Factor Investing in Fixed Income Instruments

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ABSTRACT

Factor investing in credit requires not only a deep knowledge of the underlying systematic factors, but also expertise in their implementation, which can be influenced by lack of liquidity, interactions with other systematic risks, or increasing regulations to adopt sustainability measures. Previous research has focused on formulating general factor models to identify the optimal set of common factors, but important questions remain unanswered. This dissertation seeks to fill a gap in the literature on factor investing in emerging market corporate bonds in the presence of illiquidity and country-specific risk. Additionally, this thesis analyzes the integration of sustainability measures into systematic factor strategies.

The first study addresses the liquidity of emerging market corporate bonds, which appears to be significantly lower than that of developed market bonds and is also influenced by macroeconomic variables. Additionally, the paper presents a liquidity forecast model that reduces the proportion of illiquid assets in a factor portfolio. The second study analyzes the cross-sectional variation of emerging market corporate bonds and finds that it is significantly affected by country-specific risk. Furthermore, it shows that an asset pricing model designed specifically for emerging markets produces better out-of-sample model fit and portfolio performance than models designed for developed markets. The final study reveals the implications of integrating sustainability targets in systematic credit strategies. The results indicate a non-linear, concave relationship between factor and impact investing, suggesting that investors can improve their sustainability/outperformance profile at marginal cost.

ALTERNATIVE ABSTRACT

Die Umsetzung von Factor Investing in Unternehmensanleihen erfordert nicht nur ein umfassendes Verständnis der zugrunde liegenden systematischen Faktoren, sondern auch Expertise in deren Implementierung. Dies wird durch verschiedene Faktoren erschwert, darunter mangelnde Liquidität, Wechselwirkungen mit anderen systematischen Risiken oder zunehmende Regulierungen zur Einführung von Nachhaltigkeitsmaßnahmen. In der bisherigen Forschung wurden allgemeine Faktormodelle entwickelt, um das optimale Set gemeinsamer Faktoren zu bestimmen. Dabei wurden jedoch wichtige Fragen nicht beantwortet. Die vorliegende Dissertation zielt darauf ab, eine Forschungslücke in der Literatur über Factor Investing in Unternehmensanleihen aus Schwellenländern unter Berücksichtigung von Illiquidität und länderspezifischem Risiko zu schließen. Des Weiteren erfolgt eine Analyse der Integration von Nachhaltigkeitsmaßnahmen in systematische Faktorstrategien.

Die erste Studie befasst sich mit der Liquidität von Unternehmensanleihen aus Schwellenländern. Diese ist offenbar deutlich geringer als die von Anleihen aus Industrieländern und wird auch von makroökonomischen Variablen beeinflusst. Zudem wird ein Liquiditätsprognosemodell vorgestellt, welches den Anteil illiquider Vermögenswerte in einem Faktorportfolio reduziert. Die zweite Studie analysiert die Querschnittsvariationen der Renditen von Unternehmensanleihen aus Schwellenländern und stellt fest, dass diese erheblich durch länderspezifische Risiken beeinflusst werden. Zudem zeigt sie, dass ein speziell für Schwellenländer entwickeltes Asset-Pricing-Modell Out-of-Sample besser performt als Modelle, die für entwickelte Märkte konzipiert wurden. Die letzte Studie widmet sich den Auswirkungen der Integration von Nachhaltigkeitszielen in systematische Kreditstrategien. Die Resultate legen nahe, dass die Beziehung zwischen Faktor- und Impact-Investing nicht linear und konkav ist. Dies impliziert, dass Investoren ihr

Nachhaltigkeits-/Outperformance-Profil zu marginalen Kosten optimieren können.

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Desislava Vladimirova

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LIST OF ABBREVIATIONS

Token	Description
ALS	Alternating Least Squares
BofA	Bank of America
BBB+	Rating category BBB+
bps.	basis points
ca.	circa
CAPM	Capital Asset Pricing Model
CDS	Credit Default Swap
CO2	Carbon dioxide
CPI	Consumer Price Index
DM	Developed markets
D2D	Distance to default
DTS	Duration Times Spread
EM	Emerging markets
EMCB	Emerging Markets Corporate Plus Index
ESG	Environmental, Social and Governance
FX	Foreign Exchange
GBM	Gradient Boosting Machine
GDP	Gross Domestic Product
GIIN	Global Impact Investing Network
GICS	Global Industry Classification Standard
G0BC	Global Corporate index
HY	High yield
HW00	High Yield Index

Token	Description
ICE	Intercontinental Exchange
IG	Investment grade
IPCA	Instrumented Principal Component Analysis
IR	Information ratio
IS	In-sample
LCS	Liquidity Cost Scores
LS	Long short
mn	millions
NA	Not applicable
OAS	Option Adjusted Spread
OLS	Ordinary Least Squares
OOS	Out-of-sample
OTC	Over The Counter
PAB	Paris-Aligned Benchmark
PAI	Principal Adverse Impact
p.p.	percentage points
Q	Quintile
RMSE	Root Mean Square Error
SDG	Sustainable Development Goals
SFDR	Sustainable Finance Disclosure Regulation
SR	Sharpe ratio
TC	Trading costs
TV	Trading volume
V	Volatility

Token	Description
VAR	Value At Risk
VIX	Volatility Index
VC	Venture Capital
U.S.	United States

1 INTRODUCTION

Factor investing is a well known concept in the equity market and less so in the fixed income market. Nevertheless, a growing body of literature examines the factor space of corporate bonds. As such, studies on factor investing compete to discover the most prominent set of factors that explain the cross-sectional variation of corporate bonds, with little concern for some practical aspects such as implementation, transferability to other fixed income asset classes, and integrity with investor preferences. This dissertation examines, in three comprehensive studies, challenges that credit factor investors face that have not been previously documented. The first two analyses focus on the less popular, but attractive from a risk-adjusted return and diversification perspective, asset class of emerging market corporate debt. The main difficulties in entering this market are the lack of understanding of its liquidity and the associated level of country-specific risk. The third study provides initial evidence on the integration of sustainability measures into credit factor strategies, thus addressing the growing investor preference to achieve both a sustainable and profitable credit portfolio. Therefore, the aim of this dissertation is not to propose further systematic factors, but to build on the existing literature by providing useful insights on the implementation of factor investing for institutional credit factor investors. The following section provides an overview of the existing literature that serves as the basis for the empirical analyses conducted in the three studies.

Systematic risk premia of bonds have been documented in literature dating back to Nelson and Siegel (1987), Litterman and Scheinkman (1991), and also Fama and French (1992), the latter of which suggested term structure and default risk as bond factors. However, literature on systematic factors for corporate bonds appeared for the first time in the early 2000s with studies by Hottinga et al. (2001) and Gebhardt et al. (2005). These studies aimed to identify promising fixed income and equity variables that can explain the systematic variation of corporate bond returns. Furthermore, Bektić et al. (2019) find evidence of cross-asset spillovers and demonstrate the relevance of the Fama-French equity factors for the predictability of corporate bond returns. Recent studies by Houweling and Zundert (2017), Brooks et al. (2018), Israel et al. (2018), and Henke et al. (2020) have led to the identification of the most successful fixed income factors in use today. These factors work not only independently, but also in combination. Among the most promising systematic factors are carry, defensive, value, momentum, and size. Parallel to conventional methods of modeling observable factors, Kelly et al. (2023) propose a new approach based on instrumental principal component analysis that conditions exposure to latent factors through the characteristics of corporate bonds. Their results suggest that only five latent factors are necessary to explain the systematic variance of corporate bond returns, and that this model can better account for variations in bond returns than previous factor models. When considering emerging markets, only Dekker and De Jong (2021) investigate credit factor performance. However, the study does not explicitly incorporate the presence of country-specific risk. Moreover, the results demonstrate a dominance of the size factor, which could be due to the substantial illiquidity of emerging market corporate debt.

Studies that explore corporate bond liquidity compare various proxies to adequately measure future credit liquidity (Schestag et al. (2016)). However, these findings have not been extended to illiquid assets. The use of liquidity proxies is necessary since bonds are traded on the OTC market and trading data is frequently unobservable. Several studies have documented key liquidity determinants, such as volatility, trading costs, age, size, and bond credit rating (Alexander et al. (2000), Lee and Cho (2016), Hotchkiss and Jostova (2017)). Nonetheless, no attempt has been made to measure the liquidity of EM corporate bonds or to identify EM-specific liquidity determinants that might help investors make investment decisions. Consequently, there are no established estimation models for trading factor strategies on illiquid assets, such as emerging market debt. Failing to account for liquidity in factor strategies may drastically decrease the portfolio's outperformance and make systematic strategies ineffective.

Finally, previous literature has predominantly focused on the pricing of sustainability measures, including carbon footprint and ESG scores for equities (Bolton and Kacperczyk (2021) Bolton and Kacperczyk (2022), Hsu et al. (2023), Görgen et al. (2019), Pedersen et al. (2021)), as well as the green bond premium in fixed income (Baker et al. (2018), Hachenberg and Schiereck (2018), Zerbib (2019), Partridge and Medda (2020), Tang and Zhang (2020), Fatica et al. (2021), Immel et al. (2021), Flammer (2021)). Nevertheless, there are other sustainability measures that have yet to be scrutinized in the literature. Furthermore, there is a widespread belief that investing in sustainable assets leads to a linear reduction in performance. Institutional investors who utilize factor strategies are primarily profit-driven, and there is limited evidence of the coexistence of factor and sustainability-oriented investment approaches (Pedersen et al. (2021), Geczy et al. (2021)). However, the degree of greenness varies depending on the sustainability metric used. In addition, fixed-income investors now have even more options to combine sustainability criteria with factor strategies with the availability of labeled bonds. Therefore, an analysis of sustainability metric integration in credit factor investment strategies is needed.

This dissertation presents new insights into fixed income factor investing in several ways. First, it analyzes the possible liquidity determinants of emerging market corporate debt, providing a general understanding of the liquidity of this asset class. Additionally, it proposes and evaluates liquidity estimation models within the context of credit factor strategies, therefore, it offers a liquidity adjusted factor framework. The second study diverges from factor investing approaches proposed in developed markets and instead examines the key drivers of the cross-section of emerging market bond returns. The approach used in this analysis refrains from making assumptions about observable factors and enables quantification of the influence of country-specific risk on corporate bond returns, thus documenting differences in the systematic return drivers of developed and emerging market debt. Finally, this dissertation studies the pricing of various sustainability aspects, the correlation between factor investing and sustainability investing in credit, and their implications. This examination reflects the changing preferences of investors towards sustainability and challenges the idea of integrating such standards into factor strategies. In the remainder of this introduction, the main findings of the three studies are briefly presented and summarized.

The first study examines the liquidity of emerging market corporate bonds by investigating the determinants of liquidity and estimating a liquidity management model. It analyzes hard-currency EM corporate bonds from January 2010 to December 2020, using trading volume as a proxy for liquidity. To identify significant explanatory variables of EM debt liquidity, a regression model first considers the interactions of trading volume with transaction costs and ex-ante volatility, and then incorporates bond and firm variables found for DM bonds, as well as macroeconomic variables that reflect the higher sovereign risk of emerging markets. The results support previous literature, but also identify variables such as the 5-year sovereign credit default swap spread and short-term interest rate volatility that account for the variation in EM trading volume. In addition, a significant discrepancy in liquidity between EM and DM bonds is observed. Thus, the study proposes a two-step approach for estimating liquidity using various methods, which is tested against a simple technique relying solely on past trading volume data. Several variables, including past trading volume, are found to be critical in generating a liquidity forecast. The model demonstrates superior predictive power on an out-of-sample dataset. A complex liquidity estimation model is worthwhile when trading illiquid factor signals, such as momentum strategies, because it reduces the percentage of illiquid assets in a credit portfolio.

The second study examines the factors that impact emerging market corporate bond returns, with a particular focus on country-specific risks. It uses a hybrid asset pricing model based on instrumental principal component analysis, which combines the advantages of beta-based and characteristic-based models (Kelly et al. (2019)). This permits exploration of the factor space of EM bonds without relying on ad hoc assumptions about the underlying factors, and also allows factor loadings to be instrumentalized by bond, firm, and country characteristics. The study is conducted on hard-currency EM bonds for the period from January 2010 to December 2022. Before specifying the final model setup, the first results provide compelling evidence of the profound impact of country-specific risk on EM bond returns. Moreover, more than half of the country characteristics are statistically significant in the model with ten latent factors. In addition, the inclusion of country variables leads to improved out-of-sample measures of both total and cross-sectional R-squared relative to a model without country characteristics. The study also evaluates the effectiveness of the EM-specific model relative to well-known factor models, including the five-factor characteristic-based framework recommended by Kelly et al. (2023). The OOS results show that the model incorporating country information explains significantly more variation in EM bond returns. This is not only due to the instrumental factor loadings via country variables, but also to the model's ability to capture the EM factor space without making any initial assumptions. Comparing the return forecasts of different models in an actual factor strategy, it can be observed that the EM IPCA model yields the highest Jensen's alpha of 2% per annum and an information ratio of 1, which are statistically significant. Therefore, investors seeking to diversify their portfolios by investing in emerging market credit should adjust their return expectations to account for significant country risk.

The final study examines the impact of integrating sustainability metrics into fixed income factor portfolios. The analysis is based on USD IG bonds from August 2017 to August 2022, and the sustainability metrics examined are Scope 1 carbon intensity, SDG scores, and green bonds. As suggested by Pedersen et al. (2021), the effect of incorporating sustainability into a portfolio depends on the ability of sustainability measures to predict returns and on investors' preferences for levels of greenness. Accordingly, attention is first turned to the pricing of various sustainability instruments, where two key observations are made. First, as the demand for sustainable assets increases, sustainable bonds trade at spreads that are 3 to 5 basis points tighter than those of comparable bonds. However, there is no evidence of a significant green or brown premium. This suggests that measures of sustainability cannot explain the variation in corporate bond returns. The second part of the study analyzes the consequences of integrating sustainability into factor portfolios. This is important because investors who prefer systematic strategies are typically profit-oriented. Optimizing portfolios with the dual objective of achieving sustainability exposure and systematic risk premia yields favorable results for both sustainability-focused and factor investors. The results show that the sustainability-factor frontier is non-linear and concave, reflecting the low correlation between sustainability metrics and individual credit factors, as well as the skewed distribution of certain metrics, such as carbon footprint. Overall, the results suggest that factor investors aligning their portfolios with sustainability metrics can do so at marginal cost, while sustainability-focused investors can potentially outperform the benchmark with little exposure to systematic risk premia and still meet their sustainability goals.

The remainder of the dissertation is structured as follows. The subsequent three sections contain the three individual studies, each with a separate introduction and conclusion. Section 5 presents a comprehensive conclusion on the primary findings of the studies and proposes potential areas for advancement and further research.

2 MANAGING LIQUIDITY OF EMERGING MARKETS CORPORATE DEBT

2.1 Abstract

Emerging markets (EM) corporate bonds are perceived to offer attractive diversification potential and risk-adjusted returns, but to be illiquid. This study expands the empirical evidence by examining the liquidity of EM debt by solving a triangular structured system. We find EM bond liquidity to both share common determinants with developed markets (DM) and be influenced by macroeconomic factors. As the overall level of liquidity is lower to DM, we propose a liquidity estimation model, which allows systematic factor investors to decrease the share of illiquid assets in their portfolio by roughly 3 p.p. and 10 p.p. during the COVID-19 pandemic.

