half and using the first half to estimate the model. We then roll the estimation procedure forward one month at a time, until the end of the sample. Results are reported for IPCA models with $K = 5$. The sample period is 2004 to 2023.

| | 1 | 2 | 3 | 4 | 5 | 6 |
	JKP	JKP + SUS	JKP + SUS (Med-Sect)	JKP + SUS (Med-Sect)	JKP + SUS (BXS)	JKP + SUS (Norm)
Stock-Level:						
Total R²	36.22	36.22	36.89	37.02	36.85	36.87
Time Series R²	31.91	31.91	32.64	32.65	32.62	32.60
Cross Section R²	23.93	23.93	24.45	24.60	24.35	24.23
Relative Pricing Error	73.75	73.75	73.94	73.80	73.66	73.68
Managed Portfolios:						
Total R²	98.10	98.10	96.94	96.96	96.59	95.90
Time Series R²	57.19	57.19	54.10	60.24	36.11	30.15
Cross Section R²	86.74	86.74	80.19	80.19	78.96	77.42
Relative Pricing Error	0.61	0.61	1.11	1.44	1.00	1.72
Stock Level OOS:						
Total R²	30.70	30.70	30.84	30.77	30.74	30.59
Time Series R²	-65.69	-65.69	-59.38	-55.80	-55.05	-50.48
Cross Section R²	23.81	23.81	23.92	23.87	23.85	23.68
Relative Pricing Error	77.03	77.03	76.67	76.92	74.55	76.46
Managed Portfolios OOS:						
Total R²	42.22	42.22	56.34	61.19	36.54	25.31
Time Series R²	37.22	37.22	26.63	18.57	15.26	17.16
Cross Section R²	44.00	44.00	43.80	44.76	30.47	23.93

The table 5 compares various IPCA models ($K = 5$), focusing on the integration of sustainability characteristics. The baseline model, JKP, shows a Total R^2 of 36.22% at the stock level, which remains unchanged when sustainability characteristics are added directly (JKP + SUS). However, when sustainability data are imputed, Total R^2 increases, indicating improved explanatory power at the stock level. In managed portfolios, the out-of-sample Total R^2 for the Med-Sect imputation method increases significantly from 42.22% in the JKP model to 61.19%, suggesting a better fit. Despite these improvements, some models, such as JKP + SUS (Norm), exhibit increased relative pricing errors, rising from 0.61 to 1.72 in managed portfolios, highlighting potential trade-offs like overfitting or noise introduction. Thus, while the inclusion and imputation of sustainability characteristics can enhance model performance, however, the imputation method matters.

Negative Time series Calculating out-of-sample Time Series R^2 for an unbalanced panel presents significant challenges. Many stocks provide limited observations, with some producing nearly zero realized returns and resulting in negative R^2 values. For example, in $K = 3$, Table 2 presents a Time Series R^2 of -6.15%. However, by excluding stocks with only a single observation—those most prone to a negative out-of-sample R^2—the Time Series R^2 increases to 12.53%.

Which sustainability metrics matter? Figure 9 plots for each factor in separate panels with the characteristics in each panel in decreasing order. A quick look on the absolute largest coefficient in each panel suggests a large role for analytics renewable energy, energy purchase and litigation expense.

Even if some companies lack specific material metrics because they are not part of a particular industry, their returns can still covary with sustainability-managed portfolios. Covariance plays a critical role in linking companies to sustainability metrics, even when their core operations do not directly align with environmental or social factors. Similar to the Fama-French model's approach to risk factors, companies that exhibit covariance with metrics like green revenues or carbon footprint reductions indirectly position themselves within the sustainability framework. These metrics assess environmental impact and efforts to reduce ecological footprints. Companies positively correlated with such metrics may attract sustainability-focused investors, even if they do not operate in traditionally green industries. This suggests their performance is influenced by factors driving sustainability, highlighting opportunities for aligning corporate strategies with emerging sustainability trends.
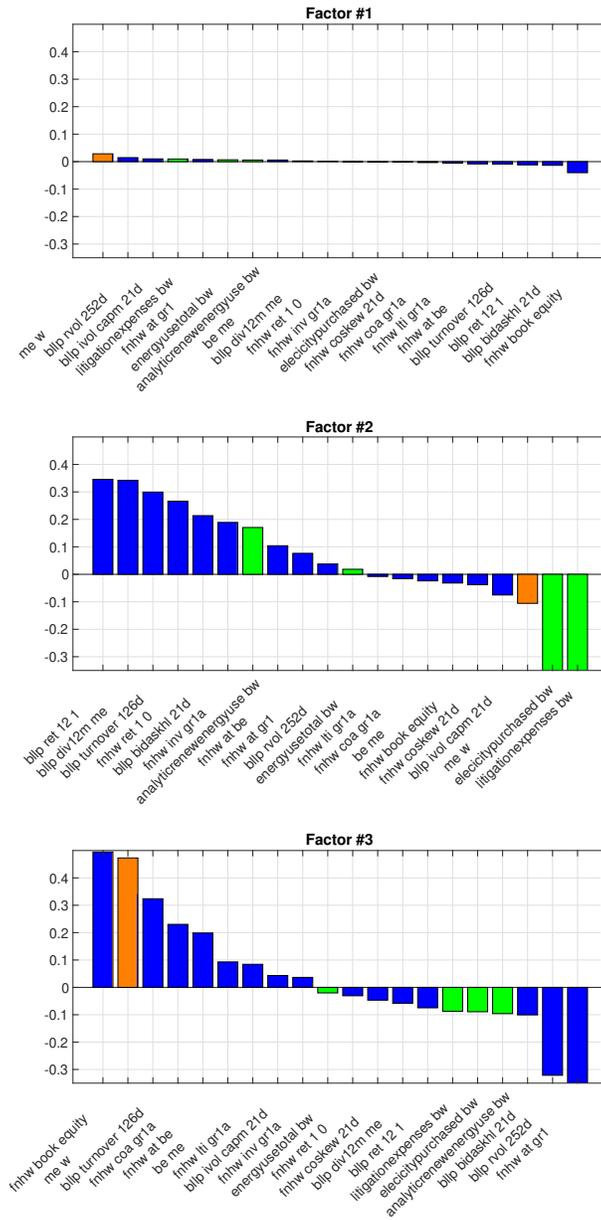
Figure 9: **IPCA gammas**: JKP + SUS (BXS))
The figure shows IPCA gammas for each of the 3 factors in the IPCA model from Table. The sample period is 2004 to 2023.

