Dimensionality Reduction: Do Green Factors Explain Returns?

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Abstract

Current asset pricing literature has produced mixed evidence on whether investors are pricing environmental risks in financial markets. This thesis challenges those findings leveraging on an innovative asset pricing framework, Instrumented Principal Component Analysis proposed by Kelly et. al (2019,2023), to identify common risk sources in the corporate bond market by employing a large panel of financial and environmental characteristics, the goal is to find whether any of the environmental characteristics are related to a sustainably linked risk factor that influences bond returns, thus IPCA will find whether there is any environmental risk on beyond financial risks. IPCA possesses advantages compared to traditional methodologies in literature. The framework estimates time-varying betas, allowing factors to be functions of bond and company-specific characteristics, and does not require strong-form assumptions about the factors. This methodological innovation enables the identification of latent sustainably linked risk factors without predefine factor structure.

This thesis extends Kelly et al.'s (2023) panel of characteristics by including 22 environmental characteristics beyond the financial characteristics proposed in Kellyet.al (2023). Additionally, I estimate two IPCA specifications: a baseline model where environmental characteristics are used as reported and a second specification where environmental characteristics are lag-adjusted, as proposed by Zhang (2024). I find that environmental characteristics are instruments for latent risk factors and provide independent information about the cross-section of returns for bonds. Thus, characteristics such as the ESG controversies scores have predictive power, suggesting that companies with less negative exposure to media on ESG controversies earn higher average returns.

Keywords: Bonds, Asset Pricing, Principal Components Analysis, Latent Factors, Dimensionality Reduction, Characteristics, Sustainability Risks.

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Resumo

A literatura atual sobre precificação de ativos produziu evidências inconclusivas sobre se os investidores estão precificando riscos ambientais nos mercados financeiros. Esta tese desafia essas descobertas ao implementar uma metodologia inovadora de precificação de ativos, a Análise de Componentes Principais Instrumental (IPCA) proposta por Kelly et. al (2019,2023), para identificar fontes comuns de risco no mercado de títulos corporativos, empregando um grande painel de características financeiras e ambientais, o objetivo é descobrir se alguma das características ambientais está relacionada a um fator de risco ligado à sustentabilidade. O IPCA estima betas dinâmicos, permitindo que os fatores sejam funções de características específicas do título e da empresa, e não exige pressupostos do investigador os fatores. Essa inovação metodológica permite a identificação de fatores de risco latentes sem uma estrutura fatorial predefinida.

Esta tese amplia o painel de características de Kelly et al. (2023), incluindo 22 características ambientais além das características financeiras propostas em Kelly et.al (2023). Além disso, estimo duas especificações do IPCA: um modelo de base onde as características ambientais são usadas conforme publicadas e uma segunda especificação onde as características ambientais são ajustadas no tempo, conforme proposto por Zhang (2024). Esta tese apresenta evidencias empíricas de que as características ambientais são instrumentos para fatores de risco latentes e fornecem informações independentes acerca dos retornos médias das obrigações. Assim, características como ESG controversy scores e ESG controversy grades têm poder preditivo, sugerindo que empresas com menos exposição negativa aos media sobre controvérsias ESG obtêm retornos médios mais altos.

Palavras-chave: Obrigações, Precificação de Ativos, Análise de Componentes Principais, Fatores Latentes, Redução de Dimensionalidade, Características, Riscos de Sustentabilidade**.**

Título: Redução de Dimensionalidade: Os Fatores Verdes Explicam os Retornos?

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1. Introduction

Climate change poses an urgent challenge due to the ongoing increase in emissions. Such emissions are projected to increase the average global temperature by two degrees Celsius compared to pre-industrial levels. This challenge brings the risk of irreversible economic disruptions. Addressing this crisis requires achieving carbon neutrality and the implementation of solid regulatory measures (Hoegh-Guldberg et al., 2018). Climate change goes beyond an environmental issue, it is a multidimensional problem that has consequences for the financial system, posing a systemic risk to the financial markets (Principles for Responsible Investment 2024).

This ongoing threat sparked interest in sustainable finance. However, the transition to a carbon-neutral economy is a capital-intensive process estimated to require trillions of dollars annually. More specifically, the energy sector is estimated to need about $4.5 trillion annually until 2050 to achieve carbon neutrality (IEA, 2021). Therefore, private investors can play a crucial role in bridging the funding gap for this transition.

Climate change can affect the financial system through 2 distinctive channels: physical and transition risks. Physical risks arise from exposure to climate events, such as extreme weather events, which can significantly damage assets, infrastructure, and human lives. The consequences of physical assets include reduced productivity, lower profitability, and diminished financial stability, raising concerns about economic output and the stability of financial markets.

Transition risks refer to the operational and financial challenges that companies encounter as they transition away from carbon-intensive operations. These risks arise from sudden policy changes, regulatory requirements, and technological changes that businesses may not anticipate. Companies that depend heavily on carbon-intensive operations are vulnerable to transition risks.

Motivated by the risks of climate change, several researchers have contributed to a growing body of literature that focuses on studying sustainability as a source of risk and return in financial markets, with a particular focus on the equity market. However, recent papers have covered other asset classes, although with limited coverage, such as options and bonds. Despite recent efforts, empirical evidence remains inconclusive, as explored in the following section. This growing body of literature led researchers to propose “green factors” to account for the risks described above, contributing to what Cochrane (2011) described as the “factor zoo” referring to the proliferation of asset pricing factors. The “factor zoo” presents challenges such as the curse of dimensionality, redundancy among factors, susceptibility to data mining, and difficulty in comparing models and factors. Consequently, it is essential to identify which factors provide independent information and which are redundant and correlated.

This thesis introduces a novel approach that overcomes the abovementioned limitations of the “factor zoo” and leverages the Instrumented Principal Component Analysis (IPCA) framework proposed by Kelly et al. (2019, 2023) to study the corporate bond market. The choice of the corporate bond market is due to its inherent complexities and significant level of institutional ownership. Fixed-income investors navigate the intricacies of selecting bonds from various issuances for the same firm, each possessing distinct features (Koijen and Yogo 2023). In contrast, the equity market typically attracts less experienced and sophisticated retail investors. Focusing on bonds is essential for two reasons: companies frequently finance themselves through debt, and the bond market is substantially larger, valued at approximately \$140.7 trillion, compared to the equity market's \$115.0 trillion (SIFMA 2024). Therefore, if sustainable-related risks are being priced in the financial markets, one strong candidate is the fixed-income market.

Motivated by these facts, this research aims to determine whether ESG-related risks are priced in the corporate bond market and whether these risks translate into a risk premium. For this purpose, this study employs a large panel of characteristics already proposed in the asset pricing literature comprising 22 environmental characteristics and 26 financial characteristics from Kelly et al. (2023). Therefore, this thesis first expands the number of factors and examines whether environmental characteristics offer any independent insights into the cross-section of bond returns. Second, I estimate another IPCA specification (IPCA-L12) that adjusts for environmental characteristics, as per Zhang (2024), and assess whether IPCA performance improves.

This thesis’s contributions are twofold. First, it provides a robust method for analyzing the interplay between environmental and financial characteristics while controlling for the large set of correlated, noisy, or spurious predictors prevalent in ESG data, thereby extending the empirical evidence of Kelly et al. (2023). Second, I present a framework that yields a parsimonious model that addresses the issues associated with the “factor zoo”.

I find that IPCA demonstrates strong and consistent predictability for both in-sample and out-of-sample. Additionally, I find evidence that, when environmental characteristics are adjusted, according to Zhang (2024), the performance of both in-sample and out-of-sample for IPCA-L12 is marginally superior to the baseline specification of IPCA. Notwithstanding, both IPCA specifications—IPCA and IPCA-L12—capture a similar latent space of risk factors and conclude that environmental characteristics are explanatory of the cross-sectional and time-series variations in corporate bond returns.

2. Literature Review

Given the implications of climate change on financial markets, researchers have started to investigate the relationship between Environmental, Social, and Governance (ESG) information and financial returns. This growing body of literature aims to study the risk-return relationship of the cross-section of returns and exposures to ESG-related risks. A key concept emerging from the literature is the "greenium" or “green premium” defined as the positive return that securities issued by environmentally and socially responsible companies (green companies) yield over environmentally and socially irresponsible firms (brown companies). Conversely, the “carbon premium” or “brown premium” represents the positive return that brown companies earn over green companies.

As described in the previous section, the existence of a “greenium”, or “carbon premium” remains inconclusive. In a study of the cross-section of U.S. stocks, Bolton and Kacperczyk (2021) found evidence of a positive relationship between unscaled carbon emissions (both direct and indirect) and stock returns, indicating that high-polluting firms tend to outperform their low-polluting peers. This analysis was later expanded to a larger panel of firms across countries, consistently revealing the same relationship (Bolton and Kacperczyk, 2023). Hsu et al. (2023) also identified a carbon premium, using emissions scaled by total assets as a proxy for carbon emissions intensity, and concluded that high-emission firms outperformed low-emission firms.

Conversely, Zhang (2024) presents a contrasting viewpoint and reveals that green firms outperform brown firms upon adjusting for appropriate lags in carbon emissions data for the U.S. stock market. The author also finds that carbon-intensive firms underperform less carbon-intensive firms outside the United States, although statistically insignificant.

Moreover, Lindsey et al. (2024) build upon Kelly et al. (2023, 2019) IPCA and find no evidence of an ESG-specific alpha in the equity market. However, the authors conclude that responsible investing does not sacrifice returns, and the Sharpe ratios are statistically unchanged. Notwithstanding, the authors conclude that ESG information is not pure noise and reveals important information about non-ESG aggregate risks.

Due to the increasing popularity of green bonds, the study of green and carbon premiums has been recently extended to the less-known bond market, focusing primarily on green bonds.

Research on green bonds has identified a modest negative green premium, meaning green bonds have a lower yield than conventional bonds. Empirical evidence of such a green premium was found in Zerbib (2019) by employing a matching procedure followed by a two-step regression to estimate the difference between a green bond and a matched conventional bond. Similar findings in the primary bond market confirm that green bonds have lower issuance yields than traditional ones (Caramichael and Rapp, 2024). Alternatively, also using a matching procedure, Larcker and Watts (2020) find no evidence of a green premium on small issuances of green municipal bonds.

Evidence from the secondary corporate bond market suggests that the intensity of carbon emissions is negatively correlated with expected returns, and such a carbon premium cannot be explained by a list of bond and firm characteristics (Duan et al., forthcoming).

Moving to the equity market, some research reveals that the cost of equity of firms with higher corporate social responsibility tends to experience a lower ex-ante implied cost of equity derived from stock prices and analysts' earnings forecasts (El Ghoul et al., 2011). Furthermore, carbon-intensive firms that fail to meet environmental standards face higher debt costs and interest rates (Chava, 2011).