Keywords: bond liquidity, emerging markets, trading volume, bid-ask spread

JEL classification: G12, G17

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3 IN THE SHADOW OF COUNTRY RISK. ASSET PRICING MODEL OF EMERGING MARKET CORPORATE BONDS

3.1 Abstract

We examine the covariances of corporate bonds in emerging markets (EM) and present an asset pricing framework using instrumented principal component analysis (IPCA) that includes characteristics at the sovereign and bond levels. Our results indicate that EM bond returns are significantly influenced by country-specific risks. Incorporating these characteristics can improve both the total and cross-sectional model fit. We demonstrate that a factor framework tailored to the nuances of the EM universe generates a significant alpha of 2% per annum and a higher information ratio than alternative asset pricing models, such as a conditional beta model designed for developed market (DM) bonds.

Keywords: corporate bonds, factor investing, emerging markets, country risk

JEL classification: G12, G17

This chapter contains Publication 2, D. Vladimirova (2024):

Vladimirova D (2024). *In the Shadow of Country Risk: Asset Pricing Model of Emerging Market Corporate Bonds*. doi: 10.1057/s41260-024-00370-3 (URL: https://doi.org/10.1057/s41260-024-00370-3).

3.2 Introduction

Factor models in credit have experienced a renaissance in the last two decades. Depending on the estimation technique, they fall into two categories: beta-based and characteristic-based models (Gebhardt et al. (2005)). Bai et al. (2019), Elkamhi et al. (2020) develop asset pricing models to estimate expected return of corporate debt. On the other hand, Hottinga et al. (2001), Houweling and Zundert (2017), Brooks et al. (2018), Israel et al. (2018), Bektić et al. (2019), Henke et al. (2020) have identified a common set of factors that explain the cross-sectional variation of corporate bond returns based on bond and stock characteristics. Kelly et al. (2023) have recently proposed a hybrid asset pricing model, whereby time-varying betas are conditioned on bond and stock characteristics. They find that only a few bond and firm characteristics are able to explain the latent factor space of corporate bond returns. While the evidence of common factors appears robust across various currency, such as USD versus EUR, and different risk levels - investment grade (IG) versus high yield (HY) bonds, there is limited indication that those factors are informative for corporate bonds in emerging markets (EM). An obstacle to applying existing models to EM credit is that corporate bonds are often issued by non-listed firms, while factor models typically rely on equity characteristics. Additionally, the returns of EM bonds can be influenced by country-specific risks. Therefore, it remains unclear what drives the cross-sectional variation of EM corporate bond returns and in particular, how much can be attributed to country risk.

Despite the numerous studies on systematic factors for developed market (DM) corporate debt, there is a lack of research on EM debt. Kang et al. (2019) and Brooks et al. (2020) develop factor models for the EM sovereign bonds. In the only existing study on factor investing in EM hard currency corporate debt, Dekker et al. (2021) reproduce the common fixed income signals from developed markets (refer to Houweling and

Zundert (2017)) and discover that size, value, momentum, and the combined portfolio substantially outperform the emerging market index. However, the model fails to account for other sources of systematic risk by applying DM credit factors to the fragmented EM universe.

In this study, we describe the cross-sectional variation of EM corporate bond returns using instrumented principal component analysis (IPCA). The IPCA model incorporates not only bond attributes but also country-specific data, which accounts for the complexity of the EM universe when constructing factors. We expect EM corporate bonds to inherit significant country risk, given that evidence from equity markets shows that EM stock returns are linked to the performance of their respective local countries (Rouwenhorst (1999), Harvey (1995)). Therefore, in our first hypothesis, we examine the extend to which country-specific characteristics can account for variations in EM bond returns. Furthermore, prior literature indicates that the liquid universe of EM bonds is considerably smaller than that of DM indices and that non-listed companies issue up to one-third of EM debt (Vladimirova et al. (2023)). This makes the application of observable factor models difficult, since they rely heavily on equity characteristics. We use the IPCA model to avoid making assumptions about the ad-hoc factors and to adapt the exposure to latent factors to the time variation of bond and country characteristics. Therefore, we hypothesize that a model which takes into account country-specific information and is not limited to a pre-determined number of observable factors would better describe the cross-sectional exposure to systematic risks compared to leading factor models.

To evaluate the impact of country-specific information on the model performance, we initialize an IPCA model with bond and country-specific characteristics. Our findings show that adding country variables to a 10-factor model increases the total R^2 by 6.5%

to 29.2% and the cross-sectional R^2 by 2.6% to 16.9%. This model performs equally well in assessing test assets, whether corporate bonds or characteristic portfolios. We discover that relevant for the model fit are not only bond variables, like face value, duration, or bond volatility[1], but also variables of synthetic country portfolios. Additionally, characteristics based on sovereign instruments, such as change in Credit Default Swap (CDS) spread and change in the value of the local currency against the USD, exhibit significant importance at a p-value of 5%. Altogether, our results indicate the need to account for country specifics when pricing EM bonds.

Using the findings of the first hypothesis, we assess the benefits of the EM-tailored IPCA model when compared to leading factor models, such as the market factor, a four-factor model for EM credit proposed by Dekker et al. (2021), and five-factor models with static and dynamic betas suggested by Kelly et al. (2023)[2]. Comparing the out-of-sample (OOS) total and cross-sectional R^2, we discover that the EM IPCA model outperforms not only the models using static betas but also the one using time-varying betas. Hence, the advantages of our IPCA framework can be observed not only in instrumenting the factor exposures via bond and country characteristics but also in the employment of a latent number of factors, which appears to differ from those used in developed markets. Finally, we report that a portfolio utilizing the EM IPCA model forecast outperforms other competing models, yielding a statistically significant Jensen's alpha of 2% per annum and an information ratio (IR) of 1.

Our research relates to the literature on corporate debt empirical asset pricing (Fama and French (1993), Gebhardt et al. (2005), Elkamhi et al. (2020), Bai et al. (2019), Kelly et al. (2023)). Additionally, using a conditional factor model, our analysis draws

[1]Bond variables are calculated as the deviation from the average level of a synthetic country portfolio.
[2]We also refer to these as DM IPCA models.

connections to the studies conducted by Avramov and Chordia (2006) and Ferson and Harvey (1999), which leverage an extensive set of variables to model expected stock returns. However, those studies rely on observable factors, while we make no ad-hoc assumptions about the number of factors used. Our study closely relates to Kelly et al. (2023), which examine the latent factor space of US corporate IG and HY bonds. We further extend that analysis by studying the cross-section of EM corporate bonds. Our study is the first to consider country characteristics that may influence the returns of EM bonds.

Our analysis also contributes to the existing factor investing literature, which explains the variation of corporate bond returns with bond and stock characteristics. Correia et al. (2012), Jostova et al. (2013), Chordia et al. (2017), Correia et al. (2018), Bektić (2019), Kaufmann and Messow (2020), Bali et al. (2021), Bartram et al. (2020), among others, develop alternative credit factors by using bond and equity information. On the other hand, Hottinga et al. (2001), Houweling and Zundert (2017), Brooks et al. (2018), Israel et al. (2018), Bektić et al. (2019), and Henke et al. (2020) propose multi-factor models to invest in corporate bonds. Furthermore, Dekker et al. (2021) utilize a factor model to elucidate the EM corporate bonds' cross-section. However, the study omits the potential of country-specific hazards, which an EM portfolio may be exposed to but not compensated. By contrast, our analysis does not rely on a pre-specified set of factors and therefore captures the exposure to systematic country risk. As the IPCA model employs a large number of characteristics to estimate time-varying betas on latent factors, we take into account information beyond bond and firm characteristics that further tailors our model to the EM universe.

Section 2 describes the data, and provides an overview of the IPCA and the methodology used to evaluate our results. Section 3 tests the hypothesis that country-specific information is significant for describing the variation of EM corporate bond returns. Section 4 compares the model performance with leading factor models in credit, regarding the findings from our second hypothesis. Section 5 provides a summary of the primary results.

3.3 Data and Methodology

3.3.1 Methodology

3.3.1.1 Model Specification

To understand the risk and return drivers of EM corporate bonds, we utilize the IPCA model framework proposed by Kelly et al. (2019). The IPCA estimation of excess return is based on empirical asset pricing methodology and is presented in the following Equation (1):

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

where the EM investable universe is structured as a panel of N assets for T periods by L characteristics. Compared to other models, IPCA has two main advantages. Firstly, it uses conditional betas, also referred to as instrumented betas. As shown in Equation (1), the betas of a bond i for the period t are computed as the product of L characteristics $z_{i,t}$ and a mapping matrix Γ_{β} of these L characteristics to K factors and a residual $\nu_{\beta,i,t}$. This approach allows for factor loadings to be directly dependent on multiple characteristics, resulting in the consideration of more information in the model. On the other hand, the IPCA model allows beta to vary over time, and as a results, it can capture the fluctuating asset's exposure to factors. Kelly (2019) notes that modifying asset identity presents a challenge for modeling excess returns. This is particularly relevant for corporate bonds, as they mature at some time, and thus their price converges to the par value of the bond. The IPCA framework has an additional benefit in that it does not presuppose any ex-ante assumptions about the observable factors. Instead, it models K latent factors similarly to PCA using factor realizations f_{t+1}. The Γ_β matrix allows for this by linearly transforming the L characteristics to K orthogonal factors.

In our model framework, we constrain the conditional intercept $\alpha_{i,t}$ to zero, assuming that the latent factors fully explain the return variation of bond excess returns. This implies that the characteristics serve as a proxy for exposure to systematic risk factors and not credit returns anomalies, which sets $\Gamma_\alpha = 0_{Lx1}$. To evaluate the optimal number of K factors for which alpha is insignificant we use a Wald-type test with a wild bootstrap with 1000 iterations and for K from 1 to 11. The bootstrapped sample created without $\Gamma_\alpha = 0_{Lx1}$ is used to re-estimate the unrestricted model and thus, $\tilde{\Gamma}^b_\alpha$. To determine the presence of unsystematic alpha, we compare the W_α of the unrestricted model, which is $\hat{\Gamma}'_\alpha\hat{\Gamma}_\alpha$, to W^b_α of each bootstrapped model, which is $\tilde{\Gamma}^{b\prime}_\alpha\tilde{\Gamma}^b_\alpha$. The p-value denotes the proportion of W^b_α values exceeding W_α. Rejecting the hypothesis that the characteristics relate to return anomalies is possible if the bootstrapped values exceed those of the unrestricted model.

When the model is restricted Equation (1) simplifies in a matrix form to:

$$r_{t+1} = Z_t\Gamma_\beta f_{t+1} + \varepsilon^*_{t+1}, \tag{2}$$

where r_{t+1} represents the returns of N bonds, Z_t has dimensions of N x L, and ε^*_{t+1} with dimensions of N x 1 represents bond residuals.

The IPCA estimation is derived from the following optimization problem:

$$\min_{\Gamma_\beta, F} \sum_{t=1}^{T-1} \left(r_{t+1} - Z_t \Gamma_\beta f_{t+1}\right)^{-1} \left(r_{t+1} - Z_t \Gamma_\beta f_{t+1}\right). \tag{3}$$

To determine the unknown parameters Γ_β and f_{t+1}, the Equations (4) and (5) have to be solved simultaneously.

$$\widehat{f}_{t+1} = \left(\Gamma_\beta' Z_t' Z_t \Gamma_\beta\right)^{-1} \Gamma_\beta' Z_t' r_{t+1} \tag{4}$$

$$\operatorname{vec}\left(\Gamma_\beta'\right) = \left(\sum_{t=1}^{T} \left[Z_t \otimes f_t'\right]' \left[Z_t \otimes f_t'\right]\right)^{-1} \left(\sum_{t=1}^{T} \left[Z_t \otimes f_t'\right]' r_t\right) \tag{5}$$

The numerical problem is solved iteratively through the alternating least squares (ALS) method. The ALS algorithm addresses the optimization problem in a quadratic form and reduces the loss function monotonically by iterating the alternate problem.

Lastly, the model estimation can also be solved approximately in terms of characteristic managed portfolios x_{t+1} as test assets instead of corporate bonds. The x_{t+1} is a vector of size L x 1, where each row l represents the return of a characteristic l weighted portfolio:

$$x_{t+1} = Z_t' r_{t+1}. \tag{6}$$

In fact, the initial Γ_β is based on the first K eigenvectors of the characteristic managed portfolios. By using characteristic portfolios, the number of parameters is greatly reduced. Rather than minimizing Equation (3) with N assets, the algorithm only uses L characteristics. This leads to faster conversion of the ALS algorithm, and also directly maps excess returns to observable characteristics.

3.3.1.2 Performance Measures

In this section, we describe the asset pricing tests used to assess the effectiveness of our model. When determining the optimal number of latent factors K, we evaluate each model in a restricted form $\Gamma_\beta = 0$. This evaluation is based on three statistics: total R^2, cross-sectional R^2, and relative pricing error.

Total R-squared

The first metric, total R^2, assesses how well the instrumented characteristics explain the common variation in corporate bond returns. It is defined as:

$$\text{Total } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - z_{i,t}'\widehat{\Gamma}_\beta \widehat{f}_{t+1}\right)^2}{\sum_{i,t} r_{i,t+1}^2}, \tag{7}$$

and it depends on the current characteristics of the assets, the Γ_β matrix which is estimated throughout the whole period, and the factor realization $\widehat{f}_{t+1}$. Note that when assessing the model in OOS, Γ_β is estimated based on the information up to period t, while the factor returns in period $t+1$ represent the average factor realization until period t. Similar to Kelly et al. (2023), return estimates are compared to zero, rather than the historical average. We hold the view that this is particularly applicable to assets universes undergoing structural changes since the EM corporate debt market has undergone considerable growth during the past decade.

Cross-Sectional R-squared

While the total R^2 provides an overall statistic of much of the bond returns can be attributed to systematic risk, it does not indicate the average monthly performance of the model. The second measure, the cross-section R^2, offers insights into the forecast quality for all bonds in a given period. As shown in Equation (8), R^2 statistics are recorded for each period and then averaged to determine the overall performance.

$$\text{Cross Section } R^2 = \frac{1}{T}\sum_t R_t^2 \quad \text{, where} \quad R_t^2 = 1 - \frac{\sum_i \left(r_{i,t+1} - z_{i,t}^{\prime} \widehat{\Gamma}_\beta \widehat{f}_{t+1} \right)^2}{\sum_i r_{i,t+1}^2} \tag{8}$$

Relative Pricing Error

Our final performance measure, the relative pricing error, was proposed in the study of Kelly et al. (2023) and it is based on Equation (9). This measure evaluates the accuracy of forecasts by measuring the similarity between estimated and realized returns. Larger values of the relative pricing error indicate a poorly specified model. A model with no predictive capacity would have a pricing error of 100%.

$$\text{Relative Pricing Error} = \frac{\sum_i \left(\frac{1}{T_i} \sum_t \left(r_{i,t+1} - \widehat{\beta}_{i,t}^{\prime} \widehat{f}_{t+1} \right) \right)^2}{\sum_i \left(\frac{1}{T_i} \sum_t r_{i,t+1} \right)^2} \tag{9}$$

Testing Instrument Significance

Finally, we describe the methodology for testing the individual variable's contribution to $\beta_{i,t}$. We calculate the total reduction in R^2 when the l^{th} row of Γ_β is set to zero, while retaining the rest of the estimated parameters. To test for statistical significance, we follow the procedure proposed by Kelly et al. (2019) and perform a Wald-type test with a wild bootstrap procedure, which compares $W_{\beta,l} = \hat{\gamma}'_{\beta,l}\hat{\gamma}_{\beta,l}$ with the bootstrapped values of $\tilde{W}^b_{\beta,l}$ (see Section 3 of Kelly et al. (2019)). This test is akin to the one used to assess the existence of unsystematic alpha before we select a restricted model.