6.   Discussion & Conclusion

We show that while sustainability disclosure and performance are related, they do not explain returns in the same way. Sustainability disclosure is linked to financial performance and lower capital costs but falls short of fully explaining returns. In contrast, sustainable performance has a distinct influence. Additionally, we demonstrate that coverage for non-reporting firms can be expanded by using available observations as predictors. Our findings indicate that imputing sustainability material metrics at the industry level provides a better explanation of returns than relying on observed metrics or industry-median imputations. ESG analysts and sustainable investors should prioritize sustainability metrics that have the greatest impact. They can also play a critical role in driving companies to improve transparency and increase reporting on these metrics. The global applicability of SASB standards is expanding, yet this study highlights gaps in corporate reporting, even among firms using SASB guidelines. These insights can assist SASB in identifying underreported metrics and reassessing their relevance. Moreover, while quantitative sustainability data provide valuable information, they often reveal limited information and do not explain methods for identifying stakeholders and material topics (Beske et al., 2020).

Non-Disclosure of Material Metrics Material metrics that are consistently underreported can lead to a misclassification of risk. Through collective non-disclosure, market participants may perceive such risks as firm-specific, misattributing outcomes to idiosyncratic causes instead of recognizing a broader, systematic pattern. This fragmentation obscures the correlations between the' exposures of firms to the common risk factor, potentially leading to a lower price of the correlated risks and inefficient capital allocation. The findings emphasize that mandatory reporting of systematic risk factors is essential not only for transparency but also to ensure accurate risk classification and efficient market functioning.

This study highlights that the determinants of sustainability disclosure are influenced by various factors, including industry-specific materiality and the availability of relevant data. This study demonstrates that focusing on material ESG items within each industry yields better insights than using all disclosed items, as it allows for a more accurate representation of a firm's sustainability practices. Additionally, the ability to expand coverage to non-sustainability-reporting firms through available observations enhances the understanding of both good and bad companies, increasing the dataset by over 200 firms.

However, a significant drawback of sustainability metrics is the inherent lack of compre-
hensive data, which can lead to misinterpretations of a company's ESG performance. The
study highlights that, while advanced imputation methods can provide a more complete
picture, they also introduce potential biases and errors, particularly when firms do not
report on all relevant sustainability characteristics. This data gap can obscure the true
risk profile of companies and complicate the investment decision-making process.

The findings indicate the large amount of missing data, suggesting a fragmented ap-
proach to sustainable disclosures across industries. This inconsistency underscores the
urgent need for standardized reporting frameworks, such as those proposed by the ISSB,
to enhance comparability and transparency in sustainability reporting.

To conclude, the analysis demonstrates that using material-only ESG items relevant
to specific industries can lead to better investment performance compared to a broader
approach that includes all disclosed items. This insight is particularly valuable for ESG
analysts and sustainable investors, as it directs attention to the metrics that truly matter
in assessing corporate sustainability and performance. Future research should explore
the implications of these findings on asset pricing and corporate risk assessment, further
elucidating the relationship between sustainability practices and financial outcomes.

References

Abhayawansa, S. 2022. "Swimming against the tide: back to single materiality for sustainability reporting." *Sustainability Accounting, Management and Policy Journal* 13 (6): 1361–1385.

Arias, D., X. Barriola, and C. R. Loza Adaui. 2024. "Corporate purpose and early disaster response: Providing evidence of dynamic materiality?" *Business Strategy and the Environment.*

Aswani, J., A. Raghunandan, and S. Rajgopal. 2024. "Are carbon emissions associated with stock returns?" *Review of Finance* 28 (1): 75–106.

Bams, D., and B. van der Kroft. 2022. "Tilting the Wrong Firms? How Inflated ESG Ratings Negate Socially Responsible Investing Under Information Asymmetries." *MIT Research Paper,* nos. 22/12.

Bender, J., C. He, S. Maffina, and X. Sun. 2023. "Peeling Back the Onion: Understanding What Goes into an ESG Rating." *Journal of Impact & ESG Investing* 4 (1).

Berchicci, L., and A. A. King. 2022a. "Corporate sustainability: A model uncertainty analysis of materiality." *Journal of Financial Reporting* 7 (2): 43–74.

———. 2022b. "Material sustainability and stock return: faith is not enough." *Journal of Financial Reporting* 7 (2): 41–42.

Berg, F., K. Fabisik, and Z. Sautner. 2020. "Rewriting history II: The (un) predictable past of ESG ratings." *European Corporate Governance Institute–Finance Working Paper* 708 (2020): 10–2139.

———. 2021. "Is history repeating itself? The (un) predictable past of ESG ratings."

Berg, F., J. F. Koelbel, and R. Rigobon. 2022. "Aggregate confusion: The divergence of ESG ratings." *Review of Finance* 26 (6): 1315–1344.

Beske, F., E. Haustein, and P. C. Lorson. 2020. "Materiality analysis in sustainability and integrated reports." *Sustainability Accounting, Management and Policy Journal* 11 (1): 162–186.

Blank, H., G. Sgambati, and Z. Truelson. 2016. "Best practices in ESG investing." *The Journal of Investing* 25 (2): 103–112.

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

Bryzgalova, S., S. Lerner, M. Lettau, and M. Pelger. 2022. "Missing financial data." *Available at SSRN* 4106794.

Buallay, A. 2019. "Between cost and value: Investigating the effects of sustainability reporting on a firm's performance." *Journal of Applied Accounting Research* 20 (4): 481–496.

Busco, C., C. Consolandi, R. G. Eccles, and E. Sofra. 2020. "A preliminary analysis of SASB reporting: Disclosure topics, financial relevance, and the financial intensity of ESG materiality." *Journal of Applied Corporate Finance* 32 (2): 117–125.

Bybee, L., B. Kelly, and Y. Su. 2023. "Narrative asset pricing: Interpretable systematic risk factors from news text." *The Review of Financial Studies* 36 (12): 4759–4787.

Caprioli, S., J. Foschi, R. Crupi, and A. Sabatino. 2024. "Denoising ESG: quantifying data uncertainty from missing data with Machine Learning and prediction intervals." *arXiv preprint arXiv:2407.20047.*

Chen, A. Y., and J. McCoy. 2024. "Missing values handling for machine learning portfolios." *Journal of Financial Economics* 155:103815.

Chen, Y.-L., and M.-C. Huang. 2024. "Recycling water: board membership and industry-peer pressures." *Management Decision* 62 (6): 1861–1884.

Chini, E., and M. Rubin. 2022. "Time-varying environmental betas and latent green factors."

