In the Shadow of Country Risk. Asset Pricing Model of Emerging Market Corporate Bonds

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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

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1 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) has 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 universe EM bonds is considerably smaller than that of DM indices and 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 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 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

[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.

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.

2 Data and Methodology

2.1 Methodology

2.1.1 Model specification

To understand the risk and return drivers of EM corporate bonds, we utilize the IPCA model framework proposed by Kelly Bryan 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, $\tilde{\Gamma}_\alpha^b$. 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_α^b of each bootstrapped model, which is $\tilde{\Gamma}_\alpha^{b'} \tilde{\Gamma}_\alpha^b$. The p-value denotes the proportion of W_α^b 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.

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

$$\text{vec}\left(\Gamma^{'}_\beta\right) = \left(\sum_{t=1}^{T} \left[Z_t \otimes f^{'}_t\right]^{'} \left[Z_t \otimes f^{'}_t\right]\right)^{-1} \left(\sum_{t=1}^{T} \left[Z_t \otimes f^{'}_t\right]^{'} r_t\right) \tag{5}$$

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 are 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.

2.1.2 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.

$$\text{Cross Section } R^2 = \frac{1}{T}\sum_t R_t^2 \quad \text{, where} \quad R_t^2 = 1 - \frac{\sum_i \left(r_{i,t+1} - z_{i,t}^{'}\widehat{\Gamma}_\beta \widehat{f}_{t+1}\right)^2}{\sum_i r_{i,t+1}^2} \tag{8}$$

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%.

$$\text{Relative Pricing Error} = \frac{\sum_i \left(\frac{1}{T_i}\sum_t \left(r_{i,t+1} - \widehat{\beta}'_{i,t}\widehat{f}_{t+1}\right)\right)^2}{\sum_i \left(\frac{1}{T_i}\sum_t r_{i,t+1}\right)^2} \tag{9}$$

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 Bryan 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 Bryan et al. (2019)). This test is akin to the one used to assess the existence of unsystematic alpha before we select a restricted model.

2.1.3 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 often 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. Lastly, 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).

2.2 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

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

where $\bar{b}_j$ refers to the average country-level characteristics based on corporate bond information, $b_{i,j} - \bar{b}_j$ 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 Model performance and country risk consideration

In our first hypothesis, we evaluate whether EM corporate bonds 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 Exhibit 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.

Exhibit 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 Exhibit 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 Bryan 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. Exhibit 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 ICPA 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]. Their restricted five-factor IPCA model 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 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) analyses 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.

Exhibit 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

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. Exhibit 3 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 eighth 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.

Exhibit 3: 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

Similar to Kelly Bryan 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 which 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.

Exhibit 4 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 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.

Exhibit 4: 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. * Significant at the 5% level. ** Significant at the 1% level.

	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		

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 $\bar{b}$ 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.

4 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 Exhibit 5, 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.

Exhibit 5: 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, Exhibit 6 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.

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.

Exhibit 6: OOS model comparison of asset pricing models.
Out-of-Sample model comparison.
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

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. Exhibit 7 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.

Exhibit 7: Performance of quintile sorted portfolios based on different 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

