Factor Investing in Emerging Market Credits*

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Abstract

We examine factor investing in emerging market hard currency corporate bonds. Size, low-risk, value, and momentum factor portfolios obtain significantly higher Sharpe ratios than the market. We find the strongest results when the four factors are combined in a multi-factor portfolio. In several tests, alphas remain significant after controlling for exposures to developed market credit factors or equity factors. The factor portfolios benefit from bottom-up allocations to countries, sectors, ratings, and maturity segments, but most alphas remain significant after controlling for these allocation effects. Higher risk-adjusted returns of factor portfolios can also be found within liquid subsamples of the market.

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1. Introduction

We examine factor investing in emerging market (EM) hard currency corporate bonds and find that portfolios based on the size, low-risk, value, and momentum factors generate economically meaningful and statistically significant alphas beyond the CAPM, beyond Fama-French-Carhart equity factors, and beyond developed market (DM) corporate bond factors as defined in Houweling and Van Zundert (2017). We show that the factors have low, often negative, pairwise correlations. A multi-factor portfolio that combines these four factors increases the alpha and its significance and reduces relative risk versus the market, thereby delivering a higher information ratio than the individual factors. We demonstrate that the alphas of the multi-factor and almost all single-factor portfolios are robust and hold within countries, sectors, ratings, maturity-segments, and bond size-segments as well as within subsamples of liquid bonds.

Our study is motivated by the increasing interest in factor investing and the growth of the EM credit market, which grew from 50 billion US dollar in 2001 to 1.8 trillion US dollar in 2018, surpassing the DM high yield corporate bond market.[1] Calomiris, Larrain, Schmukler, and Williams (2019) investigate the increased bond issuance by companies from EM countries, especially since 2008, linking it to increased investor demand for riskier bonds as part of their 'search for yield' in times of ever lower interest rates. The existing literature on EM credits is still limited and mainly focuses on topics like the interaction between corporate bonds and sovereign bonds, see e.g. Durbin and Ng (2005), Dittmar and Yuan (2008), Borensztein, Cowan, and Valenzuela (2013) and Zinna (2014), and the determinants of EM credit spreads, see e.g. Cavallo and Valenzuela (2010) and Garay, González, and Rosso (2019).

To the best of our knowledge, we are the first to examine factor investing in this asset class, providing new insights into the drivers of the cross-section of EM corporate bond returns. Most literature on factor investing focuses on DM equity markets, although factor investing in EM equities did receive some attention too: Cakici, Fabozzi, and Tan (2013) and Hanauer and Linhart (2015) documented momentum and value effects; Blitz, Pang, and Van Vliet (2013) found evidence of the low-risk anomaly; Hanauer and Lauterbach (2019) examined a broad set of factors in EM equity markets and documented similar results. Recent studies also documented the existence of factor premia in corporate bond markets, see e.g. Houweling and Van Zundert (2017) and Israel, Palhares, and Richardson (2018), who studied US investment grade and US high yield bonds, and Bektić, Wenzler, Wegener, Schiereck, and Spielmann (2019), who additionally analyzed euro investment grade bonds.

[1] We calculated the total market value of all bonds in our data set, described in Section 2 of the paper, at the first date of the sample period, January 2001, and the last date, December 2018. For comparison, the total market value of the DM high yield market was 1.5 trillion US dollar at the end of 2018, as measured by the Bloomberg Barclays Global High Yield Corporate DM index.

However, this stream in the literature is restricted to the DM credit market. With our analysis of the EM credit market, we present new out-of-sample evidence for the existence of factor premia.