Crippa, G. 2023. "ESG Data Imputation and Greenwashing." *Journal of Impact and ESG Investing.*

Deng, W., P. Polak, A. Safikhani, and R. Shah. 2024. "A unified framework for fast large-scale portfolio optimization." *Data Science in Science* 3 (1): 2295539.

Eccles, R. G., M. P. Krzus, J. Rogers, and G. Serafeim. 2012. "The need for sector-specific materiality and sustainability reporting standards." *Journal of applied corporate finance* 24 (2): 65–71.

Eubank, K. T. 1991. "Paying the Costs of Hazardous Waste Pollution: Why is the Insurance Industry Raising Such a Stink." *U. Ill. L. Rev.,* 173.

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

———. 2015. "A five-factor asset pricing model." *Journal of financial economics* 116 (1): 1–22.

Freyberger, J., B. Höppner, A. Neuhierl, and M. Weber. 2024. "Missing data in asset pricing panels." *The Review of Financial Studies,* hhae003.

Giner, B., and M. Luque-Vílchez. 2022. "A commentary on the "new" institutional actors in sustainability reporting standard-setting: a European perspective." *Sustainability Accounting, Management and Policy Journal* 13 (6): 1284–1309.

Goyal, A., and A. Saretto. 2024. "Are Equity Option Returns Abnormal? IPCA Says Yes." *Review of Financial Studies* 7:1.

Grewal, J., C. Hauptmann, and G. Serafeim. 2021. "Material sustainability information and stock price informativeness." *Journal of Business Ethics* 171 (3): 513–544.

Guerrero, S., and J. P. Viteri. 2025. "What are environmental, social, and governance scores measuring? The role of outcome and impact indicators in ESG scores." *Finance Research Letters* 72:106529.

Hummel, K., and D. Jobst. 2024. "An overview of corporate sustainability reporting legislation in the European Union." *Accounting in Europe,* 1–36.

Ioannou, I., and G. Serafeim. 2019. "Corporate sustainability: A strategy?" *Harvard Business School Accounting & Management Unit Working Paper,* nos. 19-065.

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

Jørgensen, S., A. Mjøs, and L. J. T. Pedersen. 2022. "Sustainability reporting and approaches to materiality: Tensions and potential resolutions." *Sustainability Accounting, Management and Policy Journal* 13 (2): 341–361.

Kelly, B., D. Palhares, and S. Pruitt. 2023. "Modeling corporate bond returns." *The Journal of Finance* 78 (4): 1967–2008.

Kelly, B. T., S. Pruitt, and Y. Su. 2019. "Characteristics are covariances: A unified model of risk and return." *Journal of Financial Economics* 134 (3): 501–524.

———. 2020. "Instrumented principal component analysis." *Available at SSRN 2983919.*

Khan, M., G. Serafeim, and A. Yoon. 2016. "Corporate sustainability: First evidence on materiality." *The accounting review* 91 (6): 1697–1724.

Kotsantonis, S., and G. Serafeim. 2019. "Four things no one will tell you about ESG data." *Journal of Applied Corporate Finance* 31 (2): 50–58.

Kräussl, R., J. D. Rauh, and D. Stefanova. 2024. "Is ESG a Sideshow? ESG Perceptions, Investment, and Firms' Financing Decisions." *ESG Perceptions, Investment, and Firms' Financing Decisions (May 31, 2024).*

Kuh, T., A. Shepley, G. Bala, and M. Flowers. 2020. "Dynamic materiality: Measuring what matters." *Available at SSRN 3521035.*

Kulik, A., and M. Dobler. 2023. "Stakeholder participation in the ISSB's standard-setting process: the consultations on the first exposure drafts on sustainability reporting." *Sustainability Accounting, Management and Policy Journal* 14 (7): 349–380.

Lanza, A., E. Bernardini, and I. Faiella. 2020. "Mind the gap! machine learning, esg metrics and sustainable investment." *Machine learning, ESG metrics and sustainable investment (June 26, 2020). Bank of Italy Occasional Paper,* no. 561.

Li, Z. 2024. "ESG Rating Disagreement and Corporate Total Factor Productivity: Inference and Prediction." *arXiv preprint arXiv:2408.13895.*

Lindsey, L. A., S. Pruitt, and C. Schiller. 2023. "The cost of ESG Investing." *Available at SSRN 3975077.*

Lioui, A., and S. Misra. 2023. "Carbon Pricing Confusion: The Origin and A Simple Solution." *Available at SSRN 4613025.*

Merton, R. C. 1973. "An intertemporal capital asset pricing model." *Econometrica: Journal of the Econometric Society,* 867–887.

Newey, W. K., and K. D. West. 1987. "A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix."

Pástor, L., R. F. Stambaugh, and L. A. Taylor. 2020. "Sustainable investing in equilibrium." *Journal of Financial Economics.*

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

Petersen, A., S. Herbert, and N. Daniels. 2022. "The likely adoption of the IFRS Foundation's proposed sustainability reporting standards." *The Business and Management Review* 13 (2).

Sahin, Ö., K. Bax, C. Czado, and S. Paterlini. 2022. "Environmental, Social, Governance scores and the Missing pillar—Why does missing information matter?" *Corporate Social Responsibility and Environmental Management* 29 (5): 1782–1798.

Serafeim, G. 2011. "Consequences and institutional determinants of unregulated corporate financial statements: Evidence from embedded value reporting." *Journal of accounting research* 49 (2): 529–571.

Skiadopoulos, G., B. Ahn, and P. Patatoukas. 2024. "Material ESG Alpha: A Fundamentals-Based Perspective." *Accounting Review.*

Villiers, C. de, R. Dimes, M. La Torre, and M. Molinari. 2024. "The International Sustainability Standards Board's (ISSB) past, present, and future: critical reflections and a research agenda." *Pacific Accounting Review* 36 (2): 255–273.

Xie, J., Y. Tanaka, A. R. Keeley, H. Fujii, and S. Managi. 2023. "Do investors incorporate financial materiality? Remapping the environmental information in corporate sustainability reporting." *Corporate Social Responsibility and Environmental Management* 30 (6): 2924–2952.

Xiong, R., and M. Pelger. 2023. "Large dimensional latent factor modeling with missing observations and applications to causal inference." *Journal of Econometrics* 233 (1): 271–301.

Zerbib, O. D. 2022. "A sustainable capital asset pricing model (S-CAPM): Evidence from environmental integration and sin stock exclusion." *Review of Finance* 26 (6): 1345–1388.

Zhang, B., K.-h. Lai, B. Wang, and Z. Wang. 2018. "Financial benefits from corporate announced practice of industrial waste recycling: Empirical evidence from chemical industry in China." *Resources, Conservation and Recycling* 139:40–47.