3.3.1.3 Model Comparison

We evaluate the added value of our IPCA model with country risk consideration against four leading factor frameworks - three with static betas and observable factors and one with instrumented betas on observable factors. Our initial benchmark is the market model because of its simplicity. Dickerson et al. (2023) find that empirical asset pricing models often cannot outperform the CAPM model. Kelly et al. (2023) also report that the market factor explains a significant portion of the total and cross-sectional R^2, and it frequently outperforms more complex models. Furthermore, we include the proposed factor model from Dekker et al. (2021) for systematic factor investing in EM corporate debt. The study employs four factors - bond momentum, size, value, and low-risk. These factors are constructed solely with corporate bond data, eliminating the need for equity data. The five-factor model with unconditional betas was proposed by Kelly et al. (2023). Their analysis demonstrates that a factor model based on the five most relevant bond and firm characteristics - spread, duration, bond volatility, spread to distance to default (D2D), and an equal-weighted bond market can approximate the performance of the full-scale IPCA model. As their findings suggest no distinguishable significance between D2D and credit rating, we decide to implement credit rating as the fifth characteristic. The fourth and final competing model is comparable to the third, but it employs dynamic betas instead of static ones. This means that characteristics are utilized as instruments to gauge an asset's exposure to the observable factors. Kelly et al. (2023) demonstrate that this approximation produces the same pricing error and comparable total and cross-sectional R^2 values OOS as the initial IPCA framework. We do not use factor models that require equity information, as proposed by Bektić et al. (2019), Israel et al. (2018), or Henke et al. (2020) due to the limited coverage of equity characteristics in EM corporate debt. Also, although the factor model proposed by Bai et al. (2019) uses only bond features, Dickerson et al. (2023) discover some imprecision in the factors' construction when replicating their study. After correction, the study concludes that these factors do not outperform the CAPM. Therefore, we decide against using this framework for comparison.

To align the four benchmark models with our IPCA proposal for EM corporate debt, we apply the same estimation rules. In particular, we calculate all static betas over a 36-month rolling window, as suggested by Bai et al. (2019). Additionally, for the five-factor model with instrumented betas but observable factors, we only need to estimate the Γ_β matrix because f_{t+1} is already known. Following the methodology of Kelly et al. (2023), if g_t represents the five observable factors, then the excess return estimation appears as follows:

$$r_{i,t+1} = z_{i,t}^{'}\Gamma_\beta g_{t+1} + \varepsilon_{i,t+1}^{*}. \tag{10}$$

Note, that the only difference between Equation (10) and Equation (2) is that the factor realizations are observed. We use the available bond and country variables to condition betas on observed factors instead of utilizing the set of 29 bond and firm characteristics, as done in the study of Kelly et al. (2023).

3.3.2 Data

For this study, we use the ICE BofA Emerging Markets Corporate Plus Index (EMCB) provided by ICE Merrill Lynch from January 2010 to December 2022. The index comprises corporate bonds in hard currency issued by companies with operations outside the FX G10 members. Moreover, only bonds with a minimum notional amount of USD 250 million and a time to maturity exceeding one year are eligible for inclusion. Our sample solely incorporates USD-denominated bonds with an ultimate parent country located outside the FX G10. ICE Merrill Lynch reports various information on the index constituents, such as bond duration, option-adjusted spread (OAS), credit rating, and returns.

Our analysis uses monthly credit excess returns, which are calculated as the total return of a bond in excess of the return of a duration-matched government bond. Similar to Kelly et al. (2023), we scale the excess returns with the risk measure Duration Times Spread (DTS) of the previous month. Introduced by Ben Dor et al. (2007), DTS predicts return volatility and scaling returns with DTS yields less noisy returns. We adjust the excess return of only the riskiest bonds, which have a DTS higher than the median DTS level of our sample. The return transformation follows Equation (11)

$$r^*_{i,t+1} = \frac{r_{i,t+1}}{\max\left(DTS_{i,t}, \widetilde{DTS}\right)}. \tag{11}$$

To explain the variation of the adjusted excess returns, we employ bond and country features. Kelly et al. (2023) outline a list of 29 bond and firm candidate characteristics to serve as IPCA instruments. In contrast to DM corporate bonds, EM bonds are often issued by non-listed firms. Consequently, our research examine 14 of the proposed characteristics. These are the bond's age, coupon, face value, duration, OAS, credit rating, six-month bond momentum, the product of credit rating and bond momentum, bond skewness, six-month spread change, bond volatility, bond value at risk (VAR), volatility index (VIX) beta and six-month sector momentum.

Along with the bond characteristics, sovereign risk is expected to affect EM assets due to the high default risk of EM economies. Since the credit rating of corporate bonds often correlates with that of the sovereign entity, we expect that EM debt in hard currency bears the risk of the sovereign entity's possible inability to fulfill its obligations. However, integrating country risk is complicated by the limited data coverage of the countries in the EMCB index. Another concern is that the most frequently used country variables, such as GDP, CPI, and country credit rating, are updated at most once per quarter and are reported with a lag. We mitigate these problems by incorporating two categories of country characteristics.

The first group of variables is based on sovereign instruments and includes the CDS spread and the six-month change of the CDS spread, the six-month change in the current foreign exchange rate against the USD, and the short-term interest rate. We chose these variables based on previous research findings. For example, Brooks et al. (2020) examine styles for sovereign entities and demonstrate that a momentum strategy - a combination of equally-weighted 6-month EM CDS returns, 6-month FX returns, and 6-month country equity returns - produces the highest long-short Sharpe Ratio of 0.6. Kang et al. (2019) also utilize a 6-month FX momentum signal to study the predictability of country returns. Lastly, we test whether the short-term interest rates of the EM countries relate to the returns of corporate bonds. This examination is encouraged by the findings of Kang et al. (2019), who surprisingly find that hart currency country entities are nevertheless affected by changes in the local currency, and thus demonstrating that the interdependencies are not always obvious.

We refer to the second group of country measures as characteristics of synthetic country portfolios. This is motivated by the current market segmentation of the EM universe, which requires the inclusion of fixed effects. We construct monthly equally-weighted country portfolio features using the 14 bond measures previously described. This approach allows the country-specific effect on corporate bond returns to vary over time. Including the country levels of each characteristic in the model eliminates the need for a constant as done by Kelly et al. (2023). Lastly, we demean each bond's characteristics with the corresponding country's average level. The final set of characteristics is summarized in the following Equation (12). For each period t

$$\begin{aligned} z_{i,j} &= \left[\left(b_{i,j} - \overline{b}_j^{'}, \right), \overline{b}_j^{'}, c_j^{'} \right]^{'}, \\ \overline{b}_j &= \frac{1}{K} \sum_{i=1}^{K} b_{i,j}, \end{aligned} \tag{12}$$

where $\overline{b}_j$ refers to the average country-level characteristics based on corporate bond information, $b_{i,j} - \overline{b}_j$ represents the 14 specific bond characteristics adjusted for country-level averages, and c_j denotes for variables based on sovereign instruments. Finally, we normalize the variables on a monthly basis.

3.4 Model Performance and Country Risk Consideration

In our first hypothesis, we evaluate whether EM corporate bond returns are influenced by country characteristics. We expect that EM bonds are exposed to systematic country risk and that accounting for this will improve the explanatory power of our models. To test this hypothesis, we initiate our analysis by evaluating the IPCA model's performance across various characteristic sets. In Table 3-1, the total and cross-section R^2 of restricted IPCA models are presented, utilizing the following variations: i) bond characteristics, ii) bond characteristics that have been demeaned by monthly country average, iii) average bond characteristics of a country portfolio, iv) the combined effect of demeaned and country-level bond characteristics, and v) the combined effect of iv) and country characteristics of sovereign instruments. The statistics are provided for different numbers of latent factors, K. Looking at the total R^2, it can be observed that for K=2 or higher, the model iv) using demeaned bond characteristics and the average country levels yields consistently higher R^2 values than the model i) which does not use any country information. The performance disparity increases as the number of latent factors grows. For K=10, the model that incorporates bond deviations and the average country levels of bond characteristics has an R^2 of 28.2%, which represents over a 5% improvement over the initial model i). Furthermore, it is evident that the variability in bond returns is better explained by the characteristics of country portfolios compared to the demeaned bond characteristics. Finally, including characteristics of sovereign instruments enhances the explanatory power of the model by approximately 1%, regardless of the latent factor's number.

Table 3-1: IPCA country versus bond characteristics.
Percentage of total and cross-section R^2 from IPCA specifications based on total bond characteristics b, cross sectional deviations from the average country portfolio $b-\bar{b}$, average country portfolio characteristics $\bar{b}$, the combination of average country portfolio characteristics and cross section bond deviations $b-\bar{b},\bar{b}$, and finally the IPCA specification which also includes sprecific country characteristics $b-\bar{b},\bar{b},c$.

K	Total R^2					Cross Section R^2				
	b	$b-\bar{b}$	$\bar{b}$	$b-\bar{b},\bar{b}$	$b-\bar{b},\bar{b},c$	b	$b-\bar{b}$	$\bar{b}$	$b-\bar{b},\bar{b}$	$b-\bar{b},\bar{b},c$
1	15.1	8.8	7.8	14.5	15.4	6.7	3.6	2.0	5.9	6.0
2	18.2	10.0	11.2	20.6	21.2	8.2	4.7	4.7	7.0	7.2
3	20.6	10.5	12.8	23.8	24.2	10.1	5.6	6.0	9.6	9.6
4	21.4	10.9	13.9	25.3	26.1	11.0	6.3	6.9	10.8	10.8
5	21.7	11.1	14.4	26.1	26.8	11.8	6.7	7.7	12.0	12.0
6	22.1	11.3	14.7	26.7	27.4	12.7	7.1	8.3	12.9	13.0
7	22.3	11.4	15.0	27.1	28.1	13.1	7.5	8.9	13.9	14.5
8	22.5	11.5	15.2	27.6	28.5	13.6	7.8	9.4	15.2	15.3
9	22.6	11.6	15.4	27.9	28.9	14.0	8.0	10.0	15.8	16.3
10	22.7	11.7	15.5	28.2	29.2	14.3	8.2	10.5	16.3	16.9
11	22.8	11.8	15.6	28.4	29.4	14.5	8.3	11.0	16.9	17.3

The cross-section R^2 of the various model setups is presented on the right-hand side of Table 3-1. It is noticeable that country information provides benefits in the IPCA model when K is at least five. With K=10, the consolidated model with demeaned variables and country averages yields an R^2 of 16.3%, which is by 2% higher than the original model i). As for the total R^2, the average country portfolio characteristics account for a larger portion of the variation in cross-sectional returns. Furthermore, the variables of country instruments augment the overall cross-sectional R^2 up to 0.5%. In general, the findings provide evidence of the potential of country information to explain EM bond returns. Whether the integration of such features enhances the final IPCA model will depend on the optimal number of latent factors.

After discovering initial signs of the potential of country-specific data, we can use all the characteristics from Equation (12) to determine the IPCA structure for EM corporate bonds. Including all characteristics does not pose a challenge for the IPCA model, but it is necessary to identify the factor space of bond returns. Furthermore, this enables us to assess the contribution of each characteristic to the model's performance and determine whether EM corporate bonds are exposed to systematic country risk.

As the IPCA framework requires $\Gamma_\alpha = 0$, we need to first identify the optimal number of latent factors that explain the variation in corporate bond returns. This implies that bond and country characteristics describe only systematic risk factors and not market anomalies. Following the terminology of Kelly et al. (2019), the model in which alpha holds no statistical significance is also known as a restricted IPCA model. To test whether the alpha is statistically significant, we perform a Wald-type test with a wild bootstrap, as described in Section 3.1. Table 3-2 presents the IS IPCA performance for varying numbers of latent factors, along with the Wald-test's p-value. Furthermore, we report performance metrics for both corporate bonds (Panel) and characteristic portfolios (Portfolios). Using only one factor, K=1, the model explains 15.4% of the total R^2 and 6% of the cross-sectional R^2 when the test assets are corporate bonds. However, the relative pricing error is high at 66.3%, and it increases to 104% when test assets are portfolios. The total and cross-sectional R^2 for the characteristic portfolios are 63.3% and 34.5%, respectively. These values surpass the panel R^2s because the model with L assets is less noisy than when using N bonds. Moreover, as the number of latent factors increases, all performance measures improve in both scenarios: when test assets are portfolios or bonds. When K=10, the p-value of the Wald test is statistically insignificant. Consequently, the bond and country characteristic are related Γ_β but not to Γ_α.

Since the IPCA model with K=10 successfully attributes the variation of corporate debt to systematic risk, we use its restricted form (see Equation (2)) throughout the remainder of our study. For the panel specification, the total R^2 reaches 29.3%, which is twice as high as when K=1. The cross-section R^2 also increases from 6% to approximately 17%, while the average pricing error decreases by approximately 21%. When test assets are portfolios, the model can explain almost all of the total and cross-section return variations, with only a 4.7% relative pricing error. Note that Kelly et al. (2023) find that only five latent factors are necessary to explain bond return deviations and render Γ_α statistically insignificant. This is an indication of the structural differences between EM and DM corporate bonds[3]. The restricted five-factor IPCA model of Kelly et al. (2023) also shows higher total and cross-sectional R^2, but also a higher pricing error when the test assets are corporate bonds. Overall, the IS performance of our model

Table 3-2: IPCA in-sample model performance.
The table reports in-sample total, cross section R^2 and relative pricing error in percentage for the IPCA model restricted model. We refer to panel when test assets are corporate bonds and to portfolio when test assets are characteristic portflios. The last row reports bootstrapped p-values for positive intercept. All statistics are calculated from January 2010 until December 2022.

	K										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Panel											
Total R^2	15.4	21.2	24.2	26.1	26.8	27.4	28.1	28.5	28.9	29.2	29.4
Cross Section R^2	6.0	7.2	9.6	10.8	12.0	13.0	14.5	15.3	16.3	16.9	17.3
Rel. Pricing Error	66.3	53.0	51.1	49.9	49.9	47.8	46.1	46.3	45.5	45.5	44.9
Portfolio											
Total R^2	63.3	74.0	88.0	91.1	93.2	94.2	95.5	96.4	97.1	97.6	97.8
Cross Section R^2	34.5	39.8	58.7	63.8	69.0	71.8	77.5	80.7	83.7	85.8	86.8
Rel. Pricing Error	104.0	86.7	80.3	56.9	56.1	35.8	9.3	8.7	4.9	4.7	4.3
W_a p-value											
	2.6	0.5	1.8	0.5	0.3	0.0	0.6	0.1	0.5	78.2	53.3

specification indicates that the variation of EM corporate bond returns can be attributed to risk factors, and the EM factor space seems to be more extensive than that of DM corporate debt.

[3]Even though Kelly et al. (2023) analyse a global corporate bond universe using Bank of America Merrill Lynch data, EM credit has been historically underrepresented. As of today, less than 10% of all corporate debt is issued within emerging markets and denominated in hard currency.

To understand how essential the country variables are to the final IPCA model when K=10, we report the Γ_β matrix, which contains the loadings of each characteristic on the latent factors. If both country and bond characteristics are significant for the model, they should load on dissimilar latent factors. Figure 3-1 displays the squared factor loadings of each characteristic. These findings have two implications. First, it is evident that most bond and country characteristics, which have a common underlying variable, load on different components. For example, the aggregated momentum, rating, and their cross-product are mainly related to the first factor, while their demeaned bond characteristics approximate factors seven, eight, and nine. The country variable spread and CDS spread change mostly load on the second component, while the demeaned bond spread is correlated to the eight component. Secondly, it is evident that the exposure of country variables to latent factors is greater than the exposure of bond variables. This allows investors to evaluate individual corporate bonds using aggregated information and thus supports our hypothesis that EM bonds are affected by country risks. Finally, our findings align with those of Kelly et al. (2023), who report OAS and volatility as among the most crucial variables.