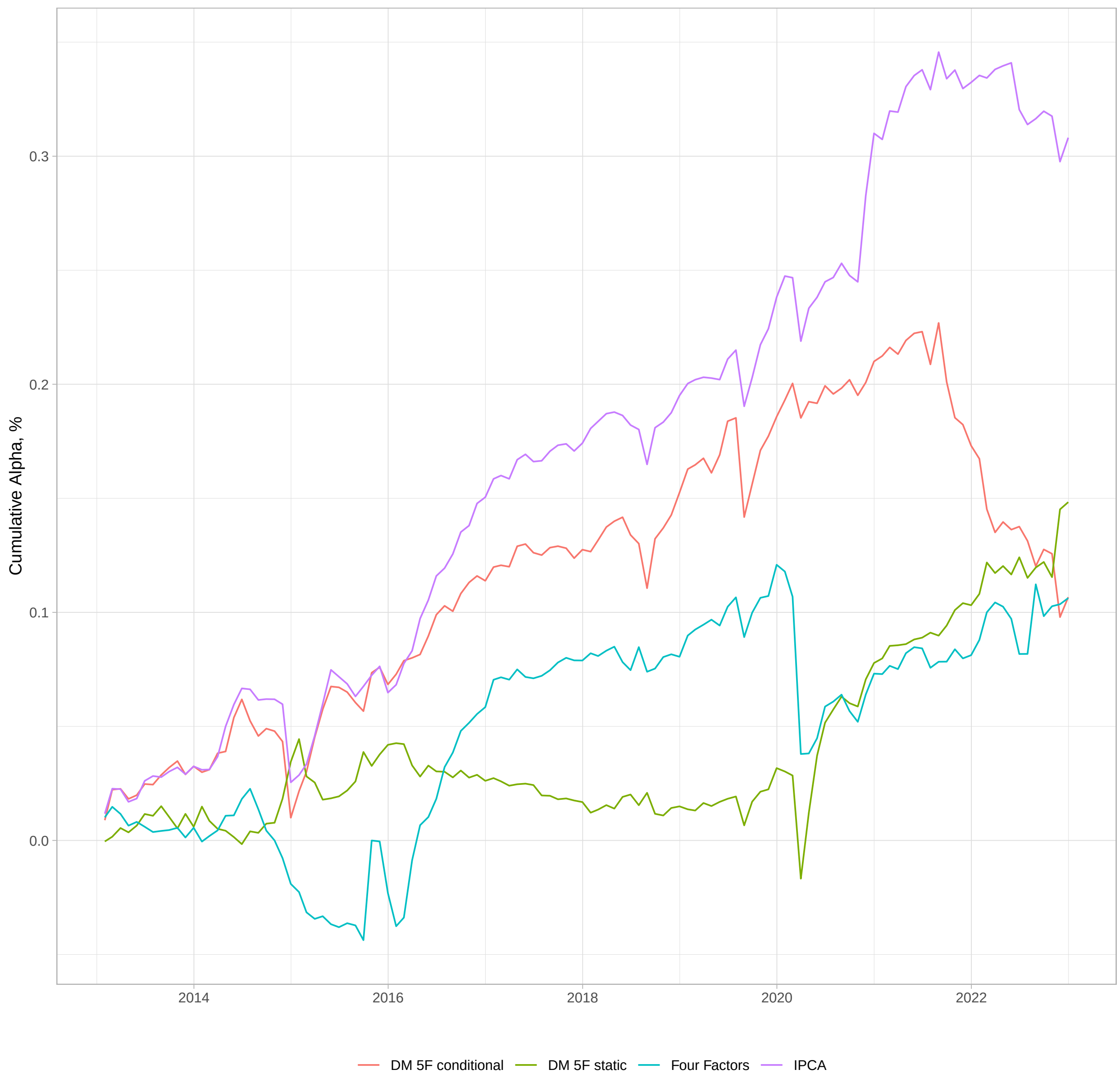
In fixed income, investors often cannot short corporate debt and are therefore only interested in the performance of long-only portfolios. Therefore, our analysis focuses exclusively on the Q5 portfolios, highlighting additional performance characteristics for the various return forecasts. We report in Exhibit 8 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%.

Exhibit 8: Performance of top quintile sorted portfolios based on different 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, Yam, and Yung (2014) based on a heteroskedasticity- and autocorrelation-consistent (HAC) covariance matrix. Turnover represents the two-sided portfolio turnover. All statistics are annualized. * Significant at the 5% level. ** Significant at the 1% level.

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 Exhibit 9. 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.

Exhibit 9: Active performance of top quintile sorted portfolios from January 2013 until December 2022.
The active performance is calculated over value-weighted market portfolio.



5 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 markets 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 necessitate an even more intricate model, given the stronger influence of the sovereign on the performance of corporate debt.

Bibliography

Avramov, D., and Chordia, T. (2006). Asset pricing models and financial market anomalies. In *The Review of Financial Studies* (Vol. 19, pp. 1001–1040).

Bai, J., Bali, T., and Wen, Q. (2019). Common risk factors in the cross-section of corporate bond returns. In *Journal of Financial Economics* (Vol. 131, pp. 619–642).

Bali, T., Subrahmanyam, A., and Wen, Q. (2021). Long-term reversals in the corporate bond market. In *Journal of Financial Economics* (Nos. 2; Vol. 139, pp. 656–677).

Bartram, S., Subrahmanyam, A., and Wen, Q. (2020). Book-to-market, mispricing, and the cross-section of corporate bond returns. In *Tech. rep., National Bureau of Economic Research.*

Bektić, D. (2019). Residual equity momentum spillover in global corporate bond markets. In *The Journal of Fixed Income* (Nos. 3; Vol. 28, pp. 46–54).

Bektić, D., Wenzler, J.-S., Wegener, M., Schiereck, D., and Spielmann, T. (2019). Extending fama-french factors to corporate bond markets. In *The Journal of Portfolio Management* (Nos. 3; Vol. 45, pp. 141–158). Institutional Investor Journals Umbrella.

Ben Dor, A., Dynkin, L., Hyman, J., Houweling, P., Leeuwen, E. van, and Penninga, O. (2007). DTSSM (duration times spread). In *The Journal of Portfolio Management* (Nos. 2; Vol. 33, pp. 77–100). Institutional Investor Journals Umbrella.