A different segment of sustainable finance literature studied equilibrium models and revealed that investor preferences for green financial instruments significantly impact asset returns. Research by Pástor et al. (2021) indicates that green stocks have a negative alpha due to heightened investor demand for green assets and their role as a hedge against climate risk. A subsequent study by Pástor et al. (2022) emphasizes the differences between realized and expected returns, showing that the outperformance of green stocks is attributed to heightened increases in climate concerns and that after controlling for increases in climate concerns, the alpha flatness.

Moreover, research in the options market has found that climate policy uncertainty and environmental risks are reflected in the pricing of options. Thus, firms with high carbon intensity suffer from higher cost of protection against downside tail risks and variance risks, which increase during heightened political uncertainty. Therefore, options for carbon-intensive firms come at a premium (Ilhan et al., 2021).

The present thesis contributes to the existing literature by utilizing an innovative framework that considers time-varying risk premia, emphasizes dimensionality reduction of the factor zoo, and does not impose strong-form assumptions about the risk factors or predefined the factor to be studied in an *ad-hoc* manner. This approach enables the introduction of a comprehensive panel of characteristics that interact with one another, resulting in a latent space of risk factors.

The thesis is organized as follows. Section 3 provides a brief summary of the characteristics extracted, also highlights the statistical distribution of the characteristics and the corporate bonds returns. Additionally provides a comprehensive understanding of the filtering criteria to normalize the dataset. Section 4 explores lays the theoretical foundation for the estimation of IPCA and IPCA-L12, for both restricted and unrestricted versions. Additionally, provides an explanation for the statistical tests applied for both the individual instruments and alpha in the unrestricted version. Section 5 presents empirical findings, both in-sample and out-of-sample, measures the statistical performance of the models specified, provides evidence on the marginal impact of environmental factors in explaining average corporate bond returns, as well as evaluating the profitability of characteristic-managed portfolios in a mean-variance setting net of transaction costs. Finally, Section 6 concludes with a discussion on the significance of environmental characteristics, the limitations of this analysis, and suggestions for future research.

3. Data

This analysis collects prices and characteristics of corporate bonds from companies listed in the four major US indexes: NYSE, NASDAQ, S&P 500, and Dow Jones, aiming for comprehensive coverage of the American market. The data covers the period from 2010 to 2024, focusing on publicly traded bonds available on December 31, 2024, and was sourced from Refinitiv.

The securities went through a filtering process to meet current bond literature standards. The filtering process adheres to the criteria established by Bai et al. (2019):

1. Filtered out private placements' bonds, which are not traded on public markets, and those issued under private placements and the 144A rule.
2. Bonds not quoted in US dollars.
3. Securities excluded included commercial paper and loans, structured securities, perpetual bonds, and convertible bonds to ensure a standardized calculation of returns.
4. Bonds with a maturity of less than one year are excluded because such securities are removed from significant indexes, which leads to index-tracking investors adjusting their positions, distorting the returns.
5. Securities with floating rates and trade settlement periods exceeding three days are also excluded.
6. Bonds priced above 2000 dollars or below 5 dollars are excluded from the sample to implicitly eliminate those that have defaulted or are near default.

The filtered bond sample comprises 355 companies and 7 296 bonds, totaling 429 450 month-bond observations across 10 economic sectors. The sample is primarily represented by Financials (45.0%), followed by Industrials (14.6%) and Consumer Cyclical companies (7.5%).

The monthly returns at time *t* are computed as:

$$R_{i,t} = \frac{P_{i,t} + A_{i,t} + C_{i,t}}{P_{i,t-1} + A_{i,t-1}} - 1$$

where $P_{i,t}$ corresponds to the clean price, $A_{i,t}$ to the accrued interest earned during the holding period and $C_{i,t}$ to the coupon payment, if any, during the holding month. The total return is $R_{i,t}$, and $r_{i,t}$ is the excess return over the US 1-month risk-free rate.

Additionally, credit excess returns are scaled by the previous month's "Duration-time Spread" from Ben Dor et al. (2007). Scaling credit excess returns offers numerous benefits: it enables comparability of returns across issuers and bonds, ensures a consistent cross-sectional analysis so the most volatile segment of bonds does not drive the estimations, and enhances portfolio construction and risk analysis. The scaled returns are defined as:

$$r_{i,t} = \frac{\tilde{r}_{i,t}}{\max\left(DtS_{i,t-1}, \overline{\overline{DtS}}\right)}$$

where $\tilde{r}_{i,t}$ is the unscaled excess return, $r_{i,t}$ the scaled excess return, DtS the duration time spread of the previous month and $\overline{\overline{DtS}}$ the forward-looking measure's upper limit is 0,25, similar to Kelly et al. (2019,2023).

Sourcing data from Refinitiv presents limitations, including issues with data quality for prices and the low availability of some characteristics for the companies in the sample studied. Research by Kelly et al. (2019, 2023), Bai et al. (2019), and Dickerson et al. (2023) use specialized bond databases like ICE, TRACE, and Mergent-FISD, where prices and returns are calculated on actual intraday transactions.

This transaction data is crucial for the bond market, which tends to be more illiquid. In contrast, Refinitiv data does not provide bond transaction data, putting infrequently traded bonds at a disadvantage. Therefore, prices for illiquid bonds are determined through matrix pricing, which relies on prices of bonds with similar credit risk and dealer quotes for the bond in question. This implies that this thesis might have a different statistical distribution of returns than the ones presented in the literature review and introduction. Nevertheless, a return distribution based on matrix pricing may not accurately represent what a marginal investor would trade in the market.

Regarding the characteristics in the final dataset, it includes 25 out of the 29 characteristics outlined by Kelly et al. (2023), except for credit ratings due to availability limitations, which consequently prevents the computation of momentum*ratings. I further considered yield-to-maturity as a financial characteristic. Furthermore, this thesis originally retrieved 61 characteristics that assess companies' environmental performance and potential sources of environmental risk, however due to the filtering criteria only 22 remained. This diverse range of characteristics and methods for measuring sustainability will enable IPCA to evaluate whether any aspect of sustainability influences the cross-section of returns, on top of financial risks. Another limitation to consider in this dissertation is the limited availability of valid observations for environmental characteristics, the strict criteria applied led to a strong reduction of green measures.

Additionally, I collect data from alternative databases. From the Federal Reserve Economic Data (FRED), I collected monthly observations for the term spread, which is the yield difference between the 10-year Treasury and the 3-month Treasury, to compute the financial characteristic VIX Beta as defined in Kelly et. al (2023). Also, for VIX Beta, I gathered monthly observations from the FRED default spread, consisting of Moody's Baa Corporate Yield spread over the 10-year Constant Maturity.

From the Fama and French data library I retrieved monthly observations for the 3-factor model and the 5-factor model, to compute the VIX Beta as previously mentioned. Additionally, I used the variables in the 3 Fama and French factor model to retrieve the 1-month treasury bill of the United States

The dataset was normalized to prevent outliers from distorting estimations. Out of the original 61characteristics, I excluded those with over 80% missing observations to guarantee that the IPCA had sufficient bond-month observations, leaving out 39 environmental and 2 financial characteristics. For details on characteristics, refer to the appendix.

Furthermore, I trimmed the statistical distributions of the variables at the 98th percentile to eliminate outliers. Nevertheless, this adjustment proved insufficient, as several outliers persisted, certain variables, such as the book-to-market ratio, still exhibited significantly large negative values, which suggest the presence of distressed companies attributed to implicit negative equity book values. Consequently, in addition to trimming the statistical distribution, I dropped observations with the following criteria:

1. Book-to-price, market leverage, and book leverage ratios below zero.
2. Options-adjusted spreads less than 20 basis points or greater than 2000 basis points.
3. Yield to maturity greater than 2000 percent.
4. Debt-to-EBITDA ratios less than -2 or exceeding 100.

The normalization process resulted in a dataset with 286 082 bond-month observations and 5 964 bonds for 337 companies and 48 characteristics, comprising 26 financial characteristics and 22 environmental characteristics. The characteristics are cross-sectionally ranked and demeaned to fit an [-0,5,0,5] interval, as defined in Kelly et al. (2019,2023). The standardization of the data to fit an interval of [-0,5,0,5] serves to allow a direct comparison of latent risk factors, decrease the impact of statistical or accounting outliers.

Table 1. Descriptive statistics for the dataset.

Table 1 reports descriptive statistics for the characteristics before being cross-sectionally ranked and demeaned, covering the period from January 2010 to December 2024. Environmental characteristics originally reported as grades from Refinitiv are converted to numerical values, starting from A+ =1 to D- =12.

Characteristic/Statistic	Mean	St. dev	Min.	50^{th} perc.	Max.
Total Returns	0,20%	2,60%	-30,30%	0,30%	7,40%
Credit Excess Returns	0,00%	2,60%	-30,50%	0,10%	7,00%
Coupon	4,40%	1,60%	0,70%	4,30%	10,20%
Bond Age (Years)	5,80	5,60	0,00	3,90	35,20
Bond Amount Out. (m USD)	484	651	0,00	300	7496
Book to Price	0,71	0,47	0,00	0,68	2,33
Debt to EBITDA	11,58	14,63	-1,75	5,37	95,06
Duration (Years)	8,80	4,20	0,00	8,50	17,40
Option Adjusted Spread (Bps)	154,10	68,20	20,00	148,30	405,30
Yield to Maturity	4,50%	1,20%	-0,50%	4,70%	7,10%
Equity Momentum	7,20%	18,30%	-63,00%	6,50%	62,30%
Earnings to Price	0,07	0,06	-1,49	0,07	1,07
Market Cap. (m USD)	136 368	237 850	405	91 763	3 326 596
Equity Rolling Volatility	9,10%	3,40%	2,70%	8,30%	42,40%
Total Debt (m USD)	229 939	279 959	0,00	44 915	1 089 914
Bond Momentum	1,70%	6,30%	-37,80%	2,60%	16,30%
Industry Bond Momentum	1,90%	6,10%	-25,50%	2,70%	13,50%
Book Leverage	3,10	2,20	0,00	2,50	33,60
Market Leverage	2,60	2,00	0,00	1,80	17,50
Turnover Volatility	0,40%	0,70%	0,00%	0,10%	4,30%
Operating Leverage	3,12	3,05	-13,90	2,10	19,86
Profitability	23,30%	12,10%	-4,80%	21,00%	74,60%
Profitability 5y Change	0,30%	7,80%	-6,20%	0,10%	25,40%
Distance to Default	5,81	2,59	0,00	5,26	41,13