Similar to Kelly et al. (2019), we analyze the statistical significance of the characteristics by assessing the importance of each variable while controlling for the remaining L characteristics. With the exception of country variables established by sovereign instruments, all other characteristics are included twice in Γ_β - once as monthly characteristics of equally-weighted country portfolios and once as demeaned bond characteristics. As a result, it is necessary to assess whether a feature is overall relevant to the model and

Figure 3-1: Factor loadings on characteristics.
The values are calculated from the squared Γ_β matrix.

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
Momentum x Rating, $\bar{b}$	0.26	0.02	0.10	0.02	0.02	0.02	0.00	0.00	0.01	0.01
OAS, $\bar{b}$	0.00	0.24	0.00	0.02	0.16	0.01	0.06	0.03	0.04	0.00
Rating,$\bar{b}$	0.22	0.08	0.00	0.10	0.02	0.09	0.03	0.00	0.00	0.02
Volatility, $b-\bar{b}$	0.05	0.00	0.20	0.00	0.00	0.00	0.04	0.00	0.00	0.06
Oas Change, $\bar{b}$	0.02	0.00	0.02	0.05	0.04	0.01	0.18	0.01	0.06	0.02
Face Value, $\bar{b}$	0.00	0.02	0.00	0.00	0.09	0.04	0.01	0.18	0.02	0.07
Volatiliy, $\bar{b}$	0.02	0.00	0.18	0.11	0.18	0.05	0.02	0.00	0.13	0.06
VAR, $\bar{b}$	0.00	0.08	0.00	0.11	0.00	0.17	0.00	0.05	0.03	0.09
Face Value, $b-\bar{b}$	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.00	0.02	0.16
CDS Spread Change	0.00	0.12	0.00	0.01	0.00	0.00	0.01	0.00	0.07	0.15
Coupon, $\bar{b}$	0.00	0.01	0.14	0.13	0.04	0.06	0.07	0.03	0.01	0.03
Momentum, $\bar{b}$	0.14	0.01	0.01	0.03	0.12	0.00	0.05	0.04	0.02	0.00
Duration, $b-\bar{b}$	0.04	0.01	0.14	0.02	0.00	0.01	0.00	0.07	0.01	0.06
Sector Momentum, $\bar{b}$	0.08	0.04	0.02	0.13	0.00	0.00	0.00	0.00	0.00	0.00
OAS, $b-\bar{b}$	0.00	0.00	0.01	0.01	0.01	0.04	0.06	0.12	0.00	0.00
Duration, $\bar{b}$	0.03	0.04	0.00	0.02	0.03	0.12	0.06	0.01	0.04	0.00
Age, $\bar{b}$	0.01	0.07	0.00	0.00	0.12	0.00	0.00	0.00	0.06	0.01
Skewness, $\bar{b}$	0.00	0.08	0.02	0.02	0.00	0.12	0.02	0.06	0.03	0.00
Oas change, $b-\bar{b}$	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.09	0.04	0.00
FX Rate Change	0.00	0.08	0.00	0.06	0.04	0.06	0.00	0.01	0.08	0.00
CDS Spread	0.00	0.01	0.02	0.00	0.00	0.01	0.02	0.04	0.07	0.06
VIX beta, $\bar{b}$	0.02	0.00	0.01	0.00	0.00	0.02	0.07	0.00	0.02	0.02
Age, $b-\bar{b}$	0.00	0.00	0.01	0.00	0.01	0.00	0.07	0.02	0.04	0.00
Rating, $b-\bar{b}$	0.00	0.00	0.01	0.00	0.01	0.05	0.06	0.00	0.04	0.01
Momentum x Rating, $b-\bar{b}$	0.02	0.01	0.01	0.05	0.03	0.01	0.04	0.06	0.03	0.02
Short−term Interest Rate	0.00	0.02	0.00	0.00	0.01	0.05	0.02	0.05	0.06	0.04
Sector Momentum, $b-\bar{b}$	0.02	0.00	0.02	0.02	0.00	0.00	0.02	0.01	0.06	0.00
Momentum, $b-\bar{b}$	0.02	0.01	0.00	0.04	0.02	0.02	0.01	0.05	0.01	0.01
Coupon, $b-\bar{b}$	0.00	0.00	0.01	0.00	0.02	0.00	0.03	0.00	0.00	0.05
VAR, $b-\bar{b}$	0.02	0.01	0.02	0.03	0.01	0.00	0.00	0.03	0.00	0.03
VIX beta, $b-\bar{b}$	0.00	0.00	0.02	0.00	0.01	0.00	0.01	0.00	0.00	0.01
Skewness, $b-\bar{b}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Latent factors

which sub-component makes a greater impact. Additionally, we use a bootstrap of 1000 samples to conduct a Wald-type test for measuring the variables' statistical significance.

Table 3-3 presents variable importance based on total R^2 reduction and statistical significance. Column two shows the importance of a characteristic as a whole, column three as an average characteristic of a country portfolio, and column four as the deviation of an individual bond from the aggregated country average. Among the characteristics b and c, bond volatility, duration, face value, credit rating, spread change, sector momentum, and age stand out with p-values under 1%. Their contribution to the total

Table 3-3: IPCA variable importance.
The table reports the variable importance of each individual characteristic as total contribution b, c, average country contribution $\bar{b}$, and contribution of the bond deviations from the average country effect $b - \bar{b}$. The contribution of characteristic l is measured as the reduction in total R^2 from setting all elements in row l of Γ_β to zero. The significance of each characteristic is based on bootstrapped significance test decribed in Section 2.1. ***0.1% significance; **1% significance; *5% significance.

	b, c	$\bar{b}$	$b - \bar{b}$
Age	2.2**	1.9*	0.4***
Coupon	3.1*	2.8*	0.3**
Face Value	1.2***	1.1***	0.2***
Duration	4.4***	1.9**	2.9***
Momentum	5	4.3	1
Momentum x Rating	9	8.3	1.3
OAS	5.5*	4.9	0.6**
Rating	8.2**	7.6	0.5**
Skewness	2.3	2.2	0.1
Oas Change	2**	1.5*	0.4**
Volatility	6.6***	3.5*	3.3***
VAR	3.6*	2.3	1.4**
VIX beta	1	0.7	0.4**
Sector Momentum	4**	3.6*	1**
CDS Spread	0.6		
CDS Spread Change	2.2*		
FX Rate Change	1.9*		
Short-term Interest Rate	0.6		

R^2 varies from 1.1% for face value to 8.2% for bond credit rating. Moreover, the OAS, the coupon and the VAR of corporate bonds are also statistically significant with a p-value of 5%. From the variables that exist on a country level, it is observed that the changes in the CDS spread and the FX rates against the USD are statistically significant. Omitting these variables from the model yields a reduction in R^2 of 2.2% and 1.9%, respectively.

Furthermore, columns three and four provide information on the relative importance of different sub-components for the model specification. The results demonstrate that all bond characteristics that were significant overall also have significant sub-components. Notably, the bond characteristics calculated as deviations from equally-weighted country portfolios are highly significant. However, it is interesting to find that half of the country-level characteristics $\overline{b}$ are carrying relevant information for the model. This indicates the impact of country risk on the variation of EM bond returns.

In a nutshell, we find that most of the bond variables proposed by Kelly et al. (2023) contribute significantly to the EM IPCA framework. Additionally, our results indicate that country-specific variables play a vital role in describing the factor space of EM bond returns. Finally, we find that the aggregated attributes of country portfolios refine the model estimation and these features exhibit a high contribution to the overall R^2.

3.5 OOS Performance and Comparison with existing Models

In the previous section, we analyzed the IPCA model's performance calibrated over the entire period. However, a pricing model must perform well in OOS to be competitive. In Table 3-4, we report the OOS model's performance. Note that in OOS, unlike in IS, the Γ_β matrix is recalibrated monthly using expanding window data with a minimum of 36 months. The factor returns for period $t + 1$ are calculated as the average factor realizations until period t, ensuring that the return forecast is free of forward-looking bias. When the test assets are corporate bonds, the IPCA model with 10 factors achieves a total R^2 of 24.2% out-of-sample, compared to 29.2% in-sample. These differences are expected, as the IS model uses the entire data set to estimate the Γ_β matrix. Notably, when comparing the IS and OSS cross-sectional R^2, the model demonstrates relative stability and accounts for 17% of the variation in returns.

Moreover, the relative pricing error in OOS rises from 45.5% to 55.5%. Our findings contrast with those of Kelly et al. (2023), who discover high stability between IS and OOS performance. One possible reason for the discrepancy is the exponential growth in market value of the EM universe, as well as structural modifications in the index countries. For instance, by the end of 2010, Chinese bonds made up only 6% of the EM index, but by the end of 2022, their share had risen to nearly 30%. As the EM IPCA model requires additional latent factors to adequately account for the variability in corporate bond returns, this leads to increased complexity of the model. The analysis by Kelly et al. (2023) utilizes only five factors, resulting in fewer parameters to define. Our OOS results for characteristic portfolios suggest comparable conclusions. Overall, the IPCA model exhibits consistent performance in OOS testing.

Table 3-4: IPCA OOS model performance.
The table reports out-of-sample total, cross-section R^2 and relative pricing error in percentage for the IPCA model restricted model with K=10. We refer to panel when test assets are corporate bonds and to portfolio when test assets are characteristic portflios. All statistics are calculated from January 2013 until December 2022.

	Total R^2	Cross Section R^2	Rel. Pricing Error
Panel	24.2	17.0	55.5
Portfolio	91.6	85.1	21.0

To determine if the IPCA model, which includes country effects, has better performance, we must compare it to other asset pricing models. In particular, Table 3-5 presents the OOS results of the IPCA model and other models mentioned in Section 3.1.2. Moreover, we report statistics for the whole period as well as for sub-periods: 2013-2016, 2017-2019, and 2020-2022 to account for any structural changes of the EM universe. Looking at the statistics calculated over the entire period, we find a clear separation between the unconditional and conditional beta models. The model that solely employs the market beta obtains a total R^2 of 4.6%, cross-sectional R^2 of 4.3%, and exhibits a notably higher pricing error of 96%. Interestingly, the four-factor model that utilizes bond momentum, size, value, and a low-risk signal fails to achieve superior OOS performance, with an even lower cross-sectional R^2 than the market model. Likewise, the five-factor model with static betas only accounts for 6.5% of the total R^2 and has a slightly lower pricing error when compared to other static models. Only when bond and country characteristics are used to instrument loadings on the observable factors, serious performance improvements are noticeable. The five-factor model with conditional betas proposed by Kelly et al. (2023) provides more than twice the total and cross-sectional R^2s of the static five-factor model. This highlights the advantages of utilizing instrumental variables, such as bond and country characteristics, which allows for time-varying factor loadings.

Finally, the EM IPCA model outperforms the competing models in all three performance measures. When compared to models that use static betas with observable factors, IPCA delivers up to five times greater total R^2, four times higher cross-sectional R^2, and significantly reduced relative pricing errors. Looking at the performance differences between the EM IPCA model and the DM five-factor model with conditional betas, we can evaluate the added value of using latent factors instead of pre-specified observable factors from developed markets. It is evident that the EM IPCA model provides a better description of the EM factor space, as it almost doubles the performance of the model using dynamic betas on observable factors. This also provides evidence that EM and DM corporate bonds are spanned by different sets of factors.

Table 3-5: OOS model comparison of asset pricing models.
The table reports out-of-sample total, cross-sectional R^2 and relative pricing error in percentage for the IPCA model restricted model with K=10 in comparison to alternative models. The market model, the four factor model and the DM five factor static model are based on constant beta loading on the respective factors estimated in a rolling window of 36 months. The DM five factor conditional model uses instrumented betas calculated on observable factors, while the IPCA calculates the instumented betas on unobservable factors. All statistics are calculated from January 2013 until December 2022.

	Total R^2	Cross Section R^2	Rel. Pricing Error
2013-2016			
Market	4.1	3.2	94.7
Four Factors	3.8	2.4	95.5
DM 5F static	3.9	3.2	96.4
DM 5F cond	11.0	8.6	103.3
IPCA	17.1	15.1	96.9
2017-2019			
Market	3.6	3.6	92.6
Four Factors	4.2	3.4	93.4
DM 5F static	3.4	3.4	96.0
DM 5F cond	12.5	10.3	88.8
IPCA	21.0	16.9	87.2
2020-2022			
Market	4.7	6.3	96.1
Four Factors	5.0	4.7	95.5
DM 5F static	7.1	6.8	89.1
DM 5F cond	15.9	12.9	78.2
IPCA	25.3	19.4	61.2
2013-2022			
Market	4.6	4.3	96.0
Four Factors	4.8	3.4	95.5
DM 5F static	6.5	4.3	89.1
DM 5F cond	15.2	10.4	74.3
IPCA	24.2	17.0	55.5

As the IPCA model requires a large data set to find the optimal parameters, there is a concern that its superior performance may be driven by the most recent estimates using the longest data set. Looking at the various sub-periods, it is apparent that the IPCA model estimation improved over time, and it is most effective during the period of 2020-2022. However, it is evident that among the various asset pricing models, the IPCA-based model reveals the highest total and cross-sectional R^2 for each sub-period. As a result, it can be concluded that utilizing bond and country attributes to instrument betas to underlying factors currently provides the most accurate representation of the variation of EM corporate bond returns.

A full comparison of various asset pricing models requires assessing their efficacy in the investment process. As such, we analyze how well the factor models can predict the subsequent return of EM corporate bonds. We create quintile portfolios based on forecasted returns and rebalance them monthly. Table 3-6 compares the performance of the quintile portfolios to that of the market portfolio. Notice, that the reported performance is calculated from bond excess return, which is not scaled by DTS. The Q1 portfolio includes bonds with the lowest expected return forecasts, while the Q5 portfolio selects the best-performing assets based on the signal. By examining the average return and SR of the portfolios, it is apparent that only the IPCA and the five-factor model with conditional betas can establish a linear connection between estimated and realized returns. For both Q1 models, the annual returns generated are 1.9% and 2.4% respectively, compared to the index portfolio's 3.1%. Meanwhile, the Q5 long portfolios yield 5.9% and 4.2% p.a. Additionally, when comparing the two portfolios, we observe that the IPCA model better separates corporate bonds based on their returns, with a performance gap between the long and short portfolios of 4%. This is in contrast to the five-factor model with conditional betas, which yields a 1.8% performance of a long-short strategy. Besides, the Q1 IPCA portfolio has the lowest Sharpe Ratio compared to the others, while the Q5 IPCA portfolio achieves the highest Sharpe Ratio of 0.8. This is consistent with our prior findings that the IPCA model provides the highest cross-sectional R^2 value.

Table 3-6: Performance of quintile sorted portfolios based on asset pricing models.
This table reports performance statistics of quintile sorted portfolios based on different signals over the period from January 2013 until December 2023. The Q1 portfolio contain the assets with the lowest expected return forcast, while Q5 portfolio the one with the highest return forecast.