Zhang, S. 2024. "Carbon returns across the globe." *The Journal of Finance.*

A.   Descriptive Statistics

This section presents additional descriptive statistics. We report the results of difference tests that compare the characteristics of firms that report at least one sustainability metric with those that do not.

Table 6: **Descriptive Statistics: firm characteristics**
This table presents descriptive statistics of the firm characteristics. Variables definitions are from (Jensen et al., 2023).

	num_obs	perc_total	mean	std_dev	5th	25th	median	75th	95th
me	1250435.00	1.00	874224.86	25141.16	607.61	1102.07	2402.34	6718.02	36617.08
be_me	1212715.00	0.97	61.92	2.39	0.08	0.24	0.46	0.80	1.54
niq_at	1008792.00	0.81	4668006.11	27068632.74	-0.03	0.00	0.01	0.02	0.06
debtlt_be	1201171.00	0.96	132.91	148.49	0.00	0.06	0.34	0.79	2.71
niq_su	934459.00	0.75	2.38	18.11	-2.68	-0.76	0.00	0.77	2.61
div12m_me	1117230.00	0.89	2.72	0.34	0.00	0.01	0.02	0.03	0.07
ret_1_0	1249481.00	1.00	2.02	0.80	-0.15	-0.05	0.01	0.07	0.20
ret_12_1	1205350.00	0.96	622.49	2072.45	-0.39	-0.09	0.10	0.35	1.03
at_gr1	1226504.00	0.98	3909.27	8730.46	-0.14	-0.01	0.07	0.19	0.73
inv_gr1a	1148192.00	0.92	-377439.09	2333601.17	-0.02	-0.00	0.00	0.01	0.06
lti_gr1a	1054784.00	0.84	-5.15	38.98	-0.03	-0.00	0.00	0.00	0.05
coa_gr1a	1057382.00	0.85	-1212549.45	7195596.80	-0.07	-0.01	0.01	0.05	0.13
at_be	1218947.00	0.97	407.46	52.75	1.17	1.58	2.17	3.40	13.17
ivol_capm_21d	1228843.00	0.98	1.77	0.02	0.01	0.01	0.01	0.02	0.04
coskew_21d	1228843.00	0.98	-0.25	0.32	-0.51	-0.21	-0.01	0.20	0.52
turnover_126d	1228597.00	0.98	0.67	0.01	0.00	0.00	0.00	0.01	0.02
bidaskhl_21d	1242664.00	0.99	0.76	0.00	0.00	0.00	0.00	0.01	0.02
book_equity	1218981.00	0.97	462049.25	14410.65	127.47	470.91	1162.19	3329.76	19820.36
rvol_252d	1217129.00	0.97	2.42	0.15	0.01	0.02	0.02	0.03	0.04

Table 7: **Top 10 most and least observed SASB metrics in the sample.**
The table shows the percentage of missing values and the industry code associated with each metric.

Binary			Numerical		
Field	Miss (%)	Ind. Code	Field	Miss (%)	Ind. Code
Most Observed					
tr_iso14000	35.66	EM-MD	tr_analyticexecutivemembersgende	48.72	FN-IB
tr_pmreduction	35.66	EM-MD	tr_analyticexecutivemembersgende	48.24	TC-IM
tr_supplychainhspolicy	35.66	EM-MD	tr_analyticexecutivemembersgende	47.22	CG-MR
tr_pmreduction	35.5	IF-EU	tr_co2emissiontotal	47.02	IF-EU
tr_policydataprivacy	34.75	TC-TL	tr_analyticexecutivemembersgende	46.73	TC-SI
tr_climatechangerisksopp	33.19	IF-WU	tr_analyticexecutivemembersgende	46.33	SV-PS
tr_productrecall	32.83	TR-AU	tr_analyticexecutivemembersgende	46.07	FN-AC
tr_csrreporting	23.65	FN-EX	tr_analyticexecutivemembersgende	43.23	CG-EC
tr_pmreduction	19.57	TR-RA	tr_f_oillngrsrvprovtot	36.7	EM-EP
tr_pmreduction	17.27	TR-CL	tr_f_natgasrsrvprovtot	36.25	EM-EP
Least Observed					
tr_policyindigenousrightsconsult	95.63	RR-FM	tr_tircontractors	99.97	HC-DY
tr_watermanagementplandetails	93.73	FB-AG	tr_accidentalspills	99.96	RT-EE
tr_watermanagementplandetails	93.63	IF-RE	tr_reitgreenbuildingcertifiedper	99.95	IF-EN
tr_policyindigenousrightsconsult	93.33	EM-CO	tr_productsrecoveredrecycle	99.91	HC-BP
tr_stghgemissionsquantifiedtarge	92.56	EM-MD	tr_waterwithdrawalinstressedregi	99.9	RR-ST
tr_stghgemissionunquantifiedproc	92.56	EM-MD	tr_waterwithdrawalinstressedregi	99.88	EM-RM
tr_policyindigenousrightsconsult	92.55	EM-EP	tr_waterrecycled	99.86	FB-RN
tr_policyminimumwage	92.4	FB-RN	tr_percentagegreenproducts	99.84	CG-AM
tr_ltghgemissionsquantifiedtarge	92.34	EM-MD	tr_reitgreenbuildingcertifiedper	99.83	IF-HB
tr_ltghgemissionunquantifiedproc	92.34	EM-MD	tr_revenueenvproducts	99.81	HC-MS

B.   Data choices: Screens, winsorization, lag conventions, and linking

In this section, we provide additional details on the data construction.

Screens

- Following Jensen et al. (2023), we select unique stock-month observations, at a main exchange, primary, and common issuance.

- We exclude nano and micro stocks. Those that are below the 20th percentile of the NYSE market cap to try to keep as homogenous as possible the cross-section of characteristics.

- We focus on a subset of characteristics from the data, selecting those characateristics that have been previously studied either in the IPCA setting, or as imputation variables.

Lag conventions   To ensure that the data we use is publicly available, we adopt the following lag conventions:

- Accounting data is assumed to be available four months after the fiscal end following Jensen et al. (2023).

- SASB reporters are assumed to report on the FY up to June. If they report after June, we assumed they are reporting the next fiscal year.

- Data downloaded via the LSEG API is assumed to be point in time. For each variable, we report the specific month when the data was reported (as of LSEG). Initially, missing data was handled by forward-filling metrics for up to 12 months. If no new data appeared at $t + 13$, the metric was considered missing. However, this approach proved too conservative. To account for reporting variability, the forward-fill window was extended to 18 months.