Brooks, J., Palhares, D., and Richardson, S. (2018). Style investing in fixed income. In *The Journal of Portfolio Management* (Nos. 4; Vol. 44, pp. 127–139).

Brooks, J., Richardson, S., and Xu, Z. (2020). (Systematic) investing in emerging market debt. In *The Journal of Fixed Income* (Nos. 2; Vol. 30, pp. 44–61). Institutional Investor Journals Umbrella.

Chordia, T., Goyal, Y., Nozawa, Y., Subrahmanyam, A., and Tong, Q. (2017). Are capital market anomalies common to equity and corporate bond markets? In *Journal of Financial and Quantitative Analysis* (Vol. 52, pp. 1301–1342).

Correia, M., Kang, J., and Richardson, S. (2018). Asset volatility. In *Review of Accounting Studies* (Vol. 23, pp. 37–94).

Correia, M., Richardson, S., and Tuna, I. (2012). Value investing in credit markets. In *Review of Acconting Studies* (Vol. 17, pp. 572–609).

Dekker, L., Houweling, P., and Muskens, F. (2021). Factor investing in emerging market credits. In *The Journal of Beta Investment Strategies.* Institutional Investor Journals Umbrella.

Dickerson, A., Mueller, P., and Robotti, C. (2023). Priced risk in corporate bonds. In *SSRN Electronic Journal.*

Elkamhi, R., Jo, C., and Nozawa, Y. (2020). A one-factor model of corporate bond premia. In *Tech. rep., University of Toronto and Hong Kong University of Science and Technology.*

Fama, E., and French, K. (1993). Common risk factors in the returns on stock and bonds. In *Journal of Financial Economics* (Nos. 1; Vol. 33, pp. 3–56).

Ferson, W., and Harvey, C. (1999). Conditioning variables and the cross section of stock returns. In *The Journal of Finance* (Vol. 54, pp. 1325–1360).

Gebhardt, W., Hvidkjaer, S., and Swaminathan, B. (2005). The cross-section of expected corporate bond returns: Beta or characteristics? In *Journal of Financial Economics* (Vol. 75, pp. 85–114).

Harvey, C. (1995). Predictable risk and returns in emerging markets. In *The Review of Financial Studies* (Nos. 3; Vol. 8, pp. 773–816).

Henke, H., Kaufmann, H., Messow, P., and Fang-Klingler, J. (2020). Factor investing in credit. In *The Journal of Index Investing* (Nos. 1; Vol. 11, pp. 33–51). Institutional Investor Journals Umbrella.

Hottinga, J., Leeuwen, E. van, and Ijserloo, J. van. (2001). Successful factors to select outperforming corporate bonds. In *The Journal of Portfolio Management* (Nos. 1; Vol. 28, pp. 88–101). Institutional Investor Journals Umbrella.

Houweling, P., and Zundert, J. van. (2017). Factor Investing in Corporate Bond Market. In *Financial Analysts Journal* (Nos. 2; Vol. 73).

Israel, R., Palhares, D., and Richardson, S. (2018). Common Factors in Corporate Bond Returns. In *Journal of Investment Management* (Nos. 2; Vol. 16, pp. 17–46).

Jostova, G., Nikolova, S., Philipov, A., and Stahel, C. (2013). Momentum in corporate bond returns. In *The Review of Financial Studies* (Vol. 26, pp. 1649–1693).

Kang, J., So, K., and Tziortziotis. (2019). Embedded betas and better bets: Factor investing in emerging market bonds. In *Journal of investment management* (Nos. 3; Vol. 17, pp. 27–46). Institutional Investor Journals Umbrella.

Kaufmann, H., and Messow, P. (2020). Equity momentum in european credits. In *The Journal of Fixed Income* (Vol. 30). Institutional Investor Journals Umbrella.

Kelly, Bryan, Palhares, Diogo, and Pruitt, S. (2023). Modeling corporate bond returns. In *The Journal of Finance*.

Kelly Bryan, Pruitt, Seth, and Su, Y. (2019). Characteristics are covariances: A unified model of risk and return. In *Journal of Financial Economics* (Nos. 3; Vol. 134, pp. 501–524).

Rouwenhorst, K. G. (1999). Local return factors and turnover in emerging stock markets. In *The Journal of Finance* (Nos. 4; Vol. 54, pp. 1439–1464).

Vladimirova, Desislava, Schiereck, Dirk, and Stroh, M. (2023). Managing liquidity of emerging markets corporate debt. In *Journal of Fixed Income* (Nos. 4; Vol. 32).