Quintile	Avg. Return	Avg. Volatility	SR
Index			
	3.1	5.5	0.6
Four Factors			
Q1	3.9	6.0	0.7
Q2	2.5	4.6	0.5
Q3	2.4	4.4	0.5
Q4	2.4	6.0	0.4
Q5	4.2	8.5	0.5
DM 5F static			
Q1	4.0	7.8	0.5
Q2	1.9	5.7	0.3
Q3	2.3	4.3	0.5
Q4	2.6	4.1	0.6
Q5	4.5	6.9	0.7
DM 5F conditional			
Q1	2.4	6.0	0.4
Q2	2.8	5.4	0.5
Q3	3.3	5.6	0.6
Q4	3.4	5.2	0.7
Q5	4.2	7.1	0.6
IPCA			
Q1	1.9	5.8	0.3
Q2	2.1	5.1	0.4
Q3	3.2	5.2	0.6
Q4	3.7	5.8	0.6
Q5	5.9	7.3	0.8

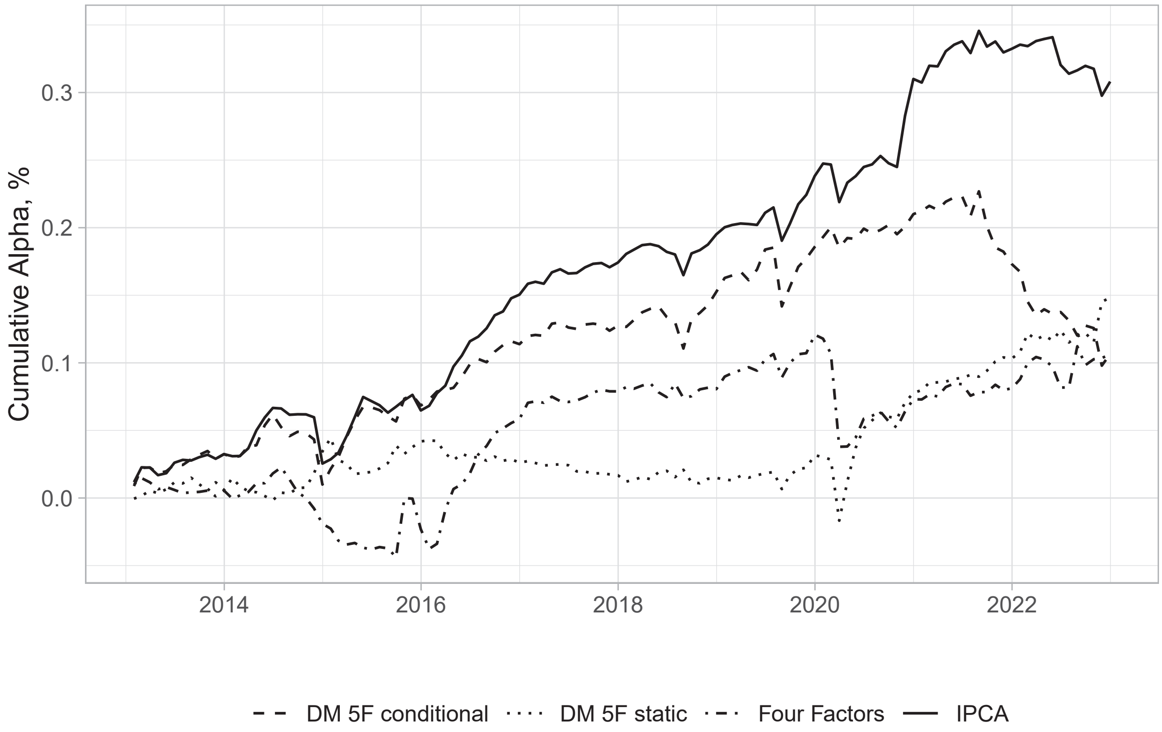
In fixed income, investors often cannot short corporate debt and are only interested in the performance of long-only portfolios. Therefore, our analysis focuses exclusively on the Q5 portfolios, highlighting additional performance characteristics for the various return forecasts. We report in Table 3-7 Jensen's alpha, IR, and the turnover of the top quinitile portfolios. It is evident that the IPCA portfolio generates the highest Jensen's alpha of nearly 2% p.a., which is also the only statistically significant result. Similarly, this portfolio achieves the highest IR of 1, while the competing models exhibit IR in the range of 0.3 to 0.5. Lastly, all portfolios have reasonable two-sided turnover, where the four-factor model signals is the slowest with a turnover of 151% p.a., and the IPCA signals it the fastest with a turnover of 219%.

Table 3-7: Performance of top quintile sorted portfolios based on asset pricing models. This table reports the Jensen's alpha, Information Ratio and the turnover of the top quintile sorted portfolios based on different signals over the period from January 2013 until December 2023. Jensen's alpha is calculated as the intercept of regressing the portfolio return on the value-weighted index return. The reported significance is based on a one-sided t-test. We test the portfolios' IR for significance using a two-sided chi-squared test proposed by Wright et al. (2014) based on a heteroskedasticity- and autocorrelation-consistent (HAC) covariance matrix. Turnover represents the two-sided portfolio turnover. All statistics are annualized. ***0.1% significance; **1% significance; *5% significance.

Portfolio	Jensen's Alpha	IR	Turnover
Four Factors	-0.4	0.3	151
DM 5F static	1.0	0.5	149
DM 5F conditional	0.6	0.4	218
IPCA	1.9*	1.0*	219

Finally, we visualize the cumulative active return of the Q5 portfolios over time in Figure 3-2. The graph illustrates the consistent alpha of the IPCA model, which outperforms the other models throughout the entire holding period. Overall, we find evidence that the IPCA model accounting for the specifics of the emerging markets provides the best results in OOS compared to other established models. Therefore, we encourage systematic credit investors willing to invest in EM corporate debt to consider country risk when modeling credit factors.

Figure 3-2: Active performance of top quintile sorted portfolios.
The active performance is calculated over value-weighted market portfolio from January 2013 until December 2022.



3.6 Conclusion

In this study, we propose an asset pricing model using IPCA for EM corporate debt. In particular, we analyze the implications of country risk on the cross-section of bond returns and the benefits of building a distinct model rather than relying on established models from developed markets.

In our first hypothesis, we examine whether country-specific information improves the explanatory power of an IPCA model. We discover that country-specific characteristics enhance the total R^2 by 6.5% and the cross-sectional R^2 by 2.6% when K equals 10. Additionally, over half of the researched country-specific characteristics seem to be statistically significant and, therefore, relevant to the model formation.

In the second hypothesis, we compare the OOS performance of the IPCA model with that of leading factor models. Our findings suggest that the proposed model is not only stable but also dominant among other factor models. The EM IPCA model achieves a higher R^2 than models utilizing observable factors with static betas or those employing observable factors with dynamic betas. This highlights the need to tailor DM factor models to the unique characteristics of EM credit. Finally, we find that a long-only portfolio built on the EM IPCA model yields a statistically significant Jensen's alpha of nearly 2% annually, while competitive factor models yield at most 1% alpha per year, which is also statistically insignificant.

In total, our study presents the initial evidence of the significance of country-specific information for constructing asset pricing models in EM credit. We discover that the emerging market credit universe is spanned by more latent factors than Kelly et al. (2023) find for developed markets. Furthermore, incorporating country characteristics can significantly enhance the efficacy of a factor model. A natural extension of this study would be to analyze the performance of an IPCA model of EM corporate bonds denominated in local currency. We expect that local EM debt will require an even more intricate model, given the stronger influence of the sovereign risk on the performance of corporate debt.

4 BONDS WITH BENEFITS. IMPACT INVESTING IN CORPORATE DEBT

4.1 Abstract

The regulatory focus on quantifiable sustainable investing shifts investors' demand towards impact products, thus challenging their alignment with the primary target of outperformance. Our study demonstrates the implications of impact investing on actively managed systematic credit portfolios using emission intensities, SDGs, and green bonds. We discover that sustainable assets trade at tighter spreads than their peers and provide coherent evidence of impact pricing. Nonetheless, neither impact measure exhibits a significant return premium. Finally, impact investors generate at most market returns, while systematic investors benefit from the low correlation between credit factors and impact measures to achieve their preferred dual target.

Keywords: corporate bonds, impact investing, sustainability, systematic factors, credit

JEL classification: G11, G12, G18, Q54

This chapter contains Publication 3, Vladimirova D. and Fang-Klingler (2024):

Vladimirova D, Fang-Klingler J (2024). *Bonds with Benefits: Impact Investing in Corporate Debt*, volume 80 number 1. doi: 10.1080/0015198X.2023.2280035 (URL: https://doi.org/10.1080/0015198X.2023.2280035).

4.2 Introduction

In recent years, sustainable investing has become an inseparable part of the portfolio construction process. Along with ESG (Environmental, Social and Governance)-aligned strategies, there is an increasing interest in portfolios invested in firms creating measurable social or environmental value. Investors demanding such strategies are known as impact investors[4] and are often willing to trade-off performance for impact (Barber et al. (2021)). According to a survey conducted by the Global Impact Investing Network (GIIN), their assets under management increased from 502 billion USD to 715 billion USD in the period April 2019–April 2020[5]. Despite the broad definition of impact investing, institutional investors with access only to publicly traded assets have a limited number of instruments to generate environmental/social impact. In addition, they are confronted by increasing regulatory oversight. For instance, at the beginning of 2021, the European Union Sustainable Finance Disclosure Regulation (SFDR) introduced a taxonomy of sustainable funds dividing them in Article 8 (so called light green) or Article 9 (so called dark green)[6]. In particular, to obtain Article 9 classification, a fund has to follow investment rules close to the definition of impact investment. This is achieved, for example, through a net-zero carbon emission portfolio based on a Paris-aligned benchmark (PAB)[7]. In practice, as of mid-October 2022, 93% of the Article 9 funds considered principal adverse impact (PAI) measures and 47% of the funds were at least 70% invested in sustainable assets[8]. The PAI consideration entails qualitative and quantitative disclosure of which environmental and social impact measures are used by a fund.

[4] GIIN definition of impact investment: "Impact investments are investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return."

[5] GIIN Annual Impact Investor Survey

[6] Regulations on sustainability-related disclosures in the financial services sector

[7] Benchmark with a goal of net zero emissions by 2050.

[8] Morningstar SFDR Article 8 and Article 9 Funds: Q3 2022 in Review

In this study, we analyze the implications of impact investing on the performance of active fixed-income funds. Credit investors have a broad range of options, when it comes to impact strategies due to proliferation of labelled bonds[9]. We use carbon intensity scope 1, SDG score, and green bonds as proxies for impact. These are among the most popular criteria employed by Article 9 funds. As of October 2022, we find 333 Article 9 fixed-income funds, out of which roughly 26% are invested in green bonds, 21% in low carbon assets, 2.5% in SDG-compliant assets, and the remaining funds decide based on multiple criteria[10]. Net-zero carbon emission portfolios have gained popularity among market players (Bolton et al. (2022)), as investors only need to replicate a PAB actively or passively. On the other hand, the SDGs have been recently promoted by the GIIN as a channel for investors to select positive impact firms[11], as the scores depend on the firm's revenue and are therefore quantifiable. Lastly, portfolios can be directly invested in environmental projects by buying green bonds, as their use of proceeds is strictly predefined.

Following Pedersen et al. (2021), our first hypothesis addresses the pricing of the different sustainability measures. We expect that sufficiently high investor demand for impact should be reflected in the credit spreads of corporate bonds. If high impact is associated with tighter spreads and potentially lower expected returns of corporate debt, this would reduce its attractiveness to performance-driven institutional investors. Secondly, we examine the trade-off between impact goals and expected return maximization for active investors. We hypothesize that due to low correlation between sustainable measures and credit factors, achieving dual target is possible.

[9] Social, sustainability, and green bonds

[10] The numbers are based on Article 9 fixed-income funds existing in the fondsweb.com database. We exclude microfinance, convertible bond, and sovereign bond funds.

[11] GIIN Achieving the Sustainable Development Goals: The Role of Impact Investing

Examining our first hypothesis, we find all three proxies of impact (carbon intensities, SGD score, and green bonds) to be statistically significant determinants of corporate bond spreads, where bonds issued by positive impact firms exhibit between 3 and 5 bps tighter spreads depending on the measure. Therefore, our results align the findings of Bolton and Kacperczyk (2021) that carbon emissions are priced in the equity markets. For green bonds, we document tighter credit spreads than their comparable non-green peers, which contradicts the findings of Flammer (2021) and Tang and Zhang (2020) on corporate green bonds but confirms the evidence of Zerbib (2019), Hachenberg and Schiereck (2018), and Baker et al. (2018). Since impact measures can potentially influence not only spreads but also firms' fundamentals, we construct benchmark-oriented optimized portfolios to isolate potential positive and negative impact premiums. Our results indicate that the chosen impact measures are not statistically significant performance indicators and pure impact credit portfolios generate similar or slightly lower credit returns than the index. This is similar to the observation of Pedersen et al. (2021), as the study shows that strong ESG stocks might have higher prices, but not all ESG characteristics can predict future stock returns.

In the second hypothesis, we explore the trade-off between pure impact and outperformance strategies. For each impact measure, we obtain a frontier of portfolios that maximize the combination of a credit multifactor score and impact for varying weights of the components and discover a concave relationship, which is consistent across all scenarios. Active investors willing to align their portfolio with impact goals can reduce their emissions by half, double their SDG score, or triple their weight in green bonds relative to a benchmark without sacrificing outperformance. This is similar to the findings of Andersson et al. (2016) and Bolton et al. (2022) for passive decarbonized equity portfolios. Impact investors, on the other hand, can allocate small exposures to systematic strategies and outperform the corresponding benchmark while still pursuing the original sustainability target.

Our study contributes to the literature on impact investing, but also to the growing literature on credit factor investing. We provide broad evidence on the pricing of impact measures in corporate spreads using multiple impact characteristics. While the spread differential of green and non-green corporate bonds has been previously documented, our study examines the largest set of corporate bonds and expands the analysis to realized returns. Our analysis is also the first to examine SDG scores. Furthermore, our findings broaden the application of factor strategies in credit, demonstrating that these can be also useful for conservative impact investors.

The paper is structured as follows. Section 2 sets out the main hypotheses and summarizes the related literature. Section 3 describes the used data and methodology. Section 4 presents the results of the hypotheses. Finally, Section 5 provides the conclusions on the main findings.

4.3 Hypotheses Development and related Literature

4.3.1 Pricing of Impact Instruments

The influence of the growing numbers of impact proxies on corporate bonds pricing has not yet been widely documented. Academic literature has so far concentrated on the pricing of carbon emissions in the equity markets and the existence of green bond premium in the fixed-income markets. For example, the studies of Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2022), Hsu et al. (2023), and Görgen et al. (2019) find carbon premium for high emission intensity firms. Furthermore, Matsumura et al. (2014), as well as Berkman et al. (2019) document a negative relationship between carbon emissions and firm value. However, there is no existing evidence on the importance of carbon emissions for corporate bonds. For green bonds, literature findings are primarily based on municipal bonds, and while some studies discover a significant green premium (primary market - Baker et al. (2018); Fatica et al. (2021); Partridge and Medda (2020); secondary market - Hachenberg and Schiereck (2018); Zerbib (2019); Immel et al. (2021)), others examining the same period document its absence (Larcker and Watts (2020); Karpf and Mandel (2018); Bachelet et al. (2019); Hyun et al. (2020)). More importantly, the studies on corporate bonds do not report green bonds to be more expensive than comparable non-green bonds (Flammer (2021); Tang and Zhang (2020)). Nevertheless, this evidence originates from sample periods until 2018, and thus the results are based on the sparse number of green bonds. Lastly, we do not find literature exploring the relationship between SDGs and corporate bond prices. Due to the different sample periods and universes, prior studies provide inconclusive and insufficient information on the pricing of impact measures on the corporate bond market.