Using the factor definitions of Houweling and Van Zundert (2017), we show that size, low-risk, value, and momentum top-quintile factor portfolios generated significantly positive risk-adjusted returns over the 2001-2018 sample period with Sharpe ratios ranging from 0.57 to 0.85, versus 0.37 for the market. Portfolios based on size, value, and momentum significantly outperform the market; the low-risk factor portfolio delivers a return that is not statistically different from that of the market, but it does so with about one third of the volatility. Controlling for market exposures, we find alphas that are economically meaningful and statistically significant, with annualized CAPM-alphas ranging between 1.46% and 5.03% and *t*-values ranging between 2.49 and 4.76. Due to the low pairwise correlations between the factors, a multi-factor portfolio that allocates equally to the four single-factor portfolios obtains an information ratio of 1.19, which is higher in magnitude and has a higher *t*-value than the information ratios of the single-factor portfolios.

We show that allocating to factors in the EM credit market is attractive, even if one already allocates to factors in the DM credit market or in the equity market. The multi-factor portfolio and most of the single-factor portfolios have significantly positive alphas after controlling for exposures to DM credit or equity factors. Interestingly, most EM credit factor portfolios are significantly related to their DM counterparts, and positively though insignificantly related to their equity counterparts, and therefore seem to benefit from broader factor premia.

Part of the risk-adjusted outperformances of the factor portfolios is driven by bottom-up country allocation. If we prevent this country allocation by constructing country-neutral factor portfolios, we find that the Sharpe ratios and the alphas generally decline. Reassuringly, virtually all results remain statistically significant. For example, the Sharpe ratio of the multi-factor portfolio declines from 0.73 to 0.66, but remains significant with a *t*-value of 4.51; the annualized alpha controlled for exposures to DM credit factors declines from 2.45% to 1.84%, but remains significant as well, with a *t*-value of 4.97. These results indicate that factor premia exist within, but also across countries. In similar analyses, we show the existence of factor premia within and across sectors, ratings, maturity-segments and bond size-segments. In other robustness checks we show that our results are robust to portfolio construction choices and are present in liquid subsets of our dataset.

2. Data and methodology

In this section we discuss our dataset of EM hard currency corporate bonds, and other data used in our analyses, as well as the methodology to construct factor portfolios.

2.1. Emerging markets hard currency corporate bond data

To construct our bond universe we follow the index methodology of the Bloomberg Barclays Emerging Hard Currency Aggregate index: at each point in time we include bonds from all countries that were either classified as low or middle income countries by the World Bank, or as non-advanced countries by the IMF. We obtain historical country classifications from the website of the World Bank[2] and the IMF.[3]

The sample consists of bonds denominated in US dollar, euro, and pound sterling issued by companies and government-related agencies from these countries. We only include agencies if their bonds have no guarantee of timely repayment by the government.[4] The motivation for excluding government-guaranteed bonds is that these reflect the credit risk of the sovereign instead of the corporate issuer. Examples of excluded issuers are Afreximbank (African Export-Import Bank), Bank Gospodarstwa Krajowego (Polish national development bank) and NBAD (National Bank of Abu Dhabi).

Bonds of these eligible issuers are included when they have at least one year until maturity and a minimum amount outstanding of 150 million.[5] We exclude bonds for which prices are based on matrix pricing.[6] Bloomberg Barclays provides a bond's option-adjusted spread, option-adjusted spread-duration, credit rating, amount outstanding, time to maturity and market value at the end of each month. Next to total returns, the dataset also contains excess returns over duration-matched government bonds of the bond's currency denomination (i.e. US Treasury bonds, German bunds, or UK gilts). In our analysis we use these excess returns, thereby focusing on the credit component of a bond's total return. No survivorship bias is present in our sample. Whenever a default occurs, returns are based on the final traded price of the bond, reflecting the market's expected recovery rate.