Merging   To link firms across different databases, we use the following resources:

- SASB Masterfile (*SICS_Mapping_Master_240630.xlsx*) to Compustat: Linking table from Capital IQ between historical ISIN and GVKEY (`ciq.wrds_isin`).

- LSEG Mapping table (*SASB_Submetrics_to_LSEG_Mapping_231219_1.0.xlsx*): Linking table from LSEG ESG database fields to SASB metrics.

- LSEG to Compustat: Linking the table from Capital IQ between historical ISIN and GVKEY (`ciq.wrds_isin`).

- S&P 1200 Constituents: we gather the historical constituents of the S&P1200 using `gvkeyx = 150918` as index identifier. However, some observations are not included in the filters imposed by Jensen et al. (2023), thus we append the data (making sure that there are no observation-month duplicates).

Naming conventions We retain the variable names from Jensen et al. (2023), but in some cases, these variables are either multiplied or divided by 100 to enhance the readability of the coefficients. When this adjustment is made, the variables are given the suffix `100` or `_100` to indicate the transformation.

C. Bryzgalova et al. (2022) and Xiong and Pelger (2023): Imputation algorithm

This appendix provides further details on the methods of Bryzgalova et al. (2022) and Xiong and Pelger (2023) to impute missing sustainable characteristics. We implement the local backward-forward-cross-sectional (BF-XS) factor model, which leverages both historical and cross-sectional information. Monthly, we estimate a latent factor model using principal components analysis (PCA) in the characteristic space to impute missing observations as common components of the factor model. This method accounts for the dependency between characteristics, unlike simple mean or median imputation. Crucially, it allows the missing pattern to depend on the latent factor model or characteristic-specific features, essential since the data is not missing at random, as shown by Bryzgalova et al. (2022) and Xiong and Pelger (2023). The initial setup involves a three-dimensional tensor

$$C_{l,i}^t,$$

representing the characteristic l of a firm i at a specific time t. There are L characteristics, ranked cross-sectionally from -0.5 to 0.5. Over T time periods, with N_t stocks available at any time t, we define C_t as an $(L \times N_t)$ matrix representing the characteristics for the N_t stocks in month t. We assume an approximate K-factor model to describe these characteristics. In the absence of missing data, latent factors and loadings can be derived using PCA applied to the characteristics covariance matrix:

$$C_{l,i}^t = F_i^t \Lambda_l^{t'} + \epsilon_{i,l}^t,$$

where $F_i^t \in \mathbb{R}^{(N_t \times K)}$ are the latent factors and $\Lambda_l^{t'} \in \mathbb{R}^{(L \times K)}$ are the factor loadings, with K predetermined. The loadings, being the eigenvectors corresponding to the largest eigenvalues of the matrix, are used to regress Y for estimating the factors.

When faced with missing data, constructing a covariance matrix without imputation is unfeasible. Consequently, this approach presents the sample covariance estimator $(L \times L)$ matrix:

$$\Sigma_{i,j}^t = \frac{1}{|Q_{i,j}^t|} \sum_{l \in |Q_{i,j}^t|} C_{l,i}^t C_{l,i}^t \in \mathcal{R}^{(N_t \times N_t)},$$

where $Q_{i,j}^t$ denotes the collection of shared metrics for stocks i and j at time t. The cardinality of this set is given by $|Q_{i,j}^t|$, with a restriction $|Q_{i,j}^t| < L$. Applying PCA to $\Sigma_{i,j}^t$ facilitates the estimation of the loading denoted by $\tilde{\Lambda}_l^t$. Define $W_{i,l}^t$ as a boolean variable that equals 0 if $C_{l,i}^t$ is unavailable and 1 if present. Following this, by regressing

$C_{l,i}^t$ onto $\tilde{\Lambda}_l^t$, we obtain:

$$\widehat{F}_i^t = \left(\sum_{l=1}^{L} W_{i,l}^t \tilde{\Lambda}_l^t \tilde{\Lambda}_l^{t'} \right)^{-1} \left(\sum_{l=1}^{L} W_{i,l}^t \tilde{\Lambda}_l^t C_{i,l}^t \right)$$

Further, by regressing C on $\widehat{F}_i^t$, we derive:

$$\widehat{\Lambda}_l^t = \left(\sum_{i=1}^{N_t} W_{i,l}^t \widehat{F}_i^t \widehat{F}_i^{t'} \right)^{-1} \left(\sum_{l=1}^{L} W_{i,l}^t \widehat{F}_i^t C_{i,l}^t \right)$$

This is computationally expensive, however, the sample covariance matrix built on metrics can be substituted by an equivalent one, based on stocks. That is, the noisy loadings can be estimated via theeigenvectors of the largest eigenvalues of the matrix

$$\Sigma_{i,j}^t = \frac{1}{|O_{i,p}^t|} \sum_{l \in |O_{i,p}^t|} C_{l,i}^t C_{l,i}^t \in \mathcal{R}^{(L \times L)}$$

is the set of all stocks for which the characteristic l and p are not missing at time t. By assumption, $|Ot| \leq N_t$.

Bryzgalova et al. (2022) defines different imputation refinements; we use their cross-sectional backward model (B-XS) using historical and contemporaneous information.

$$\widehat{C}_{l,i}^{t,B-XS} = \beta^{l,BX-XS} \left(\sum_{i=1}^{N_t} W_{i,t}^t X_i^{l,t} X_i^{l,t'} \right)^{-1} \left(\sum_{i=1}^{N_t} W_{i,t}^t X_i^{l,t} C_{i,l}^t \right)$$

In order for results to be comparable with financial data prediction, these are evaluated based on their root mean squared error (RMSE). Let $\hat{C}_{i,l}^t$ be the impute dataset. Then

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \frac{1}{L} \sum_{i=1}^{N_t} (\widehat{C}_{i,l}^t - C_{i,l}^t)^2} \quad (12)$$

and over time

$$RMSE_t = \sqrt{\frac{1}{L} \sum_{l=1}^{L} \frac{1}{N_t} (\hat{C}_{i,t}^t - C_{i,t}^t)^2}. \quad (13)$$

D.   Instrumented Principal Component Analysis

This appendix provides a detailed review of the models of B. T. Kelly et al. (2019, 2020) and Bybee et al. (2023). B. T. Kelly et al. (2019) motivates their IPCA model, assuming that asset returns follow this factor structure:

$$Dr_{i,t+1} = \alpha_{i,t} + \boldsymbol{\beta'}_{i,t} \mathbf{f}_{t+1} + \epsilon_{i,t+1}, \ \forall i = 1, \cdots, N \text{ and } t = 1, \cdots, T \quad (14)$$

The alphas $\alpha_{i,t}$ and the factor loadings $\boldsymbol{\beta}'_{i,t} \in \mathbb{R}^{(K \times 1)}$ are time dependent.[16] Therefore, the IPCA models

$$\alpha_{i,t} = \mathbf{c}'_{i,t}\boldsymbol{\Gamma}_\alpha + \upsilon_{\alpha,i,t} \tag{16}$$

$$\beta_{i,t} = \mathbf{c}'_{i,t}\boldsymbol{\Gamma}_\beta + \mathbf{v}_{\beta,i,t}, \tag{17}$$

where $\mathbf{c} \in \mathbb{R}^{(1 \times L)}$ denotes observed asset characteristics, and $\boldsymbol{\Gamma}_\alpha \in \mathbb{R}^{(L \times 1)}$ and $\boldsymbol{\Gamma}_\alpha \in \mathbb{R}^{(L \times K)}$ are parameter matrices estimated from the data.