However, there is a solid consensus on the increasing importance of social and environmentally friendly assets in financial markets. For instance, Larcker and Watts (2020) admit that a green premium might occur once the market of green bonds matures. Tang and Zhang (2020) and Barber et al. (2021) also note that green assets might be more attractive to investors due to their environmentally friendly view. Furthermore, Ilhan et al. (2020) find that carbon protection on the option markets is more expensive when public attention to climate risk is high, which may be reflected in larger investors' appetite for low-carbon assets. Pedersen et al. (2021) summarizes this concept in a theoretical model and show that depending on investor preferences and predictive power, ESG characteristics can have positive, insignificant or negative influence on expected returns.

As the market participant's attention increases toward environmental and social investment, we expect that the demand for such assets would also increase, causing the momentum of the prices of such securities. As a result, investors may be willing to pay higher prices for impact assets than for non-impact securities, in which case we should observe low carbon emissions, a high SDG score, and a green label to result in tighter corporate spreads. Furthermore, if positive impact measures are not only associated with higher demand, but also improving firm fundamentals, we would expect these measures to be informative about the future returns of corporate bonds. As such, we formulate our first hypothesis as follows:

HYPOTHESIS 1: Positive impact measures are associated with higher corporate bond prices and might translate into lower subsequent returns.

4.3.2 Impact Investing Trade-off

Institutional investors have a wide range of preferences when it comes to impact and performance goals. Some managers demonstrate readiness to actively invest in social and environmentally friendly assets even if they may demonstrate lower performance (Barber et al. (2021)), but others are primarily interested in financial performance and tie the possibility of such investment to competitive returns (Flammer (2021); Larcker and Watts (2020)). These different investment approaches are categorized by Brest and Born (2013) and Brest et al. (2018) as a concessionary and non-concessionary investment. The investment decisions of concessionary and non-concessionary investors have been often studied independently but rarely together. Kovner and Lerner (2015) and Barber et al. (2021) examine the performance of pure impact VC funds, while Andersson et al. (2016) and Bolton et al. (2022) analyze the performance of passive decarbonized equity portfolios. Only Pedersen et al. (2021) and Geczy et al. (2021)

consider the integration of sustainable investing with asset pricing models on the equity markets. Pedersen et al. (2021) provide an ESG-adjusted capital pricing asset model (CAPM) and suggest that the maximum Sharpe Ratio portfolio depends on the investor's preference for ESG and the ability of ESG information to predict returns. The results of Geczy et al. (2021) advocate that for CAPM investors holding the market portfolio, allocation to a sustainable fund leads to marginal costs, while investors believing in the four-factor model of Carhart (1997) need to forgo more of their performance. Therefore, we aim to quantify the trade-off between achieving environmental/social impact and systematic credit alpha. On the one hand, incorporating impact measures would inevitably reduce allocation to expected return signals and thus, likely to have a cost in terms of performance for non-concessionary investors. On the other hand, increased demand for sustainable solutions might force active managers to improve their sustainability profile by considering impact signals in their utility function. Furthermore, concessionary impact investors might benefit from gaining exposure to factors in order to offset the underperformance of pure impact measure tilted strategies. These propositions would depend on the distribution of the impact scores, as well as their correlation with credit factors. Therefore, we formulate our second hypothesis that:

HYPOTHESIS 2: Both credit factor investors and impact investors can benefit from a dual objective portfolio, while still pursuing their respective impact or return targets.

4.4 Data and Methodology

For the present study, we analyze the corporate bonds part of the ICE BofA Global Corporate Index (G0BC) provided by ICE Bank of America. This consists of investment grade (IG) bonds with a minimum notional size of 250 million USD. Most corporate bond characteristics are obtained from the ICE database. The G0BC index contains mostly developed market bonds, which is in line with the observation of Barber et al. (2021), who find that most VC impact funds are predominantly invested in developed countries. Issuer data, such as GICS sector codes, are provided by the Refinitiv database. The liquidity costs scores (LCS ®) used for the analysis are delivered from Barclays. Barclays' LCS is a bond-level liquidity variable that measures the cost of a round-trip transaction of a certain bond and is expressed as a percent of the bond's price.

To analyze the implications of impact investing in corporate bonds, we employ three different measures used by investors to achieve impact: emission intensity scope 1, SDG Solution Score, and green bonds. The carbon emissions data is provided by Trucosts, which is part of S&P Global. Trucost analyzes various sustainability information (e.g., ESG scores and climate change measures) for over 15,000 companies. Carbon emission data are usually reported by the company. The categorization of carbon footprint scopes is dependent on the emitting sources of the entity. Scope 1 includes all emissions related to the company's operation, scope 2 considers the operational energy consumption, and scope 3 aggregates all upstream and downstream emissions which are related to a company's operation. Unlike total emission measures, emission intensity metrics express the tons of CO2 emitted per one million USD of revenue. We rely on emission intensity scope 1 as a primary carbon measure, as this is related to companies' operations and allows for comparison of CO2 emissions across firms in different sectors and sizes.

Our second impact measure, SDG score, is provided by ISS ESG and it is part of the SDG Solution Assessment database. SDG Solution Assessment offers 15 sustainability objectives (SDGA Objective Scores) aligned with the UN SDG and it allows investors to assess the positive/negative impact of firms based on their net sales from products and services. The SDGA Objective Scores are calculated as a product of the net sales of a firm generated with relevant products and services and a numeric score mapping. The score mapping (-10, -5, 0, 5, 10) stands for Significant Obstruction, Limited Obstruction, No Net Impact, Limited Contribution, and Significant Contribution. Therefore, a score of -10 is associated with 100% net sales from products and services with obstructing impact, while 10 corresponds to 100% net sales in products and services with significant contributing impact. Finally, the SDG Solution Score is an aggregated score that considers the most distinct objective impacts of a firm.

Green bonds are the third instrument in the scope of this study which allows investors to select firms with measurable sustainable impact. Social, sustainability, and green bonds are also collectively referred to as labelled bonds, as the use of proceeds is strictly related to environmental, social, or combined projects. For this analysis, we consider only green bonds, because they are the best-represented type of labelled bonds over the past years in the corporate bond market. The green bond flag for their classification is taken from Bloomberg.

Following recent literature, we decide to not use ESG metrics, as it is often shown that ESG scores can vary significantly among different data vendors (Berg et al. (2022); Christensen et al. (2022); Brandon et al. (2021)). Data providers offer independent ESG scoring of firms, and measures from various sources have occasionally shown low or negative correlations. Moreover, Brest et al. (2018) argue that socially screened ESG funds cannot be considered an impact investment, as such portfolios offer only value alignment as opposed to value creation resulting in financial performance.

We combine the carbon and SDG measures and corporate bond data based on the bond issuer name, and all bond characteristics are aggregated based on their market value at the company level. The decision to conduct an analysis on an issuer level for the carbon intensity scope 1 and the SDG score is motivated by our aim to avoid issuer concentration, which can introduce bias into the results. Note that our green bond analysis is performed on a bond level because firms issuing green bonds can issue substantially larger non-green debt. Moreover, we analyze firms for which at least the emission intensity scope 1 is available, as this is usually the case for more than 90% of the market value of the G0BC index. Lastly, our study focuses on the period between August 2017–August 2022, as the SDG Solution score is available since August 2017.

Descriptive statistics of the final dataset are provided in Table 4-1. The first half of the table presents issuers' characteristics and indicates no substantial variation in the size of the universe over time. On average, firms issue around 4.2 billion USD in debt, with an average duration of 6 and a credit rating of 8 corresponding to BBB+. Moreover, there are noticeable performance differences in terms of OAS (Option Adjusted Spread) and excess return[12], which is due to the market turmoil at the beginning of 2020 and over the course of 2022. The last three rows of the table report the impact measures of interest. We find that an average company emits 440 tons of CO2 per one million USD revenue and generates no net impact according to their SDG score. Furthermore, roughly 1.5% of the market value of the G0BC consists of green bonds and the standard deviation of 0.5% demonstrates the fastest growth of this asset class. Finally, we report in the Appendix the distribution of carbon intensity scope 1 and SDG scores. While the SDG scores appear to be normally distributed, the carbon intensity scope 1 has an extremely right-skewed distribution, indicating the high concentration of carbon-polluting firms. As the study of Swinkels (2022) reveals, green bonds issued by corporate firms suffer from high currency and sector concentration. Overall, the descriptive statistics outline characteristics of the impact measures that need to be controlled in both research questions.

[12] The reported excess returns of issuers are in excess of the duration-matched government bonds.

Table 4-1: Descriptive statistics of investment grade issuers.
The table reports descriptive statistics of investment grade issuers within the G0BC corporate bond index for the period of August 2017 – August 2022. The individual bonds are aggregated by company issuer based on their market value, then average characteristics were computed by date, based on which the statistics over time are calculated. Excess return is a bond return in excess of a duration-matched sovereign bond. Emission Intensity Scope 1 includes all emissions related to the company's operation and it is expressed relative to sales of the issuer. SDG Score represents the Overall SDG Solution Score provided by ISS. The separate objective scores are product of the net sales of a firm from product/services and a scoring system ranging from -10 to 10. Green Bonds Index Weights stands for the market value weight of green bonds within G0BC.

	10%	**50%**	**90%**	**mean**	**std**
Issuers	2063	2145	2329	2174	98
Market Value, mn EUR	3651	4318	4587	4179	365
Maturity	7.6	7.7	7.8	7.7	0.1
Duration	5.6	5.8	6.1	5.9	0.2
Score	7.8	7.8	7.9	7.9	0.0
Oas	106.2	128.8	184.9	139.0	38.8
Excess Return %, p.m	-0.7	0.3	0.8	0.1	1.4
CO2 intensity scope 1, t/mn USD	384.6	440.9	493.1	440.7	39.8
SDG Score	-0.2	-0.1	0.1	-0.1	0.1
Green Bonds Index Weight	0.7	1.5	2.1	1.4	0.5

4.5 Empirical Results

4.5.1 Pricing of Impact Measures

We expect that investor demand for scarce impact assets would increase the price of bonds with positive environmental/social contribution and thus decrease their credit spreads. To test whether carbon intensity scope 1 and SDG score explain the variation of corporate bond spread on a firm level, we perform a pooled regression with double clustered standard errors and time fixed effects following the formula in Equation (13). As a dependent variable, we use the option-adjusted spread of an issuer. The choice of the control variables is motivated by the study of Henke et al. (2020) and includes broadly utilized bond and company characteristics able to explain corporate bond spreads. Lastly, the variable ImpactMeasure represents the carbon intensity scope 1 or the SDG score of an issuer, and we expect this to be positive for carbon emissions and negative for SDG. All independent variables have been monthly standardized[13]. Additionally, we take a logarithm of carbon intensity scope 1, due to its right skew distribution.

$$\begin{aligned}\text{OAS}_{it} = \beta_0 + \beta_1\text{Volatility30D}_{it} + \beta_2\text{log(MCAP)}_{it} + \beta_3\frac{\text{Debt}_{it}}{\text{Enterprise Value}_{it}} + \beta_4\frac{\text{Ebitda}_{it}}{\text{Total Assets}_{it}} \\ +\beta_5\text{Rating}_{it} + \beta_6\text{Duration}_{it} + \beta_7\text{OAS3m}_{it} + \beta_8\text{Impact Measure}_{it} + \delta_t + \varepsilon_{i,t}\end{aligned} \tag{13}$$

To evaluate the pricing of green bonds, we follow the established methodology of prior literature matching green and non-green bonds with similar characteristics on an issuer level (Flammer (2021); Larcker and Watts (2020); Zerbib (2019)). This is advantageous since green and non-green bonds of the same issuer only differ in use of proceeds but not in credit risk. First, we consider only senior and unsecured corporate debt and filter on plain vanilla bonds. Second, for each green bond of an issuer, we select the non-green bond with the closest duration. In the last step, we require that the matched pairs have the same currency and maturity type. Overall, we successfully match 346 unique green bonds to non-green bonds from 193 unique firms based on categorical characteristics. For comparison, Flammer (2021) matches 152 pairs of green and non-green bonds from 65 unique issuers. In addition to the matching procedure, we account for spread differences of green vs non-green bonds based on numerical bond characteristics used in Equation (13). Along with these, we consider the market value and liquidity of bonds, as Zerbib (2019) and Wulandari et al. (2018) provide evidence of liquidity and issued amount being significant explanatory variables of the yield differential between green and non-green bonds. As such, we perform a regression based on Equation (14), where GmNG_OAS

[13] Standardized variable = (variable – mean by date)/standard deviation by date

represents the spread differential for a matched pair i in month t, while the explanatory variables stand for the difference of credit rating, duration, three-month OAS, market value, and liquidity. All independent variables are standardized. Overall, we expect the intercept to be negative and significant, which would demonstrate that green bonds are more expensive than their non-green peers.

$$\begin{aligned}\text{GmNG OAS}_{it} = \beta_0 + \beta_1\text{GmNG Rating}_{it} + \beta_2\text{GmNG Duration}_{it} + \beta_3\text{GmNG }\Delta\text{OAS3m}_{it} \\ +\beta_4\text{GmNG Market Value}_{it} + \beta_5\text{GmNG LCS}_{it} + \varepsilon_{i,t}\end{aligned} \tag{14}$$

The results of the regressions based on Equation (13) and Equation (14) are reported in Table 4-2. In columns one and two, we report the pricing of carbon intensity scope 1 in credit spreads. We find the regression coefficient of log(Em. Intensity Scope 1) to be negative, but statistically insignificant. Bolton and Kacperczyk (2021) show that carbon intensity is strongly driven by sector variations. Therefore, we control for sector differences to investigate the impact of within-sector variation. Once we account for industry-fixed effects, we show that carbon emissions are a highly significant explanatory variable of corporate spread and as such, high CO2 is associated with higher credit risk within certain sectors. The sector dependency is in line with the findings of Bolton and Kacperczyk (2021), who also document that the carbon effect amplifies once the differences in industry exposures are considered.

Table 4-2: Pricing of impact measures in regression analyses.
The table reports the results of the regressions in Equation (1) in columns (1) to (4) and Equation (2) in columns (5) and (6) for August 2017–August 2022. The dependent variable of the regressions reported in columns 1-4 is the OAS of an issuer i in month t. The independent variables in these regressions are 30-day stock volatility, leverage, Ebitda/Total Assets, logarithm of issuer's market capitalization, average credit rating, duration, 3-month spread change and logarithm of Emission Intensity Scope 1/SDG Score for columns (1)-(2) and (3)-(4) respectively. The dependent variable of regressions (5) and (6) is the spread difference of a green and a non-green bond of the same issuer i in month t. The independent variables are credit rating, duration, 3-month spread change, market value and liquidity costs score of a green bond in excess of the characteristics of a non-green peer bond. All regression analyses are pooled panel regressions with double-clustered standard errors for firm and time fixed effect. The regressions in column (2), (4) and (6) include additional sector / currency - fixed effects. Robust standard errors in parentheses. ***1% significance; **5% significance; *10% significance.