Bond Skewness	0,15	0,79	-6,20	0,07	5,36
Bond Momentum Spread	1,10%	18,80%	-47,20%	-1,40%	64,50%
Spread Distance to Default	0,30	0,95	-493,16	0,25	1,50
Bond Volatility 24m	2,60%	1,20%	0,00%	2,40%	6,70%
Environmental Controversy Score	49,80	15,00	0,00	54,20	55,80
Green Capex	50,70%	44,10%	0,00%	78,40%	98,40%
Resource Reduction Policy Score	71,10	9,30	1,20	72,60	78,70
Resource Reduction Targets Score	76,10	31,00	25,60	95,90	97,90
Company Green Revenue	5,20%	15,50%	0,00%	0,00%	100,00%
Environmental Controversies Score	52,50	42,30	0,00	80,10	94,40
Governance Pillar Score	68,40	18,10	7,60	71,70	99,40
Governance Pillar Score Grade	4,30	2,20	1,00	4,00	12,00
Policy Energy Efficiency Score	65,80	13,40	0,00	66,90	84,30
Policy Environmental Supply Chain Score	70,00	25,30	0,00	77,60	91,70
Social Pillar Score	74,60	13,80	8,60	76,80	98,10
Social Pillar Score Grade	3,60	1,70	1,00	3,00	11,00
Targets Emissions Score	73,40	27,60	0,00	81,40	94,50
ESG Controversies Score	41,90	40,00	0,30	20,60	100,00
ESG Controversies Score Grade	7,50	4,60	1,00	10,00	12,00
ESG Controversies Score Growth	51,40%	247,70%	-99,50%	-2,90%	3100,00%
ESG Combined Score	52,00	14,40	8,40	48,10	93,10
ESG Combined Score Grade	6,20	1,70	1,00	7,00	11,00

Product Responsibility Score	63,20	22,90	0,00	71,50	99,80
Product Responsibility Score Grade	4,90	2,70	1,00	4,00	12,00
ESG Score	72,00	12,70	8,40	73,20	95,20
ESG Score Grade	3,90	1,50	1,00	4,00	11,00

Based on Table 1, the descriptive statistics indicate that the average time to maturity in the dataset is five years, with an average coupon rate of 4.40%. The average outstanding issuance amount is approximately $464 million. The median monthly credit excess return stands at 0.1%. Furthermore, the yield to maturity for the bonds analyzed is 4.5%, while the average duration is 8.8 years. From the descriptive statistics above it is possible to confirm that we have diverse and normalized set of corporate bonds, with no outliers possibly distorting estimations.

4. Methodology

This section introduces the methodological specifications of IPCA proposed by Kelly et al. (2019, 2023), which is a conditional factor model in which betas and alphas are allowed to be time-variant and dependent on observable characteristics that are instruments for latent factors.

This model has several advantages over traditional models, including the possibility of incorporating informative information beyond returns, unlike PCA. Unlike conventional methodologies that prespecify factors and treat them as accurate observable proxies for risks, IPCA treats factors as latent without strong functional-form assumptions. Consequently, it does not rely on prior knowledge of the cross-section of returns.

Additionally, IPCA accounts for time-varying betas and risk premia since risk exposure is time-varying, as documented in Jagannathan and Wang (1996) and Ang and Kristensen (2012). In asset pricing literature, static betas in linear regression are commonly addressed using rolling regressions. However, this approach often results in noisy and stale beta estimates, especially with short estimation windows, which are chosen arbitrarily. Additionally, it becomes computationally demanding when handling high-dimensional data, IPCA offers a more scalable alternative, making it suitable for large datasets.

In conclusion, Kelly et al. (2019, 2023) present a framework that establishes a formal statistical connection between asset characteristics and the expected returns of corporate bonds. This framework allows for identifying a common latent space of risk factors and evaluating the marginal significance of a specific characteristic, which in this thesis will be sustainability-linked instruments while controlling for a wide range of characteristics. Moreover, IPCA is particularly valuable in this thesis due to its ability to handle unbalanced data panels, which is crucial since ESG-related data coverage in 2010 was relatively limited, enabling the analysis of a larger number of companies.

4.1 Restricted Model

The restricted version of IPCA assumes that $\alpha_{i,t} = 0$, and is specified as follows:

$$
\begin{aligned}
r_{i,t+1} &= \beta_{i,t} f_{t+1} + \varepsilon_{i,t+1} \, , \\
\beta_{i,t} &= z'_{i,t} \Gamma_\beta + \upsilon_{\beta_{i,t}} \, ,
\end{aligned} \tag{1}
$$

where $\beta_{i,t}$ is the 1xK vector of dynamic factor loadings, $f_{i,t+1}$ is the K × 1 vector of common latent factors realized at t + 1, $z_{i,t}$ the Lx1 vector of observable characteristics i at time t, Γ_β corresponds to the LxK matrix that maps and weights the characteristics to latent factors and the $\upsilon_{\beta_{i,t}}$ Kx1 vector captures the residuals that are orthogonal to the instruments.

The restricted IPCA determines the linear relationship between returns and the slope coefficient of K factors that depends on the L characteristics from $z_{i,t}$ and their corresponding weights from Γ_β. The matrix Γ_β provides the statistical bridge between returns and characteristics, although time-invariant and equal for every company, the dynamic creation of characteristic-managed portfolios based on time-variant characteristics allows the betas to be time-variant and the asset identity to shift. For example, when a firm starts off as small in the sample and grows significantly over time, the value of its dynamic betas is influenced by time-varying characteristics. Additionally, this matrix is essential for dimensionality reduction, creating a parsimonious model of K latent factors (where K < L) that captures common risk exposures. This approach addresses the "factor zoo" issue identified by Cochrane (2011).

Moreover, f_{t+1} is a vector of latent factors that captures the common variation among asset returns and provides a lower representation of common sources of risk. These factors are not directly observed from the data but extracted from returns and characteristics data.

4.2 Unrestricted Model

Following Kelly et. al (2019, 2023), the unrestricted IPCA is specified as:

$$\begin{gathered} r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \varepsilon_{i,t+1}\,, \\ \beta_{i,t} = z'_{i,t}\Gamma_\beta + \upsilon_{\beta_{i,t}}\,, \\ \alpha_{i,t} = z'_{i,t}\Gamma_\alpha + \upsilon_{\alpha_{i,t}} \end{gathered} \tag{2}$$

This specification allows the possibility that characteristics explain returns without risk, thus anomalies are a possibility. The unrestricted IPCA determines the linear relationship between returns, the anomaly term, and the slope coefficient of K factors that both depend on the L characteristics from $z_{i,t}$ and their corresponding weights from Γ_β Γ_α.

To assess whether Γ_α is statistically different from zero, Kelly et al. (2019, 2023) present an asset pricing test under the null hypothesis that $\Gamma_\alpha = 0$. This test introduces a Wald-type statistic that quantifies the deviation between the estimated $\hat{\Gamma}_\alpha$ from the actual data and the $\hat{\Gamma}_\alpha$ generated from the bootstrapped sample of returns. The procedure utilizes residuals from the unrestricted IPCA to create synthetic returns samples. Bootstrapping produces an empirical distribution of Wald-type statistics, from which a p-value is computed based on the proportion of bootstrapped statistics that surpass the true sample estimation.

4.3 IPCA Solution

To estimate IPCA, we need to solve the following minimization problem, similar to an OLS regression, the minimization problem is defined as follows:

$$min_{\Gamma_\beta, f_{t+1}} \sum_{t=1}^{T-1} (r_{t+1} - Z_t \Gamma_\beta f_{t+1})'(r_{t+1} - Z_t \Gamma_\beta f_{t+1}) \tag{3}$$

where Z_t is the NxL matrix of stacked characteristics of each asset at time t. The solution space, f_{t+1} and $\Gamma_{\beta,}$, must meet the following first-order conditions:

$$\hat{f}_{t+1} = (\hat{\Gamma}'_\beta Z'_t Z_t \hat{\Gamma}_\beta)^{-1} \hat{\Gamma}'_\beta Z'_t r_{t+1}, \quad \forall t \tag{4}$$

and

$$vec(\hat{\Gamma}'_\beta) = \left(\sum_{t=1}^{T-1} Z'_t Z_t \otimes \hat{f}_{t+1} \hat{f}'_{t+1} \right)^{-1} \left(\sum_{t=1}^{T-1} \lfloor Z_t \otimes \hat{f}'_{t+1} \rfloor' r_{t+1} \right), \quad \forall t \tag{5}$$

The first-order condition in equation (4) is factor realizations ($\hat{f}_{t+1}$) of period-by-period cross-section regression coefficients of returns on the latent loading matrix β. The second first-order equation (5) corresponds to time-series regression coefficients of returns on the factors interacted with characteristics.

The system of first-order conditions has no closed-form solution, thus to find the $f_{i,t+1}$ and Γ_β which minimizes the sum of squared errors, Kelly et al. (2019,2023) propose the application of an Alternating Least Squares algorithm, given an initial guess for Γ_β, the ALS fixes Γ_β and plugs it into $\hat{f}_{t+1}$ and given the new values for $\hat{f}_{t+1}$, fix $\hat{f}_{t+1}$ and plug it into $\hat{\Gamma}'_\beta$ iterating until convergence of a tolerance less than 10^{-6}.

Kelly et al. (2019,2023) showed that singular value decomposition on characteristic-managed portfolio returns efficiently meets the first-order conditions and offers a good initial guess for Γ_β

and $f_{i,t+1}$. Alternatively, one could have estimated f_{t+1} and $\Gamma_{\beta,}$ using stock-level data, however, that is computationally intensive for large datasets.

The characteristic managed portfolio returns are constructed as follows:

$$\sum_{t=1}^{T-1} r_{t+1}^{p} r'^{p}_{t+1} = (\frac{Z' r_{t+1}}{N_{t+1}})(\frac{Z' r_{t+1}}{N_{t+1}}) \quad (6)$$

where r_{t+1}^{p} is the return on a characteristic-managed portfolio, $\sum_{t=1}^{T-1} r_{t+1}^{p} r'^{p}_{t+1}$ is the second-moment matrix of returns, Z is the matrix of characteristics for all assets, N_{t+1} corresponds to the number of non-missing observations.

The *ith* element of the second-moment matrix reflects a weighted average of stock returns, where weights are based on the *ith* characteristic value of each asset at time t, adjusted for the number of observations.

To complete the model specification, Kelly (2019,2023) imposes additional conditions on the restricted IPCA:

1. Orthogonality of factor loadings through the Γ_β matrix by imposing that $\Gamma_\beta \Gamma'_\beta = \mathrm{I}_\mathrm{k}$, ensuring that columns (factors) are orthogonal to each other and normalized.
2. The diagonal second-moment factor matrix is constrained to be diagonal with descending values, ensuring that factors are ordered by importance.
3. Non-negative means for factors.