The sample period ranges from January 2001 to December 2018, containing 198.023 bond-month observations. Because certain issuers, such as Pemex (Petróleos Mexicanos) and Petrobras (Petróleo Brasileiro), have a very large market value compared to other issuers, we cap each issuer's weight in each month at 2%.[7] If the total weight of an issuer's bonds in a particular month exceeds 2%, we proportionally scale down the market value of each of its bonds such that the issuer represents 2% of the universe. These scaled-down market values are subsequently used in all calculations as if they

[2] See https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups
[3] See https://www.imf.org/en/Publications/WEO
[4] We identify agencies without guarantee by restricting the Bloomberg Barclays 'Class 3' sector classification to 'OWNED_NO_GUARANTEE'.
[5] The Bloomberg Barclays Emerging Hard Currency Aggregate index increased its minimum inclusion threshold several times after its inception, but we apply the original amount of 150 million in all months of our sample period to avoid sudden drops in the number of bonds in our data set.
[6] Matrix pricing is used by the index provider (Bloomberg Barclays) to derive a price for an illiquid bond from prices of similar bonds that are more actively traded. We identify these matrix-priced bonds with the data field 'Price Source'.
[7] A 2% issuer cap is a common choice in the industry. Our results did not materially change when we used the original, uncapped market values. For example, the Sharpe ratio of the multi-factor portfolio changed from 0.73 with a *t*-value of 5.04 to a Sharpe ratio of 0.71 with a *t*-value of 4.95.

were the true market values, with one exception: in the construction of the size factor portfolio, we use the original market values to sort issuers from small to large.

The dataset is summarized in Table 1. Panel A contains the bond characteristics, Panel B the average composition of the dataset, and Panel C the average returns as well as the number of bonds per calendar year. Panel A shows that the average bond had a monthly excess return of 33 bps, a maturity of just below 8 years, and a size of about USD 625 million. We observe in Panel B that the majority of bonds, almost 90%, is issued in US dollars, about 10% is issued in euros, and only 1% is issued in sterling. Most bonds have an investment grade rating, mostly BBB (44%) and A (19%). Bonds with a high yield rating represent 31% of our sample, mostly BB (16%) and B (12%). Brazil, Mexico, China, and Chile are the four largest countries in the sample, which combined amount to 50% of the market value weight. Agencies represent 32% of the sample, making it the largest sector, followed by banking (17%), communications (11%) and basic industry (9%). Panel C shows that there is considerable time series variation in both the total returns and the excess returns. As expected, we find the most extreme returns around the 2008 financial crisis, with a -32% excess return in 2008, and a subsequent 33% excess return in 2009.[8] The number of bonds in the dataset increased from 135 in 2001 to 2,722 in 2018, with a full-sample average of 917 bonds per month.

[INSERT TABLE 1 HERE]

For a validation of our dataset, we compared the bottom-up calculated average returns of our universe to the published returns of two EM flagship indices of two main index providers, specifically the Bloomberg Barclays EM Hard Currency Corp & Quasi Sovereigns index and the JP Morgan CEMBI Broad index. Due to the inception dates of these indices, the largest overlapping sample period is 2004-2018. The average total returns over this period are very similar (6.3% vs. 6.0% vs. 6.2%), as are the volatilities (8.2% vs. 9.2% vs. 7.9%). Our total return series also shows high correlations with these indices: 97.6% with the Bloomberg Barclays index and 97.7% with the JP Morgan index. For the Bloomberg Barclays index we also have access to excess returns, so that we can compare the published index excess return to the bottom-up calculated excess return of our dataset. Again, we find a similar average return (2.6% vs. 2.6%) and volatility (7.9% vs. 8.7%) and a high correlation (97.3%). We thus conclude that our dataset is representative of the hard currency EM credit market.[9]

[8] In section 3.2 we will show that our results are robust to excluding the two most volatility years of our sample.

[9] For illustration we also calculate the excess return correlation between our EM excess return series and the Bloomberg Barclays investment grade and high yield indices for DM: the Bloomberg Barclays Global Aggregate Corporate index and the Bloomberg Barclays Global High Yield Corporate index, respectively. Given the inception dates of these indices, we can calculate these return correlations over our entire 2001-2018 sample period. The correlation with the investment grade index is 83.4% and with the high yield index 84.7%.