Some advantages of the IPCA model are:

- Due to the dimension reduction introduced by the matrix Γ_β, the number of observed factors L can be much larger than the number of factor loadings K.

- The factors F_t are time-dependent and are estimated from the data.

- Handling missing characteristics. It will be useful to define a $(L \times L)$ matrix $Wt = \frac{C'_t C_t}{N_{t+1}}$ and a $(L \times 1)$ vector $X_{t+1} = \frac{C'_t R_{t+1}}{N_{t+1}}$. We can interpret X_{t+1} as the $t+1$ returns on a set of L managed portfolios. The return on the lth portfolio is a weighted average of asset returns with weights determined by the value of lth characteristic for each asset at time t (normalized by the number of non-missing observations each month, N_{t+1}).

- This model is predictive, with observable factors lagged by one period relative to the returns they explain.

- $\epsilon_{i,t+1}$, $\upsilon_{\alpha,i,t}$, and $\upsilon_{\beta,i,t}$ are mean zero random noises originating from the estimation of factors and loadings. The $\epsilon_{i,t+1}$ uncovers the firm-level risk, whereas $\upsilon_{\alpha,i,t}$ and $\upsilon_{\beta,i,t}$ represent the residuals between the true factor model parameters and observable firm characteristics

The IPCA model addresses the challenges of high-dimensional factor models, where an excess of characteristics introduces noise and collinearity among factors. This complicates result interpretation and reduces out-of- sample performance. Therefore, Γ_β aggregates high-dimensional characteristics into a linear combination of exposure risks. Errors orthogonal to the dynamic loadings are captured in the $\upsilon_{\beta,i,t}$.

In the empirical analysis, we assume $\boldsymbol{\Gamma}_\alpha = 0$ while estimating $\boldsymbol{\Gamma}_\beta$. Thus, for the restricted model ($\boldsymbol{\Gamma}_\alpha = 0$), we have

$$r_{i,t+1} = \boldsymbol{\Gamma}_\beta \mathbf{f}_{t+1} + \epsilon^*_{i,t+1} \tag{18}$$

where $\epsilon^*_{i,t+1} = \epsilon_{i,t+1} + \upsilon_{\alpha,i,t} + \mathbf{v}_{\beta,i,t}$. In vector form,

$$r_{i,t+1} = \boldsymbol{\Gamma}_\beta \mathbf{f}_{t+1} + \boldsymbol{\epsilon}^*_{t+1} \tag{19}$$

---

16. Contrary to classical factor modeling, as presented by Fama and French (1993, 2015), which assumes returns follow a linear model:

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}'_{i,t}\mathbf{f}_{t+1} + \epsilon_{i,t}, \tag{15}$$

where r_{t+1} is an $(N \times 1)$ vector of assets returns, Ct is an $(N \times L)$ vector of observable characteristics and $\mathbf{\Gamma}_\beta$ is an LK mapping matrix, $\mathbf{f}_{t+1}$ is an $(K \times 1)$ vector of the combination latent factor. Then we can write the objective function of IPCA model as

$$\min_{\mathbf{\Gamma_\beta},F} \sum_{t=1}^{T-1} (\mathbf{r}_{t+1} - \mathbf{C}_t^\top \mathbf{\Gamma}_\beta \mathbf{f}_{t+1})^\top (\mathbf{r}_{t+1} - \mathbf{C}_t^\top \mathbf{\Gamma}_\beta \mathbf{f}_{t+1}) \tag{20}$$

with constraints $\mathbf{\Gamma_\beta}\mathbf{\Gamma_\beta} = \mathbf{I}_k$ and $\mathbf{FF'} = \mathrm{diag}(\lambda_1, \cdots, \lambda_k)$

To minimize the objective function the alternating least squares method (ALS) is used, switching

$$\hat{\mathbf{f}}_{t+1} = (\mathbf{\Gamma_\beta}' \mathbf{C}_t \mathbf{C}_t \mathbf{\Gamma_\beta})^{-1} \mathbf{\Gamma_\beta}' \mathbf{C}_t' \mathbf{r}_{t+1} \text{ for all } t \tag{21}$$

$$\mathrm{vec}(\hat{\beta}) = \left(\sum_{t=1}^{T-1} C_t' C_t \otimes \hat{f}_{t+1} \hat{f}_{t+1}' \right)^{-1} \left(\sum_{t=1}^{T-1} C_t \otimes \hat{f}_{t+1} r_{t+1}' \right). \tag{22}$$

here $\otimes$ denotes the Kronecker product of matrices. Formula 21 shows that latent factors represent the coefficients of returns regressed on the latent loading matrix $\beta_t \in \mathbb{R}^{(N \times L)}$, $t = (1, \cdots, T)$. Meanwhile, $\mathbf{\Gamma}_\beta$ denotes the regression coefficients of r_{t+1} on the combination of latent factors and firm characteristics.