These restrictions are necessary for IPCA since the model captures the subspace of factors without determining their orientation. Consequently, any rotation of these factors can serve as an IPCA solution. Therefore, the constraints are designed to enforce a specific rotation that yields a unique solution without altering the fit.

Furthermore, in the unrestricted IPCA, an additional restriction needs to be imposed for the determination of Γ_α:

4. The simultaneous estimation of Γ_α and Γ_β is subject to $\Gamma'_\alpha \Gamma_\beta = 0$, this is achieved through a regression of the Γ_α onto the Γ_β, the resulting residual is $\hat{\Gamma}_\alpha$. This restriction allows the betas to explain the assets' means returns as much as possible while the orthogonal unexplained residual is assigned to the intercept.

5.Empirical Results

5.1 Performance Measurement

To measure the performance of IPCA, I employ 3 statistical measures of performance, as defined in Kelly et. al (2019,2023):

1. Total R^2, measures the fraction of contemporaneous variance described by exposure to common factors.

$$Total\ R^2 = 1 - \frac{\sum_{i,t}(r_{i,t+1} - \widehat{\beta'_{i,t}}\widehat{f_{t+1}})^2}{\sum_{i,t} {r_{i,t+1}}^2} \tag{7}$$

2. Predictive R^2 measures the percentage of variance in corporate bond returns described by conditional expected returns from common factors returns. The parameter λ represents the vector of average factor returns over time.

$$Predictive\ R^2 = 1 - \frac{\sum_{i,t}(r_{i,t+1} - \widehat{\beta'_{i,t}}\ \hat{\lambda})^2}{\sum_{i,t} {r_{i,t+1}}^2} \tag{8}$$

3. Pricing error measures the sum of squared pricing errors of corporate bonds returns divided by the sum of their squared average returns.

$$Pricing\ Error\ R^2 = 1 - \frac{\sum_n(\frac{1}{|\tau_i|}\sum_{t\epsilon\tau_i}(r_{i,t+1} - \widehat{\beta'_{i,t}}\widehat{f_{t+1}}))^2}{\sum_n \frac{1}{|\tau_i|}\sum_{t\epsilon\tau_i}(r_{i,t+1})^2} \tag{9}$$

Kelly et. al (2023) employs additional performance measures such as time series r-squared and the cross-section r-squared, however I consider that such measures although bring additional insights to the analysis, they are not important. The total r-squared already provides the conclusion that a researcher needs for the empirical tests.

5.2 Characteristic-Managed Portfolios Performance

This section reports preliminary and individual evidence for characteristics predicting excess corporate bond returns in the corporate bond market. Given the importance of characteristic-managed portfolios as an initial guess for IPCA it is relevant to understand a priori direction of the strategies, their significance and profitability.

In addition to the environmental characteristics sourced in the data section, I also lag environmental characteristics by 12 months. Since Zhang (2024) finds evidence that emissions are publicly available with significant lags, with median lags of 10-12 months, depending on the variable and data provider. Zhang (2024 also finds evidence that emissions are linearly related with sales, thus, failing to account for such lags can lead to a forward-looking bias, as emissions data contain information about operational performance. Therefore, this thesis will evaluate two IPCA specifications: one without lags and another with lags, referred to as IPCA-L12, another contribution of this thesis is to determine whether IPCA-L12 performs better.

As noted previously, characteristics-managed portfolios provide a shortcut for IPCA estimation, by decreasing the computational costs in a high-dimensional setting. Therefore, this analysis will mostly base its initial estimations on managed portfolios to extract the space of latent factors.

Table 2: Characteristic-managed portfolios Sharpe ratios

Table 2 reports t-statistics for Sharpe ratios. The data covers January 2010 to December 2024. The table denotes statistical significance at the 5% level (*) and at the 1% level (**), based on Lo (2022).

Characteristic	Sharpe Ratio		Characteristic	Sharpe Ratio
Bond Age	0,24		Governance Pillar Score Grade	-0,36
Coupon	0,07		Policy Energy Efficiency Score	0,09
Face Value	-0,20		Policy Env. Supply Chain Score	-0,14
Book to Price	0,18		Social Pillar Score	-0,18
Debt to EBITDA	0,22		Social Pillar Score Grade	0,27
Total Debt	-0,07		Targets Emissions Score	0,14
Duration	-0,85	**	ESG Controversies Score	0,16
Option Adj.Spread	-0,69	*	ESG Contr. Score Grade	0,15
Yield to Maturity	-0,83	**	ESG Contr. Score Growth	0,50
Equity Momentum	0,64	*	ESG Combined Score	-0,01
Earnings to Price	-0,06		ESG Combined Score Grade	0,07
Market Capitalization	-0,24		Product Responsibility Score	-0,15

Equity Rolling Volatility	0,19		Product Resp. Score Grade	0,22	
Bond Momentum	-0,96	**	ESG Score	0,18	
Industry Bond Mom.	0,55	*	ESG Score Grade	-0,15	
Book Leverage	0,04		Env. Controversies Score Lag	-0,12	
Market Leverage	-0,11		Env. Exp. Invest. Score Lag	-0,38	
Turnover Volatility	-0,19		Resource Reduction Score Lag	0,98	**
Operating Leverage	0,23		Resource Red. Targ. Score Lag	0,43	
Profitability	-0,22		Green Revenue Percentage Lag	-0,05	
Profitability 5y Change	-0,16		Env. Mat. Sourcing Score Lag	0,00	
Distance-to-Default	-0,23		Governance Pillar Score Lag	0,34	
Bond Skewness	0,20		Gov. Pillar Score Grade Lag	-0,34	
Bond Volatility 24m	-0,32		Policy Energy Eff. Score Lag	0,18	
Spread Distance-to-Default	-0,44		Policy Env. S. Chain Score Lag	0,18	
Bond Spread Mom.	-3,33	**	Social Pillar Score Lag	-0,11	
Environmental Contr. Score	0,72	**	Social Pillar Score Grade Lag	0,14	
Env. Expenditures Inv. Score	0,44		Targets Emissions Score Lag	-0,04	
Resource Red. Policy Score	0,53		ESG Contr. Score Lag	0,21	
Resource Red. Targets Score	0,34		ESG Contr. Score Grade Lag	0,35	
Green Revenue Perc.	-0,07		ESG Combined Score Lag	0,00	
Env. Materials Sourcing Score	-0,16		ESG Comb. Score Grade Lag	0,09	

Table 2 presents preliminary evidence that a small set of characteristics are profitable and that financial characteristics appear to have better risk-adjusted returns. Additionally, the environmental characteristics show worse risk-adjusted returns than financial characteristics, with only two portfolios being significant. The significance levels for financial characteristics are generally consistent with what Kelly et al. (2023) reports.

5.3 In-Sample Performance

This section introduces the performance measurement of both IPCA and IPCA-L12. The measurements are defined in section 5.1 of this thesis. For the evaluation of IPCA and IPCA-L12, I consider only the restricted version of IPCA with 5 latent factors where returns are only explained by the dynamic loadings, according to table C1, in appendix C, the statistical significance for Γ_α indicates that returns are explained through betas, there is no anomalies so the in-sample and out-of-sample estimations make more sense in a restricted setting.

Table 3: IPCA in-sample performance

Table 3 reports the restricted IPCA and IPCA-L12 performance measures in percentage, Total $R^{2,}$ and Relative Pricing Error from January 2010 to December 2024. Each IPCA specification was estimated with 3 to 5 latent factors (K). Panel A reports the performance of individual assets, and Panel B reports on managed portfolios.

	IPCA			IPCA-L12		
	K=3	K=4	K=5	K=3	K=4	K=5
Panel A: Individual Bonds						
Total R^2 (%)	69,2	72,1	73,9	70,6	72,8	74,1
Relative Pricing Error (%)	20,8	22,0	18,1	23,2	18,0	18,0
Panel B: Managed Portfolios						
Total R^2 (%)	79,6	85,3	73,9	79,4	85,4	88,9
Relative Pricing Error (%)	31,6	11,3	18,1	15,0	3,0	3,0

The results in table 3 suggest a high degree of predictability for an asset pricing model. The comparison between IPCA specifications, leads to the conclusion that IPCA-L12 has a marginally better performance across number of latent factors (K).

Another important aspect to note, is the stability in relative errors, which monotonically decrease as the number of latent factors considered increase. For details on the latent factors extracted, refer to the appendix.

5.4 IPCA Out-of-Sample Performance

Departing from the in-sample performance, this section will evaluate whether the out-of-sample predictive power of the model and test its robustness and stability over time. This assessment is crucial to understand how well the model generalizes beyond the training sample.

The estimation process was conducted via a 36-month expanding window, the initial estimation is made 36 months after the first valid bond-month observation. Thereafter, the model systematically estimates the month-by-month realizations of factors.

Table 4: IPCA out-of-sample performance

Table 4 reports the restricted IPCA and IPCA-L12 performance measures in percentage, Total R2, and Relative Pricing Error from January 2010 to December 2024. Each IPCA specification was estimated with 3 to 5 latent factors (K). Panel A reports the performance of individual assets, and Panel B reports on managed portfolios.

	IPCA			IPCA-L12		
	K=3	K=4	K=5	K=3	K=4	K=5
Panel A: Individual Bonds						
Total R^2 (%)	67,1	69,3	71,1	67,2	70,4	71,6
Relative Pricing Error (%)	24,2	24,5	19,8	25,3	23,2	20,6
Panel B: Managed Portfolios						
Total R^2 (%)	71,0	79,0	85,2	72,1	84,2	87,1
Relative Pricing Error (%)	6,8	3,8	3,1	7,6	3,8	2,1

The main conclusion from the out-of-sample performance is the consistency and stability of the predictive power, when IPCA leaves the training sample. Another important aspect is the greater ability of IPCA to capture systematic return variation in managed portfolios of characteristics, with 5 latent factors, IPCA has a striking performance of 85,2% and 87,2%, for IPCA and IPCA-L12 respectively. In addition to the outstanding performance, the relative pricing errors reach 2,1%, in the case of IPCA-L12. Furthermore, the marginal improvements of IPCA-L12 indicate that incorporating lagged information enhances the model's ability to capture persistent return dynamics.

5.5 Marginal Contribution of Environmental Characteristics

The previous sections explored the predictability of a linear latent factor model in explaining common risk-return sources. However, the interpretability of the latent factors and which instruments are driving the estimations remains a challenge.