	Emission Intensity Scope 1		SDG Scores		Green Bonds	
	(1)	(2)	(3)	(4)	(5)	(6)
const	136.34***	134.33***	134.44***	134.17***	-3.01***	-3.01***
	(1.14)	(1.15)	(1.36)	(1.28)	(0.85)	(0.85)
Volatility30D	12.35***	10.55***	13.42***	11.42***		
	(1.66)	(1.44)	(2.08)	(1.84)		
Debt/Enterprice Value	12.93***	11.31***	14.51***	13.04***		
	(1.45)	(1.53)	(1.82)	(1.89)		
Ebitda/Total Assets	2.95***	2.65**	1.42	1.57		
	(1.11)	(1.13)	(1.40)	(1.40)		
log(Mcap)	-9.23***	-8.38***	-9.45***	-8.95***		
	(1.42)	(1.50)	(1.77)	(1.88)		
Rating	33.68***	33.45***	32.76***	32.88***	9.44***	9.43***
	(2.01)	(1.99)	(2.09)	(2.05)	(1.63)	(1.64)
Duration	16.60***	17.09***	16.55***	16.59***	14.90***	14.89***
	(1.04)	(1.02)	(1.35)	(1.36)	(1.66)	(1.70)
OAS3M Change	9.84***	10.06***	10.15***	10.36***	3.51***	3.50***
	(2.01)	(1.98)	(2.30)	(2.28)	(0.46)	(0.47)
Market Value					1.64*	1.68*
					(0.86)	(0.89)
Liquidity Costs Score					3.90***	3.89***
					(0.95)	(0.93)
log(Em. Intensity Scope 1)	-0.13	5.14***				
	(1.34)	(1.83)				
SDG Score			-3.59***	-3.15**		
			(1.28)	(1.24)		
Effects	Time	Time, Sector	Time	Time, Sector	Time	Time, Currency
No. Observations	95785	95785	61866	61866	8152	8152
Adj. R-squared	0.31	0.30	0.31	0.29	0.41	0.41

Columns three and four present the results of the pricing of SDG information in the spread of corporate debt. In both regressions, it is evident that SDG scores are priced in the credit risk of a firm, as one standard deviation increase in SDG translates to a 3.6 bps OAS reduction. Unlike carbon intensity, the SDG significance is almost unaffected by sector-fixed effects. This may result from the low SDG scores deviation within sectors compared with the skewed distribution of emission intensity scope 1.

Lastly, the pricing of green bonds is presented in columns five and six. We find the intercept to be negative and statistically significant at a p-value of 1%, and as such, green bonds are traded at roughly 3 bps tighter spreads than comparable non-green bonds. We note that this premium is not driven by currency-fixed effects as shown in regression (6), while results of unreported regressions with firm and sector-fixed effects change neither the magnitude nor the significance of the green premium. With that our findings are similar to the ones of Zerbib (2019), Hachenberg and Schiereck (2018), and Baker et al. (2018), although our analysis is the first to document a significant green premium exclusively for corporate bonds. We believe that the main difference between the studies of Flammer (2021) and Tang and Zhang (2020), who document the absence of a green premium, is driven by the size of their sample, as both analyse green corporate debt only until 2018. To verify this, we apply our regression analysis on the sample period used in the study of Tang and Zhang (2020) from January 2007 until December 2017 and we confirm the lack of green premium.

Even though our results are highly statistically significant, they indicate a modest level of pricing of impact measures. 3 to 5 basis points in spread are generally well within bid-ask spread ranges for IG corporate bonds and thus, unlikely to deter investors. Furthermore, credit returns are not driven just by spread levels and can be influenced through the interaction of impact measures and fundamentals. To investigate this possibility, we construct optimized portfolios.

The optimization problem aims to isolate the effects of impact on corporate bond return by maximizing the portfolio's exposure to low carbon/high SDG firms or green bonds while controlling for systematic risks, such as DTS, sectors, and duration. Consequently, the carbon and SDG portfolios are built on an issuer level, while the green bond portfolios are optimized on a bond level. For completeness, we calculate also portfolios targeting high carbon/low SDG firms or non-green bonds. Using the terminology of prior literature, we call the latter type of portfolios brown, while positive impact strategies are called green. Moreover, we constrain all portfolios to short sale trades and leverage and require high diversification by setting a maximum issuer weight deviation of 1% relative to the corresponding benchmark. To develop a realistic strategy, we limit the monthly two-sided turnover to 20%. Finally, we implement the risk management constraints. To control exposure to the market, as measured with the Duration Times Spread (DTS) ratio (see Dor et al. 2007), we allow the portfolio to deviate by a maximum of 0.1. We also restrict the individual sector weights and sector duration exposure to 50 bps. deviation from the benchmark, which is essential for impact variables heavily dependent on the industry, such as carbon emissions. The mathematical expression of the optimization problem is presented in Equation (15) as follows:

$$
\begin{aligned}
\text{Max } \sum_{i=1}^{I} w_i ImpactMeasure_i \\
\text{, s.t.} \\
\sum_{i=1}^{I} w_i = 1 \quad \text{fully invested constraint,} \\
w_i \geq 0 \quad \text{long only constraint,} \\
|w_i - w_{bm,i}| \leq 0.01 \quad \text{weight deviation from benchmark constraint,} \\
|\sum_{i=1}^{I} \beta_{DTS}(w_i - w_{bm,i})| \leq 0.1 \quad \text{DTS deviation constraint,} \\
\sum_{i=1}^{I} |w_{i,t} - w_{i,t-1}| \leq 0.2 \quad \text{turnover constraint,} \\
|\sum_{k=1}^{K} (w_k^s - w_{bm,k}^s)| \leq 0.005 \quad \text{sector constraint,} \\
|\sum_{k=1}^{K} Duration_s(w_k^s - w_{bm,k}^s)| \leq 0.005 \quad \text{sector duration constraint,}
\end{aligned}
\tag{15}
$$

where $\{w_i | i \in I\}$ stands for issuer/bond i weight and $\{w_k^s | s \in S; k \in K\}$ for issuer/bond k weight within a sector s.

Table 4-3 shows the results of the optimized green and brown portfolios for each impact measure, as well as the index performance. Additionally, we report a long-short portfolio (LS) achieved by the difference between the green and brown optimized portfolios. Consequently, it is also constrained for all conditions described in Equation (15).

It is observable that none of the long-short portfolios generate, on average, positive returns. In fact, the long-short portfolios based on SDG and green bond information deliver negative returns of -10 bps and -20 bps p.a. respectively. Looking at the green portfolios, which aim to maximize exposure to impact proxies, we notice that all have similar or lower than index performance but are also slightly less volatile. Among all measures, the portfolio based on green bonds underperforms the benchmark the most with an average return of 0.8% p.a. vs 1.1% for the index. Furthermore, the Jensen's alpha is negative even though insignificant for all green portfolios, which confirms our expectations that impact investing based only on the individual impact measures is rather a performance-neutral or negative performance strategy depending on the measure.

Table 4-3: Impact measures tilted portfolios.
The table reports the performance of optimized green minus brown, green, and brown portfolios for different impact measures for the period of August 2017 - August 2022. All portfolios are optimized based on Equation (3). Green portfolios are those that create largest impact by minimize exposure to carbon dioxide or maximizing exposure to green bonds or issuers with high SDG score. Brown portfolios have an opposite goal. The column alpha stands for return in excess of the benchmark's return. Jensen's alpha represents the intercept of a univariate regression, explaining the portfolio's return with the benchmark's return. The long-short portfolio's return is compared against zero with a t-test. All measures are annualized.

	Ex. Return	**Jensen's Alpha**	**T-value**	**Volatility**	**SR**	**IR**	**Rating**	**Duration**
Index	1.1			5.3	0.2		7.2	6.8
Intensity Scope 1								
brown	1.1	-0.3	-0.6	4.9	0.2	-0.0	7.7	6.7
green	1.1	-0.3	-0.8	5.0	0.2	-0.0	7.5	6.7
LS	-0.0			0.5	-0.0			
SDG Score								
brown	1.2	-0.3	-1.0	5.6	0.2	0.2	7.8	6.7
green	1.1	-0.3	-0.8	4.8	0.2	0.0	7.9	6.7
LS	-0.1			1.1	-0.1			
Green Bond								
brown	1.0	0.0	-1.0	5.2	0.2	-0.1	7.3	6.8
green	0.8	-0.3	-0.8	5.0	0.2	-0.4	7.1	6.7
LS	-0.2			0.7	-0.3			

Altogether, we find evidence across all three measures in support of the first hypothesis, and therefore, we can conclude that impact information is already incorporated in the credit spread of bonds. Moreover, we demonstrate that tilting a credit portfolio with similar to the benchmark characteristics towards impact assets results in an investment with zero or slightly negative excess returns depending on the measure. This is an important finding for our next hypothesis, where we study the integration of impact in profit-oriented systematic credit strategies.

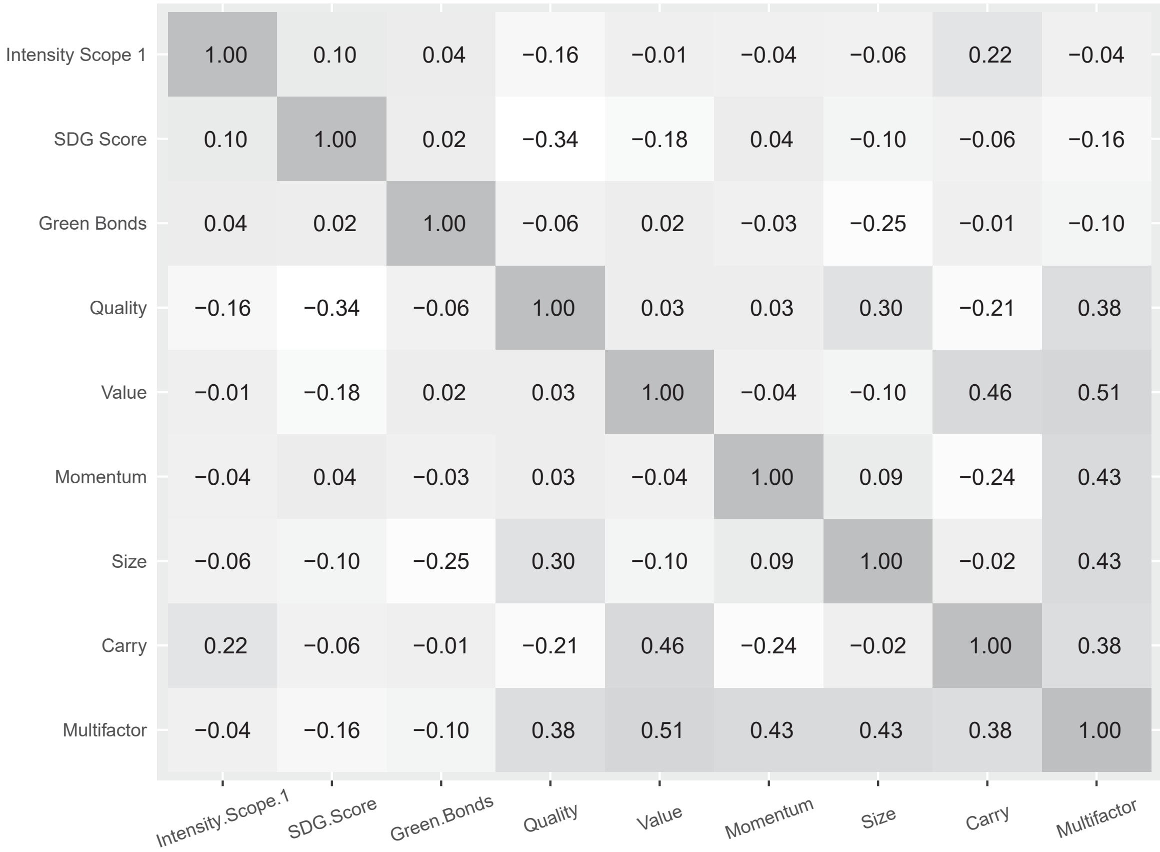
4.5.2 Factor vs Impact Investing Trade-off

Next, we analyze the performance vs impact trade-off that concessionary and non-concessionary investors face. If impact proxies are sufficiently diversified and uncorrelated with systematic factors, we expect to find a concave relationship, in which case a portfolio can improve its exposure to impact or to systematic risk premium with marginal costs. As before, we measure the level of impact via carbon intensity scope 1, SDG score, and green bond flag. To reproduce a credit strategy based on factor models, we employ a multifactor combination proposed by Henke et al. (2020) for corporate bonds, comprising value, equity momentum, size, quality, and carry signals. Their low correlation allows signal blending, which achieves higher diversification. The signal is constructed as a weighted average of the individual systematic z-scores[14].

We first analyze the co-movement of individual factors and impact metrics, which provide us with initial insights about their integration. Figure 4-1 visualizes the cross-sectional correlation of the different measures. Note that we aggregate the green bond flag to an issuer level using the total amount of green debt of a firm. Among all impact proxies, only the SDG score exhibits a noticeable negative correlation with the multifactor of -16%. This is primarily driven by the negative relationship of SDG with value and quality of -18% and -34% respectively. The quality factor is based on 14 balance sheet measures, which are combined in Piotroski's F-score (Piotroski (2000)); therefore, this

[14] Standard normal scores = (score − cross-sectional mean)/cross-sectional standard deviation.

Figure 4-1: Cross-sectional correlation matrix of impact measures and credit factors.
The figure reports the cross-sectional correlation of emission intensity scope 1, SDG score and green bonds with systematic credit factors for IG issuers part of the G0BC index. The correlation is calculated on bond issuer level. For green bonds, the overall market value of green bonds per issuer is used. The cross-sectional correlation is calculated based on August 2017 - August 2022.



factor mostly expresses the profitability of issuers. This is surprising as it implies that highly profitable and stable firms generate more revenue from negative impact activities. Carbon intensity correlates also slightly negatively with the quality signal. However, the correlation here suggests that high-quality issuers are associated with low carbon emissions. Moreover, we find from the positive correlation of carry (measured as the OAS of a bond) and carbon intensity that polluting firms are likely to experience wide credit spreads as we found earlier in the first hypothesis. Lastly, green bonds display a negative correlation only with size, which indicates that green debt is issued by firms with large outstanding debt, rather than small-size firms[15]. Overall, we find that except for SDG, the impact measures exhibit a potential to integrate well with systematic strategies.

To verify whether a dual portfolio target of achieving impact and performance is possible, we simplify the analysis to a two-asset problem. The first asset is fully invested in an impact portfolio, while the second asset represents a portfolio invested in a multifactor strategy. To achieve this, we construct an optimization problem with constraints based on Equation (15), which guarantees that the two portfolios have similar risk characteristics and diversification as the benchmark. A hybrid strategy invested in each portfolio requires a dual target objective function, shown in Equation (16). This involves the transformation[16] and normalization of the impact measures. To analyze the trade-off hypothesis, we vary the proportions of impact in the target function by creating six different scenarios starting with 0% in the impact measures ($\lambda = 0$) and increasing this to 100% ($\lambda = 1$) with a step of 20%. The objective is to maximize portfolio exposure to the new blended signal. The portfolio blending technique enables us to examine whether systematic investors willing to align their investment with sustainable goals need to forsake proportionally large expected returns and whether pure impact investors can achieve benchmark outperformance while still holding a substantial share invested in impact firms.

$$\text{Max} \sum_{i=1}^{I} w_i [\lambda Z_{ImpactMeasure_i} + (1 - \lambda) Z_{Multifactor_i}], \tag{16}$$

where $\{w_i | i \in I\}$ stands for issuer/bond i weight and λ for the weight of the impact

[15] The size factor invests systematically in small market value firms.