4.1.   Pricing Metrics

We calculate the pricing performance of the model by calculating a variety of R2's and pricing error, following (B. Kelly et al., 2023) as follows:

$$\text{Total } R^2 = 1 - \frac{\sum_{i,t} \left(\mathbf{r}_{i,t+1} - C_{i,t}' \hat{\mathbf{f}}_{t+1} \hat{\boldsymbol{\beta}}_{i,t} \right)^2}{\sum_{i,t} \mathbf{r}_{i,t+1}^2} \tag{23}$$

$$\text{Time Series } R^2 = \frac{1}{\sum_i T_i} \sum_i T_i R_i^2, \quad \text{where } R_i^2 = 1 - \frac{\sum_t \left(\mathbf{r}_{i,t+1} - C_{i,t}' \hat{\beta} \hat{\mathbf{f}}_{t+1} \right)^2}{\sum_t \mathbf{r}_{i,t+1}^2} \tag{24}$$

$$\text{Cross Section } R^2 = \frac{1}{T} \sum_t R_t^2, \quad \text{where } R_t^2 = 1 - \frac{\sum_i \left(\mathbf{r}_{i,t+1} - C_{i,t}' \hat{\beta} \hat{\mathbf{f}}_{t+1} \right)^2}{\sum_i \mathbf{r}_{i,t+1}^2} \tag{25}$$

$$\text{Relative Pricing Error} = \frac{1}{T_i} \sum_t \frac{\alpha_i^2}{R_i^2}, \quad \text{where } \alpha_i^2 = \sum_t \left(\mathbf{r}_{i,t+1} - C_{i,t}' \hat{\beta} \hat{\mathbf{f}}_{t+1} \right) \tag{26}$$

E.   LSEG Coverage: SASB Metrics

Table 8: **SICS sector and industry classifications and availability of SASB Metrics in LSEG**

Sector	Industry	SASB code	#	#	Num	Bin	Coverage
Consumer Goods	Apparel, Accessories & Footwear	CG-AA	23	7	1	6	30.43
	Appliance Manufacturing	CG-AM	9	5	2	3	55.56
	Building Products & Furnishings	CG-BF	14	9	6	3	64.29
	E-Commerce	CG-EC	40	16	13	3	40.00
	Toys & Sporting Goods	CG-TS	11	4	1	3	36.36
	Multiline and Specialty Retailers & Distributors	CG-MR	32	16	11	5	50.00
	Household & Personal Products	CG-HP	17	6	4	2	35.29
Extractives & Minerals Processing	Oil & Gas – Services	EM-SV	30	17	10	7	56.67
	Metals & Mining	EM-MM	80	28	18	10	35.00
	Oil & Gas – Midstream	EM-MD	37	15	8	7	40.54
	Oil & Gas – Exploration & Production	EM-EP	82	27	18	9	32.93
	Coal Operations	EM-CO	74	22	13	9	29.73
	Construction Materials	EM-CM	46	25	19	6	54.35
	Iron & Steel Producers	EM-IS	41	20	15	5	48.78
	Oil & Gas – Refining & Marketing	EM-RM	47	21	15	6	44.68
Food & Beverage	Alcoholic Beverages	FB-AB	24	10	6	4	41.67
	Agricultural Products	FB-AG	47	19	11	8	40.43
	Food Retailers & Distributors	FB-FR	41	19	12	7	46.34
	Meat, Poultry & Dairy	FB-MP	48	18	11	7	37.50
	Non-Alcoholic Beverages	FB-NB	31	9	6	3	29.03
	Processed Foods	FB-PF	39	12	7	5	30.77
	Restaurants	FB-RN	39	14	11	3	35.90
	Tobacco	FB-TB	8	2	2	0	25.00
Financials	Commercial Banks	FN-CB	31	6	3	3	19.35
	Consumer Finance	FN-CF	28	3	2	1	10.71
	Insurance	FN-IN	28	4	1	3	14.29
	Asset Management & Custody Activities	FN-AC	39	9	6	3	23.08
	Security & Commodity Exchanges	FN-EX	19	4	2	2	21.05
	Mortgage Finance	FN-MF	29	2	1	1	6.90

Table 8 continued from previous page

	Investment Banking & Brokerage	FN-IB	42	7	5	2	16.67
Health Care	Biotechnology & Pharmaceuticals	HC-BP	41	5	4	1	12.20
	Drug Retailers	HC-DR	24	8	5	3	33.33
	Medical Equipment & Supplies	HC-MS	23	5	3	2	21.74
	Health Care Distributors	HC-DI	13	4	2	2	30.77
	Health Care Delivery	HC-DY	48	16	13	3	33.33
	Managed Care	HC-MC	23	5	2	3	21.74
Infrastructure	Electric Utilities & Power Generators	IF-EU	56	19	12	7	33.93
	Gas Utilities & Distributors	IF-GU	19	1	1	0	5.26
	Water Utilities & Services	IF-WU	39	7	6	1	17.95
	Waste Management	IF-WM	59	19	15	4	32.20
	Real Estate	IF-RE	21	10	6	4	47.62
	Home Builders	IF-HB	23	7	6	1	30.43
	Real Estate Services	IF-RS	12	3	2	1	25.00
	Engineering & Construction Services	IF-EN	29	12	7	5	41.38
Renewable Resources & Alternative Energy	Wind Technology & Project Developers	RR-WT	23	4	4	0	17.39
	Biofuels	RR-BI	26	11	9	2	42.31
	Fuel Cells & Industrial Batteries	RR-FC	157	10	9	1	6.37
	Forestry Management	RR-FM	9	2	0	2	22.22
	Pulp & Paper Products	RR-PP	35	18	12	6	51.43
	Solar Technology & Project Developers	RR-ST	28	14	10	4	50.00
Resource Transformation	Industrial Machinery & Goods	RT-IG	25	9	7	2	36.00
	Aerospace & Defence	RT-AE	29	12	8	4	41.38
	Chemicals	RT-CH	44	25	18	7	56.82
	Containers & Packaging	RT-CP	47	23	14	9	48.94
	Electrical & Electronic Equipment	RT-EE	25	11	8	3	44.00
Services	Hotels & Lodging	SV-HL	17	10	8	2	58.82
	Media & Entertainment	SV-ME	25	5	4	1	20.00
	Professional & Commercial Services	SV-PS	28	12	8	4	42.86
	Advertising & Marketing	SV-AD	27	6	4	2	22.22
	Casinos & Gaming	SV-CA	10	4	4	0	40.00
	Education	SV-ED	18	4	2	2	22.22
	Leisure Facilities	SV-LF	12	5	4	1	41.67
Technology & Communications	Hardware	TC-HW	32	8	5	3	25.00
	Internet Media & Services	TC-IM	47	14	11	3	29.79
	Semiconductors	TC-SC	36	16	10	6	44.44