Therefore, it is crucial to investigate which characteristics drive this predictability and their marginal contributions to the Γ_β matrix. In particular, this section examines the marginal influence of environmental characteristics on corporate bond returns. This leads us to the research question of identifying whether any green characteristic can instrument for a common risk source associated with environmental performance, while also controlling for financial instruments.

To test the statistical significance of each individual instrument, we need to adjust the l^{th} row of Γ_β matrix that corresponds to the characteristic being tested. The l^{th} row in the matrix contains the characteristic's loadings for all K latent factors.

The statistical test proceeds as defined in Kelly et. al (2019, 2023):

1. Define the null hypothesis that $\Gamma_\beta = [\gamma_{\beta,1}, \dots, 0_{k*1}, \dots, \gamma_{\beta,L}]'$, where $\gamma_{\beta,l}$ is the vector with the loadings on the K factors.
2. Divide the Γ_β matrix into L rows, corresponding to the number of individual characteristics.
3. Estimate IPCA under the null hypothesis where the l^{th} row is all equal to zeros.
4. Compute Wald-type statistics $W_\beta = \widehat{\gamma'}_{\beta,l}\,\widehat{\gamma}_{\beta,l}$ that measure the distance between zero and the estimate of vector $\gamma_{\beta,l}$.
5. Proceed with a residual bootstrap estimation, like what is defined in section 4.2 for the test $\Gamma_\alpha = 0$.

Table 5: IPCA- Marginal Contribution of Environmental Characteristics Out-of-Sample

Table 5 presents the marginal contribution of each characteristic in a restricted IPCA with 5 latent factors. The marginal contribution is measured as the square root of the sum of squared elements in the l^{th} row of Γ_β. The table denotes statistical significance for the 5% level (*) and for the 1% level (**).

Characteristic	Impact		Characteristic	Impact	
Bond Age	0,04		Bond Skewness	0,03	
Coupon	0,06	**	Bond Volatility 24m	0,15	
Face Value	0,12	**	Environmental Contr. Score	0,05	
Book to Price	0,13		Env. Expenditures Inv. Score	0,07	
Debt to EBITDA	0,05		Resource Red. Policy Score	0,08	
Total Debt	0,13		Resource Red. Targets Score	0,04	
Duration	0,35	**	Green Revenue Perc.	0,03	
Option Adj.Spread	0,15		Env. Materials Sourcing Score	0,07	
Yield to Maturity	0,13	*	Governance Pillar Score Grade	0,25	*
Equity Momentum	0,03		Policy Energy Efficiency Score	0,03	
Earnings to Price	0,02		Policy Env. Supply Chain Score	0,04	
Market Capitalization	0,09		Social Pillar Score	0,15	
Equity Rolling Volatility	0,02		Social Pillar Score Grade	0,10	
Bond Momentum	0,29	**	Targets Emissions Score	0,06	
Industry Bond Mom.	0,06		ESG Controversies Score	0,31	**
Book Leverage	0,09		ESG Contr. Score Grade	0,33	**
Market Leverage	0,11		ESG Contr. Score Growth	0,05	
Turnover Volatility	0,04		ESG Combined Score	0,22	
Operating Leverage	0,04		ESG Combined Score Grade	0,23	*
Profitability	0,02		Product Responsibility Score	0,08	
Profitability 5y Change	0,02		Product Resp. Score Grade	0,10	
Spread Distance-to-Default	0,18		ESG Score	0,06	
Bond Spread Mom.	0,29	**	ESG Score Grade	0,08	
Distance-to-Default	0,18				

Based on table 5 it is possible to conclude that a mix of financial and environmental characteristics drive corporate bond returns.

Furthermore, we can infer that, given the 1% level of statistical significance, companies that score high in ESG controversies tend to earn higher average returns, as shown by the statistical significance detailed in Table 5.

Table 6: IPCA-L12 Marginal Contribution of Environmental Characteristics Out-of-Sample

Table 6 presents the marginal contribution of each characteristic in a restricted IPCA-L12 with 5 latent factors. The marginal contribution is measured as the square root of the sum of squared elements in the l^{th} row of Γ_{β}. The table denotes statistical significance for the 5% level (*) and for the 1% level (**).

Characteristic	Impact		Characteristic	Impact	
Bond Age	0,02		Company Green Revenue Percentage_lag	0,04	
Coupon	0,07	**	Environmental Materials Sourcing Score_lag	0,05	
Face Value	0,12		Governance Pillar Score Grade_lag	0,14	
Book to Price	0,08		Policy Energy Efficiency Score_lag	0,03	
Debt to EBITDA	0,05		Policy Environmental Supply Chain Score_lag	0,06	
Total Debt	0,24	*	Social Pillar Score_lag	0,21	**
Duration	0,40	**	Social Pillar Score Grade_lag	0,18	
Option Adjusted Spread	0,14		Targets Emissions Score_lag	0,06	
Yield to Maturity	0,16	**	ESG Controversies Score Grade_lag	0,33	**
Equity Momentum	0,03		ESG Combined Score_lag	0,21	
Earnings to Price	0,06		ESG Combined Score Grade_lag	0,21	

Market Capitalization	0,11		Distance-to-Default	0,12	
Equity Rolling Volatility	0,02		Environmental Controversies Score_lag	0,06	
Bond Momentum	0,29	**	Governance Pillar Score_lag	0,11	
Industry Bond Momentum	0,03		Bond Spread Momentum	0,29	**
Book Leverage	0,04		Operating Leverage	0,03	
Market Leverage	0,10		Profitability	0,05	
Turnover Volatility	0,03		Profitability 5y Change	0,02	
Bond Skewness	0,04		Spread Distance-to-Default	0,20	
Bond Volatility 24m	0,14		ESG Controversies Score_lag	0,30	**
Resource Reduction Policy Score_lag	0,07		Environmental Expenditures Investments Score_lag	0,09	
Resource Reduction Targets Score_lag	0,05				

Based on table 6 we can conclude that characteristics such as Duration (0,40), Total Debt (0,24), Bond Momentum (0,29), and Yield to Maturity (0.16) and Coupon (0,07) are the financial characteristics contributing to the performance of IPCA-L12, aligning with previous findings in Kelly et. al (2023). Moreover, environmental characteristics such as Social Pillar Score (0,21, significant at 1%), ESG Controversies Score (0,30, significant at 1%) and ESG Controversies Grade (0,33, significant at 1%) also contribute the IPCA-L12 performance and potentially signal the absorption of an environmental-linked risk factor.

The findings in table 5 and 6, suggest that investors may demand compensation for exposure to ESG-related risks. However, the instruments that captures such systematic risk are not clear, in this thesis different specifications led to the different instruments being significant, with the exception of ESG controversies, which emerged as a consistent instrument across specifications. This consistency suggests that ESG controversies may serve as a valid instrument for capturing sustainability-linked systematic risk in corporate bond pricing.

5.6 Investing in Characteristics Portfolios

Beyond evaluating statistical significance, it is essential to determine the economic significance of a characteristic, so it can represent a genuine source of systematic risk. In case a characteristic consistently generates excess returns net of transactions costs, it reinforces the research question to include environmental characteristics in asset pricing models.

This section explores IPCA average return's estimations in a mean-variance setting, and estimates systematic portfolios returns. I follow Kelly et. al (2023) and compute portfolios returns as:

$$r_{p,t+1} = \sum_{i} w_{i,t} r_{i,t} - 19bps \times \sum_{i} |w_{i,t} - w_{i,t-1}| \tag{10}$$

Where $w_{i,t}$ is the weight allocated to asset *i* at time *t.* In a setting where we are building portfolios and accounting for transactions costs, if of utmost importance to have a measure of the turnover inside the portfolio for that case, I follow Kelly et. al (2023) and define the turnover statistics as:

$$\text{Turnover}=\frac{1}{T}\sum_{i}\frac{\sum |w_{i,t}-w_{i,t-1}|}{\sum |w_{i,t-1}|} \tag{11}$$

Since we are considering profitability net of transaction costs and the turnover tends to be high, in order to resemble a real world setting I follow Kelly et.al (2023) and introduce exponential smoothing to the portfolio's allocations defined as:

$$\widetilde{w} = (1-\gamma)w_{i,t} + \widetilde{w_{t-1}}\gamma \tag{12}$$

Table 7: Performance of Characteristic-Managed Portfolios

Table 7 reports the out-of-sample turnover, gross Sharpe ratios, and net Sharpe Ratios for IPCA and IPCA-L12 specifications with five latent factors, for systematic bond strategies. Following Kelly. et al. (2023) I assume trading costs of 19 basis point. The variable γ controls weights in asset allocation based on exponential smoothing to optimal portfolios weights.

	IPCA Tangency Portfolio			IPCA-L12 Tangency Portfolio		
γ	Turnover	Gross Sharpe Ratio	Net Sharpe Ratio	Turnover	Gross Sharpe Ratio	Net Sharpe Ratio
0	1,00	4,18	2,06	1,00	5,13	2,56
0,1	1,00	4,03	2,02	1,00	4,97	2,54
0,2	0,93	3,83	1,94	0,95	4,76	2,47
0,3	0,85	3,58	1,82	0,87	4,47	2,34
0,4	0,77	3,28	1,66	0,79	4,11	2,15
0,5	0,70	2,91	1,45	0,71	3,67	1,91
0,6	0,62	2,48	1,22	0,64	3,16	1,63
0,7	0,54	2,02	0,97	0,55	2,62	1,34
0,8	0,45	1,55	0,73	0,47	2,08	1,08
0,9	0,34	1,11	0,53	0,36	1,56	0,90

Based on table 7, we can conclude that increasing γ significantly decreases the gross Sharpe ratio due to the delayed action on the signal, as stated in Kelly et. al (2023). Across all levels of γ, the IPCA-L12 specification systematically outperforms the baseline IPCA model in terms of both gross and net Sharpe ratios. This indicates that incorporating lag-adjusted environmental characteristics enhances the predictability of latent risk factors and provides better-optimized systematic portfolios. The comparison with traditional investment strategies highlights the economic relevance of IPCA-based portfolios. While Kelly et al. (2023) reports annualized Sharpe ratios of 0.26 for an equal-weighted bond portfolio, the IPCA methodology suggests gross Sharpe ratios ranging from 1.11 to 5.13, depending on the investor's tolerance for turnover. This suggests that characteristic-driven asset pricing models provide substantial improvements in portfolio efficiency and risk-adjusted returns.

Notwithstanding strategies based on high turnover, such as the ones presented in table 6 for γ smaller than 0,4 can lead the strategies profitability to erode, in case the transaction costs are not small and stable, which is the case for the corporate bond market.

Conclusion

Concluding, IPCA is a latent factor linear model with unprecedent capacity of explaining average returns in the corporate bond market, both in-sample and out-of-sample. It embodies unique characteristics that allow the framework to overcome certain inherent limitations in asset pricing literature.