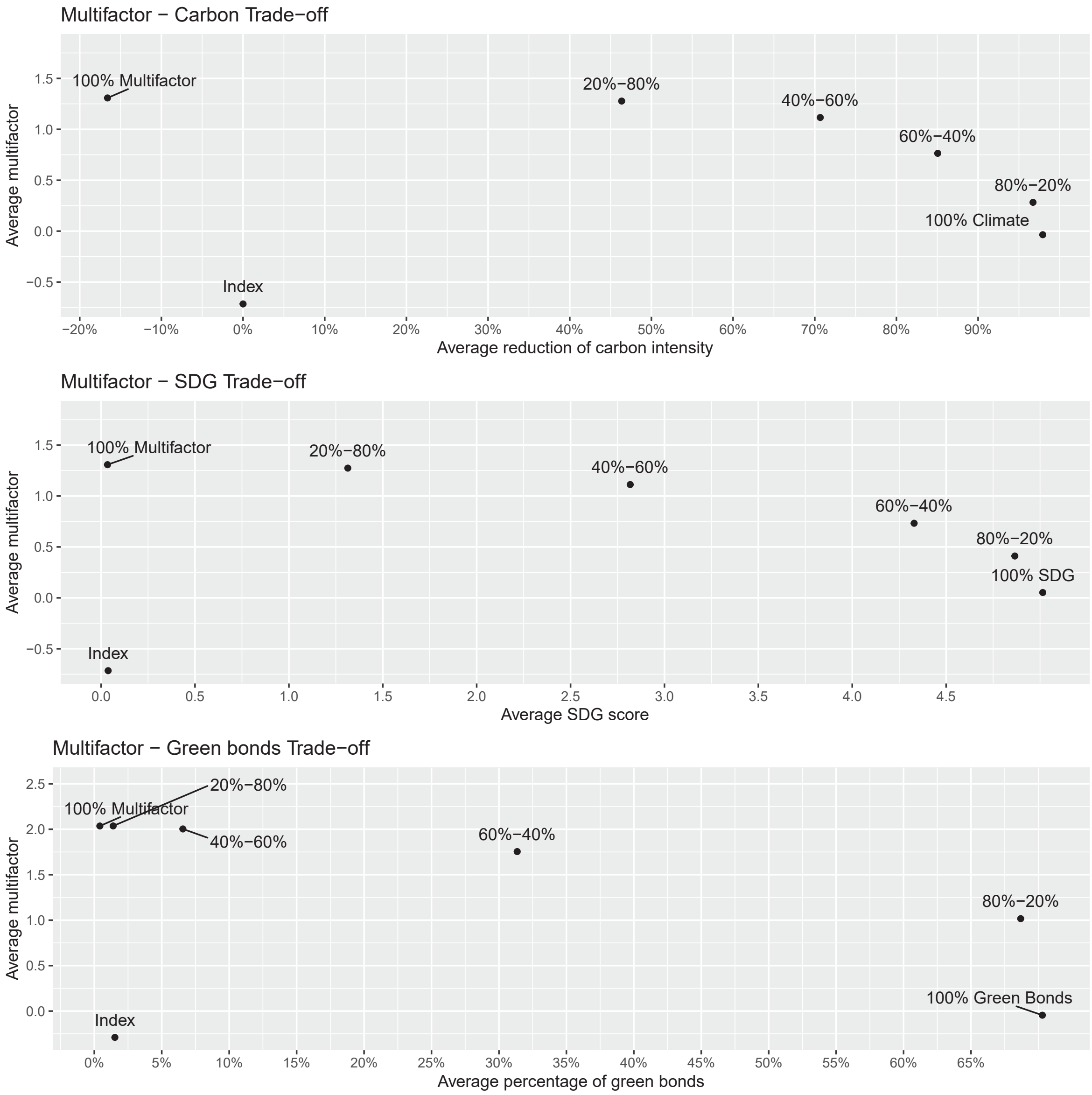
[16] Issuers with the lowest carbon emissions receive the highest normalized scores.

measure in the target function.

The impact and factor exposures of the optimized portfolios, as well as the index, are visualized in Figure 4-2. As expected, for all measures we observe a nonlinear relationship between impact and factor investing. Using carbon intensity scope 1 as a proxy of impact, it is observable that a 100% multifactor portfolio exhibit a higher exposure to carbon than the index, while the portfolio targeting minimum carbon emissions, to which we refer as 100% climate, achieves almost a 100% carbon reduction relative to the benchmark. As we previously indicated, the distribution of carbon intensity scope 1 is highly skewed and a small number of firms produce most of the CO2 emissions. Consequently, it is noticeable that a portfolio with $\lambda = 0.2$ can exhibit a 50% lower carbon score compared to the index and keep its exposure to the multifactor at the same level. On the other hand, while the pure climate portfolio has on average zero exposure to systematic factors, an allocation of only 20% to the multifactor results in an increase in z-score to 0.3 for almost unchanged average emissions.

For investors considering SDG scores to achieve impact, we observe a similar trade-off. As such, systematic investors allocating only 20% to SDG can invest in firms with an average score of 1.3 but preserve the initial exposure to factor models. In comparison, both the index and the multifactor portfolio are impact neutral, with an SDG score of 0. Concessionary investors, on the other hand, hold issuers with a high-impact contribution and average score of 5, but as we have seen in the previous hypothesis, such a portfolio has no exposure to asset pricing models and generates at most benchmark similar returns. With a dual objective of 80%-20%, investors increase exposure to the multifactor by 0.4, while the SDG profile of their holdings is unaltered.

Figure 4-2: Trade-off analysis of impact measures and multifactor credit signal.
The figure visualizes the average exposure of optimized IG portfolios to a multifactor z-score and different impact measures. 100% Climate stands for a portfolio that exclusively minimizes the carbon risk, 100% SDG stands for a portfolio maximizing its investment in issuers with high overall SDG score, while 100% Green Bonds represents a portfolio targeting exclusively green bonds investment. The 100% Multifactor is a tilted portfolio toward a systematic multifactor signal. The portfolios are optimized for August 2017 – August 2022.



Lastly, investors can access impact assets on a bond level by investing in green bonds. Unsurprisingly, a multifactor corporate bond portfolio holds on average only 0.4% in green bonds, which is driven by its low correlation with the factor signals, as well as by the low amount of green bonds in the index. A strategy with $\lambda = 0.2$ is just as green as the benchmark with a weight in green bonds of 1.4%, while a significant increase is achievable only when the multifactor tilt decreases considerably. Due to the insufficient number of green assets, a 100% impact portfolio accomplishes an average green bond weight of 70%, which is unequally distributed over time. However, concessionary investors satisfied with 70% weight in green bonds can achieve substantial allocation to credit factors, as for a $\lambda = 0.8$ the multifactor exposure increases from 0 to 1 standard deviations, while the average share of green bonds stays close to 69%.

Furthermore, to compare the strategies in terms of their historical realized performance, we report return and risk characteristics, as well as the impact measure for all portfolios in Table 4-4. Looking at the portfolios' realized return, it is observable that the outperformance is monotonically increasing with the multifactor exposure. Moreover, institutional investors willing to pursue systematic credit strategies but also align their investment with an impact agenda can dedicate a small allocation of their objective function to low carbon/high SDG or green bond assets without forgoing performance. Impact investors, on the other hand, may consider factor investing models, which enable them to outperform the benchmark for marginal changes in their impact weight. As such, it appears that green bonds are the most suitable impact measure for such a strategy, as only 20% allocation to a multifactor signal results in a 70 bps higher realized return and one standard deviation higher multifactor signals compared with a green portfolio. On the other hand, a green bond portfolio exhibits high emission intensity and low SDG scores. Therefore, we believe that there is no straightforward answer to choose among the impact measures, as this depends on the individual investor's preferences.

Table 4-4: Performance characteristics of trade-off portfolios.
The table reports the performance characteristics of optimized IG portfolios based on multifactor z-score and different impact measures. Climate stands for a portfolio that exclusively minimizes the carbon risk, 100% SDG stands for a portfolio maximizing its investment in issuers with high overall SDG score, while 100% Green Bonds represents a portfolio targeting exclusively green bonds investment. The 100% Multifactor is a tilted portfolio toward a systematic multifactor signal. The portfolios are optimized for August 2017–August 2022. All performance measures are annualized.

	Ex. Return	**Volatility**	**IR**	**Rating**	**Duration**	**Multifactor z-score**	**Em. Intensity**	**SDG Score**	**Green Bonds, %**
Index	1.1	5.3		7.2	6.8		250.5	0.0	1.5
Intensity Scope 1									
100% Mult.	1.8	4.9	0.6	7.4	6.7	1.3	292.1	0.0	2.4
20%-80%	1.7	4.9	0.5	7.4	6.7	1.3	134.4	0.2	2.5
40%-60%	1.7	4.9	0.5	7.4	6.7	1.1	73.5	0.3	3.3
60%-40	1.6	5.0	0.4	7.5	6.7	0.8	37.4	0.4	5.3
80%-20%	1.3	5.0	0.2	7.5	6.7	0.3	8.2	0.6	8.6
100% Impact	1.1	5.0	0.0	7.5	6.7	-0.0	5.2	0.7	9.0
SDG Score									
100% Mult.	1.8	4.9	0.6	7.4	6.7	1.3	292.1	0.0	2.4
20%-80%	1.8	4.8	0.5	7.4	6.7	1.3	263.9	1.3	2.7
40%-60%	1.6	4.7	0.4	7.5	6.7	1.1	212.3	2.8	3.8
60%-40	1.5	4.8	0.4	7.7	6.7	0.7	170.9	4.3	6.3
80%-20%	1.3	4.9	0.2	7.8	6.7	0.4	152.7	4.9	7.2
100% Impact	1.1	4.8	0.0	7.9	6.7	0.0	104.6	5.0	8.9
Green Bond									
100% Mult.	2.4	4.5	0.8	7.6	6.7	2.0	334.2	-0.0	0.4
20%-80%	2.4	4.5	0.8	7.6	6.7	2.0	343.1	0.0	1.4
40%-60%	2.3	4.6	0.8	7.6	6.7	2.0	276.3	0.1	6.6
60%-40	2.1	4.8	0.8	7.6	6.7	1.8	247.8	0.2	31.4
80%-20%	1.5	5.2	0.4	7.5	6.7	1.0	232.5	0.4	68.7
100% Impact	0.8	5.0	-0.4	7.1	6.7	-0.0	191.7	0.3	70.3

Overall, we find evidence that performance-driven investors can achieve impact value alignment, while impact investors can generate higher performance without deviating significantly from their primary mission. While all three proxies of impact exhibit a concave relationship to a multifactor strategy, there are some subtle differences that may influence the choice of institutional investors for an impact measure. Finally, we remark that all optimized impact portfolios achieve higher levels of all three impact measures. This indicates a potential for combining individual scores for Article 9 type funds.

4.6 Conclusion

In this study, we examine the pricing of different impact measures and their integration in relative return credit strategies based on factor models. The three impact proxies – carbon intensity scope 1, SDG score, and green bond label are analyzed for IG corporate bonds for August 2017 until August 2022. In our first hypothesis, we discover all three measures to be priced in while controlling for other spread determinants and fixed effects. Green bonds or bonds issued by firms with high SDG scores/low carbon emissions, tend to exhibit tighter credit spreads of up to 5 bps. Furthermore, by constructing benchmark-oriented portfolios optimized towards impact measures, we find that these strategies generate returns similar to the index or slightly lower.

In the second hypothesis, we analyze the combination of impact and performance-driven strategies. Based on optimized portfolios with a dual target, we demonstrate that factor investors willing to align their portfolios with impact goals can achieve a substantial reduction of emission intensity or increase in SDG/green bond firms against small performance losses. On the other hand, pure impact investors can benefit from exposure to systematic strategies, which enable them to achieve higher performance relative to the benchmark while still being predominantly invested in impact assets. Therefore, we find that the concave relationship between impact and factor investing can help both non-concessionary and concessionary institutional investors to better manage their portfolios.

Our findings support the relatively unexplored stream of literature on impact investing by expanding this from the view of institutional credit investors. We provide the first evidence of the pricing of SDG information and assume that our results are relevant not only for credit but also for equity investors. We believe that our analyses on impact investing in fixed-income portfolio management could encourage institutional investors to engage more in impact creation and achieve higher transparency regarding their investment goals. A natural continuation of our research would be to evaluate the performance–impact characteristics of traded impact portfolios of asset managers, such as Article 9 classified funds, and to examine the efficiency of their investments from an asset pricing perspective.

4.7 Appendix

Table 4-5: Distribution of carbon intensity scope 1 and SDG.
This table reports the descriptive statistics of the carbon intensity scope 1 and SDG scores for the period of August 2017 until August 2022 of bonds issuers part of the ICE BofA Global Corporate Index (G0BC). Different statistics are calculated as time-average of respective measures by date.

	Mean	**St. Deviation**	**Min**	**10%**	**50%**	**90%**	**Max**
CO2 intensity scope 1, t/mn	409.4	1324.1	0.0	0.5	13.2	971.8	25317.5
SDG Score	-0.2	3.8	-10.0	-5.0	0.1	3.9	10.0

5 CONCLUSIONS

Factor investing in credit has become increasingly popular in recent years. This dissertation aims to contribute to the existing literature by exploring areas that have been under-researched. As a result, the findings are relevant to multiple streams of research. To begin with, the first study expands on the literature regarding corporate bond liquidity by analyzing the liquidity of the lesser-documented emerging markets credit asset class. This analysis presents a practical approach to implementing liquidity estimates in systematic credit strategies, showing the benefits of mitigating illiquidity. Additionally, the thesis offers valuable insights into the asset pricing of emerging markets corporate bonds, contributing to the expanding body of factor investing research. The instrumental principal component analysis results unquestionably reveal the impact of country-specific risk on the cross-sectional bond returns. In contrast to attempts by others to leverage systematic return with observable factors, this analysis takes a more fundamental approach by comprehending the drivers of systematic returns in emerging markets. Additionally, this thesis adds to the literature on sustainable investing by examining its relationship with factor investing. As such, the findings present the initial empirical evidence on the trade-off between sustainability and systematic credit factors, and that dual targeting can be beneficial for both sustainability and factor-oriented investors.

Despite the exponentially growing interest in factor investing in credit, questions surrounding the factors' implementation and effectiveness remain unanswered. This dissertation aims to address the implementation of these factors under illiquidity risk, country-specific risk, and shifting preferences toward sustainability. Overall, I find that the returns of observable factors in fixed income are often challenged as most systematic factors have been studied in a frictionless market under common settings. While this dissertation highlights some issues, more research needs to be done in three main directions. Firstly, the increasing number of suggested systematic factors in credit raises the risk of creating a factor zoo, a common problem in equity. Therefore, future research should ensure that factors possess sufficient versatility to be employed in alternative asset classes, such as emerging market credit. Additionally, literature addressing market liquidity problems of corporate debt seldom links to the implementation of systematic credit strategies, which rely heavily on turnover. Finally, sustainable investment has become an essential aspect of constructing portfolios, and as institutional investors increasingly demand the incorporation of various sustainability criteria while maintaining profitability, future research must adapt to changing preferences.

This dissertation offers the first empirical evidence of the challenges faced by credit factor investors when investing in emerging markets. Moreover, it demonstrates the feasibility of incorporating sustainability measures into systematic strategies. However, currently this is only possible for strategies invested in developed markets. A logical extension of this dissertation would be to analyze the factor space of emerging market corporate bonds denominated in local currency, taking into account the necessary liquidity assumptions and sustainability preferences.

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DECLARATION OF HONOR

I declare upon my word of honor that the dissertation submitted herewith is my own work. All sources and aids used have been listed. All references or quotations in any form and their use have been clearly identified. The dissertation has not been submitted for examination purposes to any institution before.

Ich erkläre hiermit ehrenwörtlich, dass ich die vorliegende Arbeit selbstständig angefertigt habe. Sämtliche aus fremden Quellen direkt und indirekt übernommene Gedanken sind als solche kenntlich gemacht. Die Dissertation wurde bisher keiner anderen Prüfungsbehörde vorgelegt und noch nicht veröffentlicht.

Desislava Vladimirova

Frankfurt am Main, 2023