Table 8 continued from previous page

|							
	Software & IT Services	TC-SI	50	15	11	4	30.00
	Telecommunication Services	TC-TL	29	8	6	2	27.59
	Electronic Manufacturing Services & Original Design Manufacturing	TC-ES	25	7	7	0	28.00
Transportation	Car Rental & Leasing	TR-CR	5	1	0	1	20.00
	Rail Transportation	TR-RA	30	15	10	5	50.00
	Marine Transportation	TR-MT	33	14	9	5	42.42
	Cruise Lines	TR-CL	42	15	10	5	35.71
	Auto Parts	TR-AP	17	10	8	2	58.82
	Airlines	TR-AL	23	10	5	5	43.48
	Air Freight & Logistics	TR-AF	32	18	12	6	56.25
	Road Transportation	TR-RO	27	19	13	6	70.37
	Automobiles	TR-AU	21	6	4	2	28.57
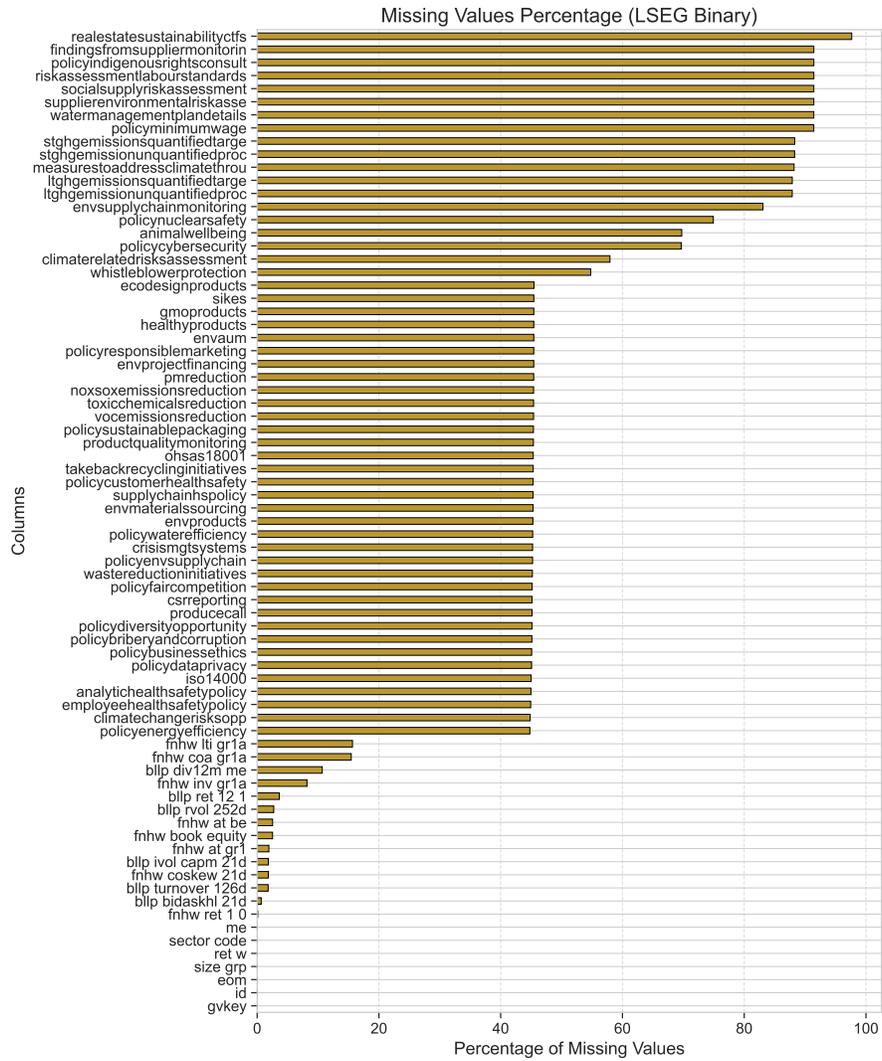
Figure 10: **Missing characteristics (binary)**
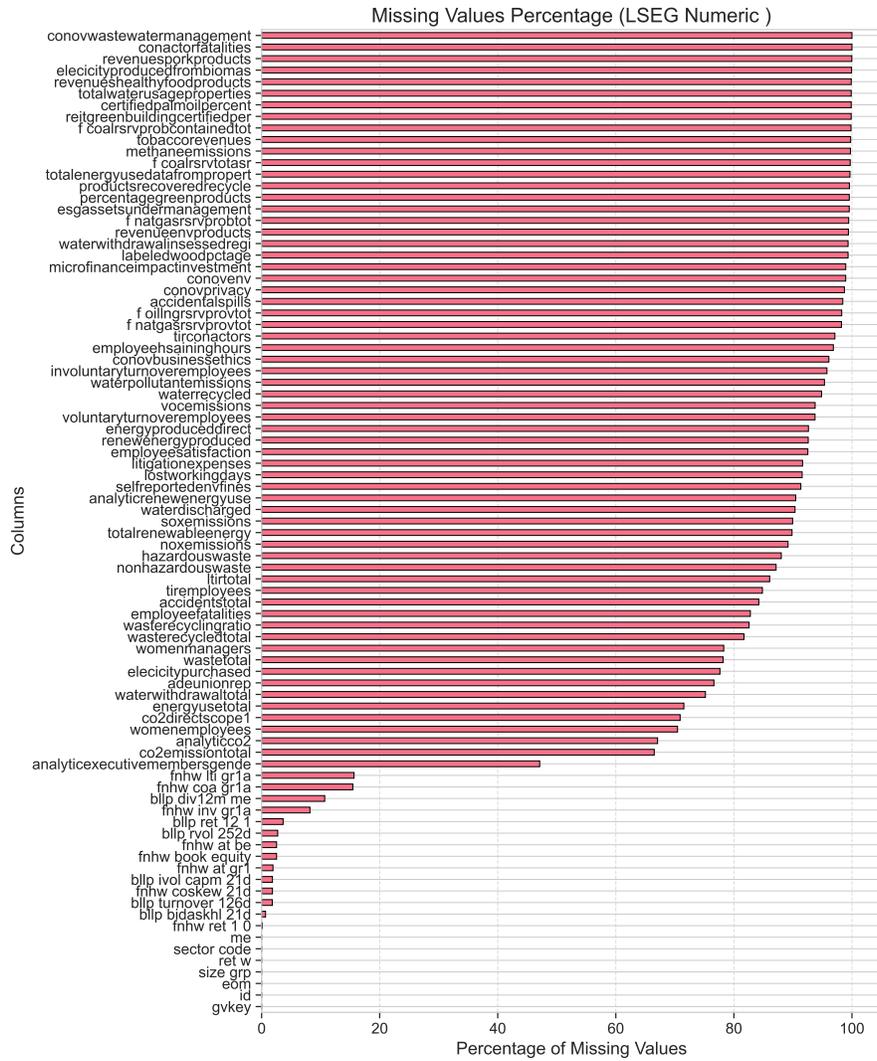
Figure 11: **Missing characteristics (numerical)**

Figure 12: **Missing characteristics:** Materiality matrix by sector