For this thesis IPCA served an important purpose, of identifying specific environmental characteristics that offer independent information about the cross-section of returns in the corporate bond market and based on the empirical evidence obtained there are certain instruments that capture common latent risk sources. The instruments were ESG controversies scores and ESG controversies grades. This contrasts with the findings of Lindsey et al. (2024), who research the influence of ESG grades and their pillars on the cross-section of stock market returns. The empirical findings in this thesis also contrast with those of Bolton and Kacperczyk (2021, 2023) and Hsu et al. (2023), which suggest that carbon-intensive firms outperform green companies. Notwithstanding, the empirical evidence of this thesis also diverges from those of Duan et al. (forthcoming), who conclude that no environmental characteristics can explain average returns after accounting for financial characteristics.

The mixed evidence in sustainable finance can be attributed to several reasons, including the different methodologies employed, which may not be suitable given the possible high dimensionality in the asset pricing world, as well as the strong assumptions about the structure of factors proposed by researchers, that tend to be defined *ad hoc* by the researcher.

Moreover, traditional asset pricing literature, also tends to leverage on prior knowledge of the cross-section of returns.

Notwithstanding sustainable finance data suffers from a lack of standardization, that means different measures from different data providers can lead to opposing views on the same research question, additionally researchers do not have visibility on how certain measures were constructed or how good the underlying data used for the variable constructed is, take as an example ESG scores and ESG grades.

In contrast, the approach presented in this thesis takes a different methodological stance, and by not making any strong assumption on the cross-section of returns or predefining factors *ad hod*, I integrate all available green measures in Refinitiv and assesses how they interact with financial characteristics already studied in the literature.

This research concludes that while financial characteristics explain variations in returns, several green measures have predictive power. For instance, ESG Controversies Scores and Grades imply that companies with minimal exposure to environmental, social, and governance controversies and adverse media events generally achieve higher average returns. Other metrics, such as scores for governance and social pillars, alongside the lagged ESG Combined Score Grade, also seem to exhibit predictive power, however, their statistical significance is linked to the baseline IPCA specification, which, according to Zhang (2024), may be flawed. Evidence from Tables 2, 5, and 6 suggests that a characteristic measuring ESG controversies may be more effective in explaining returns.

This analysis is limited to U.S.-based bonds and firms, which means that conclusions about a sustainability-related risk premium cannot be generalized to foreign markets. Additionally, the quality of the data poses challenges, as this analysis heavily relies on Refinitiv, and the returns used for this panel may not accurately reflect the reality of market participants. The illiquidity of the bond market can further distort returns on such securities.

Furthermore, access to environmental characteristics in the original dataset was limited due to numerous missing values. Consequently, excluding variables with 80% invalid values resulted in the loss of several characteristics related to emissions growth, emissions scopes, and both scaled and unscaled emissions, thereby narrowing the range of characteristics that could instrument for a latent risk factor.

Regarding methodological limitations, IPCA assumes linear relationships between characteristics and returns. However, Gu et al. (2019) suggest that non-linearities are important in financial markets, thus a non-linear IPCA could yield different statistical significance, levels of risk premia, extract a different set of latent factors, since the asset pricing world has embedded non-linearities.

Future avenues of empirical research could explore other non-linear IPCA specifications, extend the study of green risk sources to other asset classes such as stock market, fixed-income market, options market and other derivatives. Moreover, for a factor to be a true source of risk it needs to be generalized across geographies, thus researchers could take the initiative to explore other developed financial markets. The priority should be developed markets, since emerging markets can suffer for inherent liquidity problems and lack of sophisticated investors that rationally price sources of risk in the market.

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Appendix

Appendix A: Characteristics Summary

Table A1: Summary of the characteristics used in IPCA after all filtering criteria

This table provides a summary of the characteristics used and a brief description with references. From the paper Kelly et. al (2023) this thesis excludes credit ratings due to limited availability of data and consequently the momentum * rating was not possible to compute. Later, due to the 80% non-NaN criteria I had to exclude the characteristics VIX-Beta and VaR 95 as defined in Kelly et.al (2023).

Characteristic	Description	Reference
Bond age	Number of years the bond is publicly traded.	Israel et. al (2018)
Coupon	Bond coupon in percentage	Chung et.al (2019)
Amount outstanding	The amount outstanding of bonds outstanding in USD	Israel et. al (2018)
Book to price	Ratio of common and preferred equity divided by market capitalization for the issuer	Bartram et. al (2020)
Debt to EBITDA	Debt divided by EBITDA	Kelly et.al (2023)
Total debt	Firm's total debt	Kelly et.al (2023)
Duration	Measure of the sensitivity of a bond's price to changes in yield	Israel et.al (2018)
Option adjusted spread	Measure of the security's extra return over the return of a comparable treasury security after accounting for options	Israel et. al (2018)
Yield to maturity	Yield to maturity	Author

Equity momentum	Six-month equity momentum	Gebhardt et. al (2005b)
Earnings to price	Net income from the recent four quarters divided by market cap.	Correia et.al (2012)
Market Capitalization	Equity market capitalization	Choi et. al (2018)
Equity rolling volatility	Rolling180 days equity volatility	Campbell et. al (2003)
Bond momentum	Six-month bond momentum	Gebhardt et. al (2005b)
Industry bond momentum	Industry adjusted momentum returns	Jorion et. al (2009)
Book leverage	Common equity and debt and minority interest minus cash and inventories, divided by common equity minus preferred stock	Asness et. al (2019)
Market leverage	Sum of market capitalization, debt and minority interest and preferred stock minus cash and inventories divided by common equity	Asness et. al (2019)
Turnover volatility	Quarterly standard deviation of sales divided by total assets.	Correia et. al (2019)
Operating leverage	Op. leverage is sales minus EBITDA, divided by EBITDA.	Gamba et. al (2019)
Profitability	Profitability for nonfinancial companies: sales minus cost-of-goods-sold, divided by assets. For financials: sales minus total expenses plus	Choi et. al (2018)

	depreciation, divided by common and preferred equity	
Profitability 5y change	Profitability 5 years change	Asness et. al (2019)
Distance-to-default	Computed as defined in Shumway (2001)	Israel et. al (2018)
Bond skewness	Bond skewness of returns over a rolling window of 60 months	Bai et. al (2019)
Bond volatility 24m	Bond return volatility over a rolling window of 24 months	Bai et. al (2019)
Spread distance-to-default	Option-adjusted spread, divided by one minus the cumulative distribution function of Shumway (2001)	Correia et. al (2012)
Bond spread momentum	Log of the spread six months earlier minus current log spread.	Israel et.al (2019)
Environmental controversies score	Score for companies involved in environmental controversies due to its operations	Author
Environmental expenditures investments score	Score to evaluate the sustainability of a company's investments	Author
Resource reduction policy score	Score for company's policies that reduce resources use or lessen the environmental impact	Author
Resource reduction targets score	Score for objectives to be achieved on resource efficiency	Author

Company green revenue percentage	Percentage of revenues coming from green products	Author
Environmental materials sourcing score	Score for the sustainability of materials sourced from the supply chain	Author
Governance pillar score	Measures the company’s systems and processes that the board and executives act in the best interest of shareholders	Author
Governance pillar score grade	Grade from A+ to D- to measure governance	Author
Policy energy efficiency score	Score for energy policies towards energy efficiency and sustainability	Author
Policy environmental supply chain score	Score for policies to include environmental efforts in its supply chain	Author
Social pillar score	Me	Author
Social pillar score grade	Grade from A+ to D- to measure social score	Author
Targets emissions score	Score on the target of emissions to be reduced on business operations	Author
ESG controversies score	Measures the company’s exposure to environmental social and governance controversies and negative events in media	Author
ESG controversies score grade	Grade from A+ to D- to measure ESG controversies	Author

ESG controversies score growth	Growth in ESG controversies score	Author
ESG combined score	Overall company score based on the reported information in the environmental, social and governance pillars	Author
ESG combined score grade	Grade from A+ to D- to measure ESG combined score	Author
Product responsibility score	Measures the company’s capacity to produce responsible products	Author
Product responsibility score grade	Grade from A+ to D- to measure product responsibility score	Author
ESG score	Overall company score based on self-reported information in the environmental, social and governance pillars	Author
ESG score grade	Grade from A+ to D- to measure ESG score grade	Author

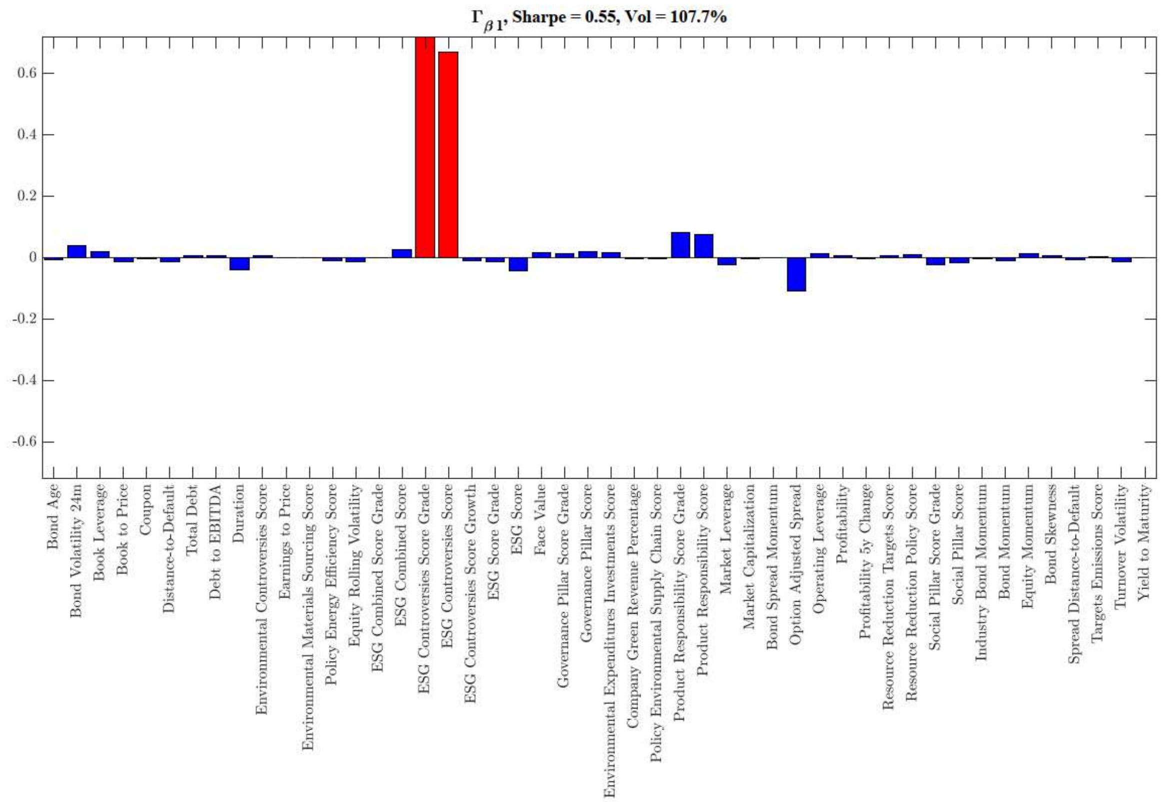
Table A2: ESG Grades Conversion to Numerical Values

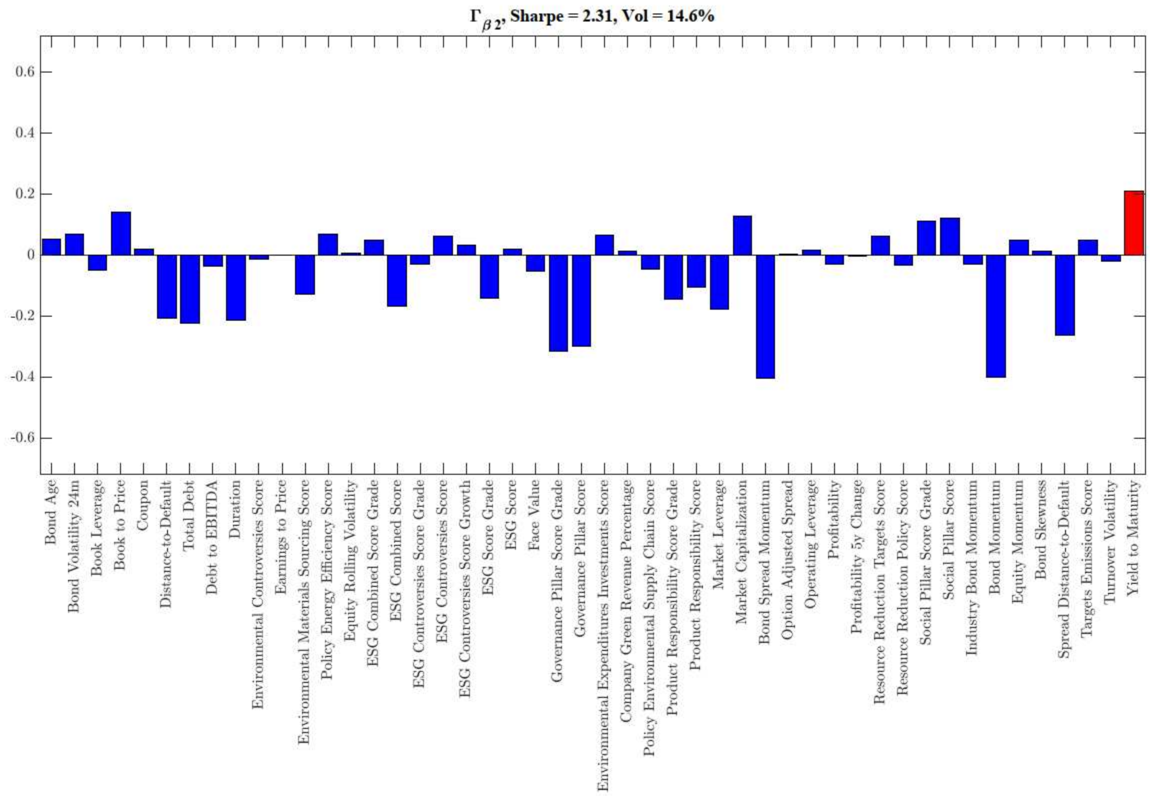
This table summarizes the grading system from Refinitiv, and the correspondent numerical value used for estimation purposes.

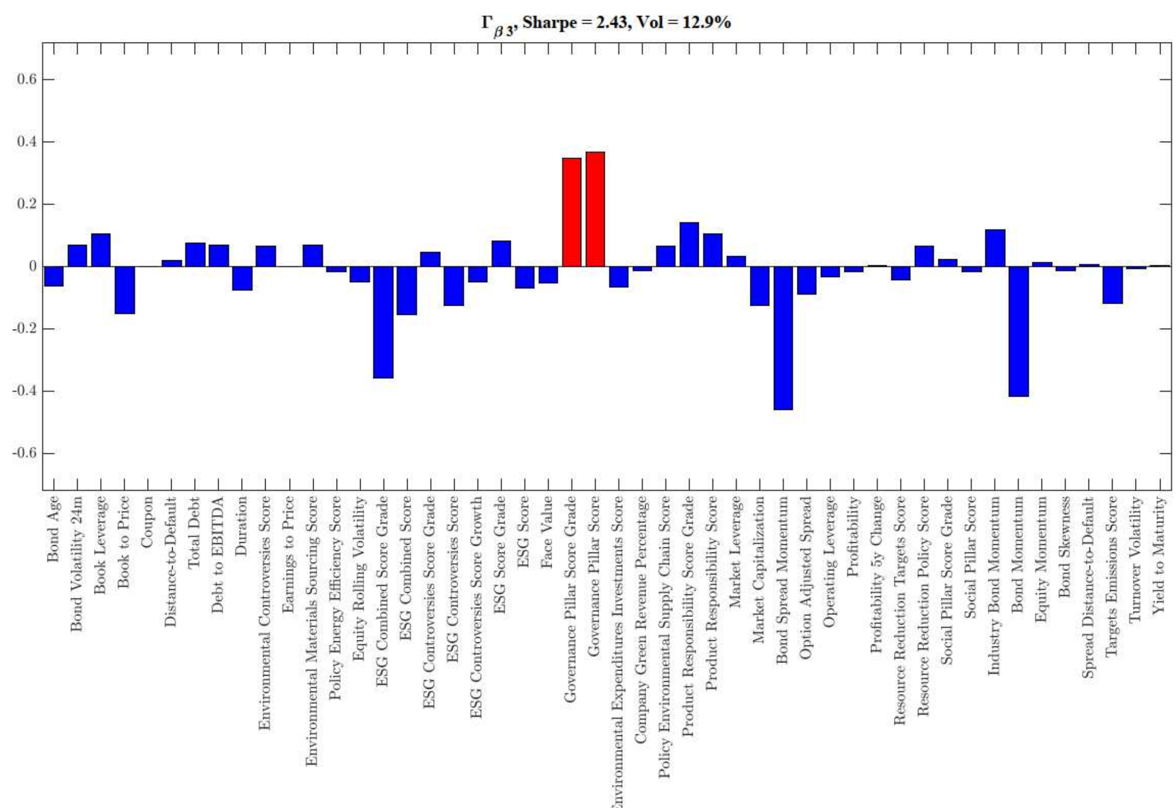
Grades	Numerical Value
A+	1
A	2
A-	3
B+	4
B	5
B-	6
C+	7
C	8
C-	9
D+	10
D	11
D-	12

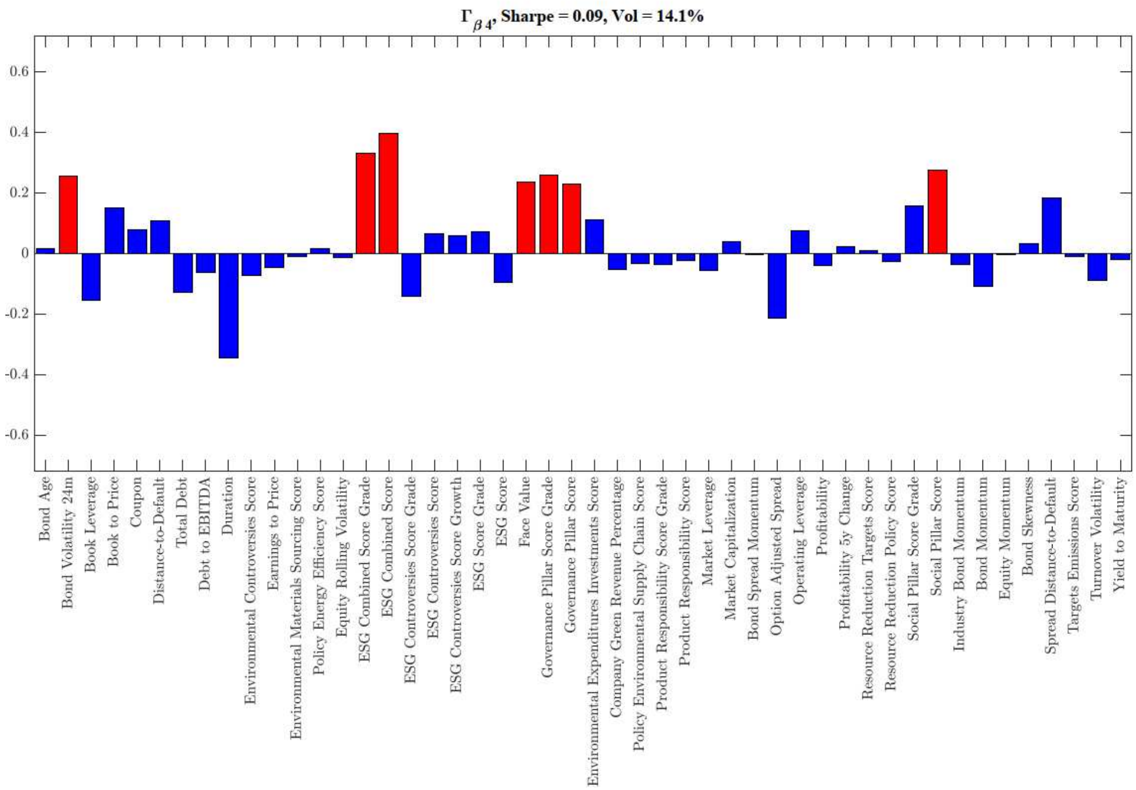
Appendix B: In-Sample Latent Factor Estimation

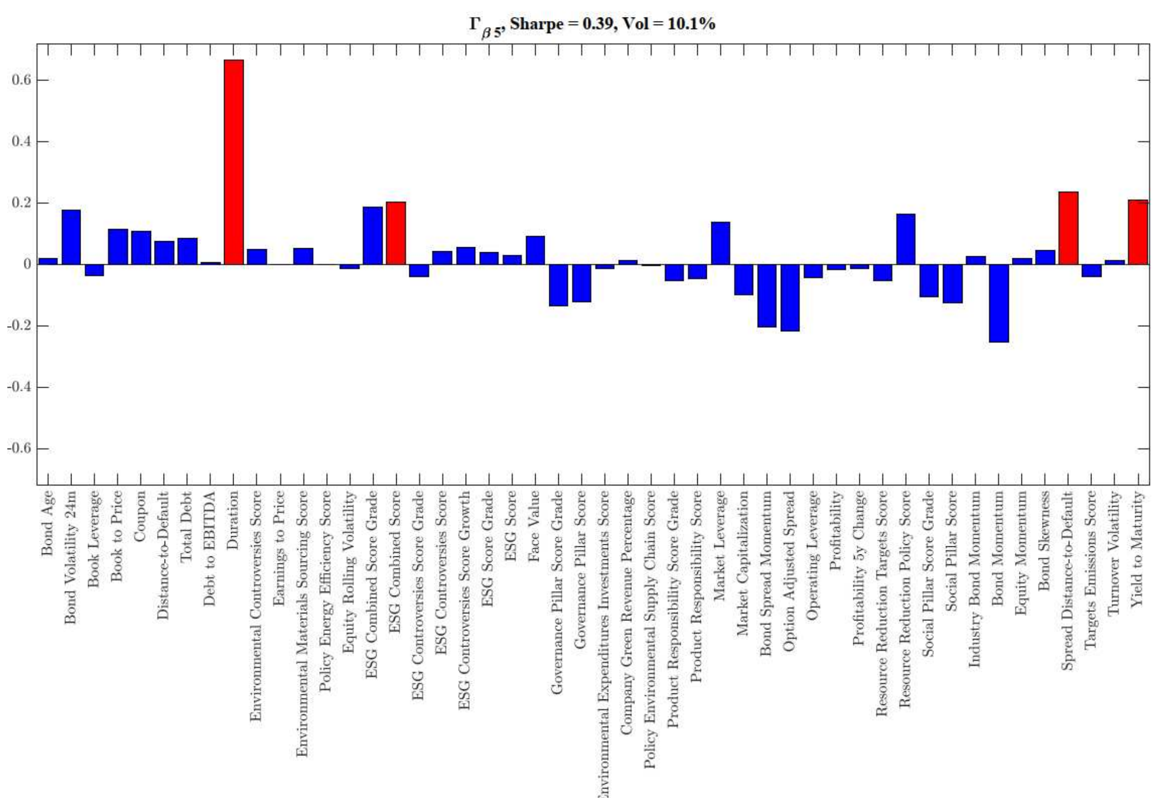
Graph B1: Latent factors for IPCA K=5




$\Gamma_{\beta 2}$, Sharpe = 2.31, Vol = 14.6%
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
Bond Age
Bond Volatility 24m
Book Leverage
Book to Price
Coupon
Distance-to-Default
Total Debt
Debt to EBITDA
Duration
Environmental Controversies Score
Earnings to Price
Environmental Materials Sourcing Score
Policy Energy Efficiency Score
Equity Rolling Volatility
ESG Combined Score Grade
ESG Combined Score
ESG Controversies Score Grade
ESG Controversies Score
ESG Controversies Score Growth
ESG Score Grade
ESG Score
Face Value
Governance Pillar Score Grade
Governance Pillar Score
Environmental Expenditures Investments Score
Company Green Revenue Percentage
Policy Environmental Supply Chain Score
Product Responsibility Score Grade
Product Responsibility Score
Market Leverage
Market Capitalization
Bond Spread Momentum
Option Adjusted Spread
Operating Leverage
Profitability
Profitability 5y Change
Resource Reduction Targets Score
Resource Reduction Policy Score
Social Pillar Score Grade
Social Pillar Score
Industry Bond Momentum
Bond Momentum
Equity Momentum
Bond Skewness
Spread Distance-to-Default
Targets Emissions Score
Turnover Volatility
Yield to Maturity


$\Gamma_{\beta 3}$, Sharpe = 2.43, Vol = 12.9%
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
Bond Age
Bond Volatility 24m
Book Leverage
Book to Price
Coupon
Distance-to-Default
Total Debt
Debt to EBITDA
Duration
Environmental Controversies Score
Earnings to Price
Environmental Materials Sourcing Score
Policy Energy Efficiency Score
Equity Rolling Volatility
ESG Combined Score Grade
ESG Combined Score
ESG Controversies Score Grade
ESG Controversies Score
ESG Controversies Score Growth
ESG Score Grade
ESG Score
Face Value
Governance Pillar Score Grade
Governance Pillar Score
Environmental Expenditures Investments Score
Company Green Revenue Percentage
Policy Environmental Supply Chain Score
Product Responsibility Score Grade
Product Responsibility Score
Market Leverage
Market Capitalization
Bond Spread Momentum
Option Adjusted Spread
Operating Leverage
Profitability
Profitability 5y Change
Resource Reduction Targets Score
Resource Reduction Policy Score
Social Pillar Score Grade
Social Pillar Score
Industry Bond Momentum
Bond Momentum
Equity Momentum
Bond Skewness
Spread Distance-to-Default
Targets Emissions Score
Turnover Volatility
Yield to Maturity


$\Gamma_{\beta 4}$, Sharpe = 0.09, Vol = 14.1%
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
Bond Age
Bond Volatility 24m
Book Leverage
Book to Price
Coupon
Distance-to-Default
Total Debt
Debt to EBITDA
Duration
Environmental Controversies Score
Earnings to Price
Environmental Materials Sourcing Score
Policy Energy Efficiency Score
Equity Rolling Volatility
ESG Combined Score Grade
ESG Combined Score
ESG Controversies Score Grade
ESG Controversies Score
ESG Controversies Score Growth
ESG Score Grade
ESG Score
Face Value
Governance Pillar Score Grade
Governance Pillar Score
Environmental Expenditures Investments Score
Company Green Revenue Percentage
Policy Environmental Supply Chain Score
Product Responsibility Score Grade
Product Responsibility Score
Market Leverage
Market Capitalization
Bond Spread Momentum
Option Adjusted Spread
Operating Leverage
Profitability
Profitability 5y Change
Resource Reduction Targets Score
Resource Reduction Policy Score
Social Pillar Score Grade
Social Pillar Score
Industry Bond Momentum
Bond Momentum
Equity Momentum
Bond Skewness
Spread Distance-to-Default
Targets Emissions Score
Turnover Volatility
Yield to Maturity


$\Gamma_{\beta 5}$, Sharpe = 0.39, Vol = 10.1%
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
Bond Age
Bond Volatility 24m
Book Leverage
Book to Price
Coupon
Distance-to-Default
Total Debt
Debt to EBITDA
Duration
Environmental Controversies Score
Earnings to Price
Environmental Materials Sourcing Score
Policy Energy Efficiency Score
Equity Rolling Volatility
ESG Combined Score Grade
ESG Combined Score
ESG Controversies Score Grade
ESG Controversies Score
ESG Controversies Score Growth
ESG Score Grade
ESG Score
Face Value
Governance Pillar Score Grade
Governance Pillar Score
Environmental Expenditures Investments Score
Company Green Revenue Percentage
Policy Environmental Supply Chain Score
Product Responsibility Score Grade
Product Responsibility Score
Market Leverage
Market Capitalization
Bond Spread Momentum
Option Adjusted Spread
Operating Leverage
Profitability
Profitability 5y Change
Resource Reduction Targets Score
Resource Reduction Policy Score
Social Pillar Score Grade
Social Pillar Score
Industry Bond Momentum
Bond Momentum
Equity Momentum
Bond Skewness
Spread Distance-to-Default
Targets Emissions Score
Turnover Volatility
Yield to Maturity

Appendix C: Alternative Estimations

Table C1: Unrestricted IPCA Alpha Significance

Following Kelly et. al (2023), this table tests whether $\Gamma_\alpha = 0$ with a Wald-type test, with bootstrapped residuals, as described in section 4.2 for the unrestricted IPCA. This test follows Kelly et.al (2023) and uses a t-distribution with seven degrees of freedom and 1000 simulations.

	IPCA			IPCA-L12		
$H_0: \Gamma_\alpha = 0$	K=3	K=4	K=5	K=3	K=4	K=5
P-Value (%)	97,1	98,0	98,0	98,2	99,0	99,0

Based on table A3 it is possible to conclude that for most specifications there are no alpha to be left to be explained, thus expected returns are explained mainly through betas and characteristics align with the dynamic betas.

Table C2: IPCA Out-of-Sample Performance for Unscaled Returns

Following Kelly et. al (2023), table C2 reports an alternative estimation of the performance for IPCA and IPCA-12 for unscaled returns. Previous estimations were done with DtS scaling of returns. This table reports out-of-sample performance for individual bonds and managed portfolios.

	IPCA			IPCA-L12		
	K=3	K=4	K=5	K=3	K=4	K=5
Panel A: Individual Bonds						
Total R^2 (%)	70,1	72,1	74,2	69,1	71,5	73,3
Relative Pricing Error (%)	25,2	21,3	20,6	24,2	22,8	19,7
Panel B: Managed Portfolios						
Total R^2 (%)	57,0	69,2	79,4	64,9	76,2	83,0
Relative Pricing Error (%)	20,9	7,2	8,0	18,6	12,4	13,6

Based on table C2, it Is possible to conclude that scaling returns brings a normalization of the performance of IPCA. When compared scaled and unscaled performance we confirm that they are close, however scaling returns brings a normalization to the most volatile segment of the bonds. We can conclude that no segment of the bonds is driving statistical significance.

Table C3: Performance of Characteristic-Managed Portfolios

Following Kelly et. al (2023), table C3 reports the out-of-sample performance for unscaled returns for IPCA with five latent factors and I assess the profitability of trading the tangency portfolio with transaction costs at 19bps

	IPCA Tangency Portfolio			IPCA-L12 Tangency Portfolio		
γ	Turnover	Gross Sharpe Ratio	Net Sharpe Ratio	Turnover	Gross Sharpe Ratio	Net Sharpe Ratio
0	1,00	4,41	2,37	1,00	4,71	0,73
0,1	1,00	4,3	2,35	1,00	4,57	0,63
0,2	0,95	4,15	2,29	0,96	4,40	0,51
0,3	0,87	3,95	2,20	0,88	4,18	0,39
0,4	0,80	3,7	2,06	0,81	3,93	0,26
0,5	0,72	3,38	1,88	0,73	3,61	0,14
0,6	0,64	3,00	1,67	0,66	3,23	0,03
0,7	0,56	2,57	1,42	0,58	2,78	-0,07
0,8	0,47	2,09	1,17	0,49	2,26	-0,14
0,9	0,36	1,59	0,90	0,37	1,67	-0,14

Based table C3, it is possible to verify that the performance tends to decrease specially for higher γ with transaction costs, when compared to scaled returns.