2.2. Constructing factor portfolios

We construct portfolios on the size, low-risk, value, and momentum factors, as well as a multi-factor portfolio that allocates 25% to each individual factor portfolio. We construct the single-factor portfolios by sorting bonds on a particular factor and taking long (short) positions in the top (bottom) 20% of bonds. We present results for both long-short and long-only factor portfolios, but we do most analyses on long-only portfolios due to the practical difficulties and limited abilities to short corporate bonds. Our base case is to calculate market value (instead of equally) weighted returns to limit the exposure to smaller, less liquid bonds; we discuss results for equally-weighted portfolios in the robustness section. We hold bonds for a fixed 12-month period using the overlapping portfolios methodology of Jegadeesh and Titman (1993). In contrast to what is common practice in the DM corporate bond universe, where asset managers and index providers typically create separate investment grade and high yield funds and indices, EM issues of all ratings are typically combined in one single universe. Therefore, in our main analyses we create factor portfolios in a combined investment grade and high yield EM corporate bond universe. In a robustness check we will show the effects of creating factor portfolios separately within the investment grade and high yield segments.

Next we describe the definitions of the size, low-risk, value, and momentum factors, following the definitions of Houweling and Van Zundert (2017).

Size

Banz (1981) was the first to document the size effect in equity markets: stocks of smaller firms outperformed stocks of larger firms. Evidence on a size premium in corporate bond markets is limited. Hottinga, Van Leeuwen, and Van IJserloo (2001) found a positive but insignificant outperformance for bonds of issuers with the smallest market values. Houweling and Van Zundert (2017) documented that allocating to the size factor leads to higher Sharpe ratios in the US investment grade and high yield markets. Bektić et al. (2019) showed that bond portfolios of companies with a small market value in the equity market generated significant outperformance in the US credit market, but not in the euro market.

We define the size factor as the total market value of all bonds in our universe from the same issuer, identified by the issuer's ticker. We sort bonds in ascending order on their issuer's total market value. The top (bottom) quintile portfolio contains the bonds of the 20% smallest (largest) issuers.

Low Risk

Haugen and Heins (1972) and Black, Jensen, and Scholes (1972) provided the first evidence of the low-risk effect for equities: risk-sorted portfolios displayed a flatter risk-return relationship than the

CAPM would predict. More recent studies showed that the low-risk effect is also present in the corporate bond market, often using credit rating and/or maturity as risk measures, see e.g. Ilmanen, Byrne, Gunasekera, and Minikin (2004), Houweling and Van Zundert (2017), and Israel et al. (2018).

We define the low-risk factor using both rating and the time to maturity. Shorter-dated investment grade bonds are seen as low risk, and longer-dated high yield bonds as high risk. At each point in time, we create the low-risk long portfolio by selecting the 20% shortest investment grade bonds and the bottom portfolio by selecting the 20% longest high yield bonds.

Value

Basu (1977) first documented the value effect for stocks: cheap stocks, as identified by a low book-to-price ratio, outperformed expensive stocks. Several studies found evidence of the value effect in the corporate bond market, see e.g. L'Hoir and Boulhabel (2010), Correia, Richardson, and Tuna (2012), Houweling and Van Zundert (2017) and Israel et al. (2018). Although the precise definition of the value factor varied between these studies, they all regressed credit spreads on risk measures and used the residuals to identify relative mispricings.

We define the value factor as the percentage difference between the market credit spread and the fair (i.e. estimated) credit spread. We estimate fair spreads using the following cross-sectional regression on rating dummies, maturity, and spread change:

$$OAS_{i,t} = \alpha_t + \sum_{r=1}^{R} \beta_t^r I_{i,t}^r + \gamma_t \, M_{i,t} + \delta_t \Delta OAS_{i,t} + \varepsilon_{i,t}$$

$OAS_{i,t}$ is the option-adjusted credit spread for bond *i* in month t. $I_{i,t}^r$ is a dummy variable that equals 1 if bond *i* has rating *r* in month *t*. In total we distinguish 21 ratings, ranging from AAA, AA+, AA, etc to C.[10] $M_{i,t}$ is the time to maturity for bond *i* in month *t*. $\Delta OAS_{i,t}$ is the demeaned past three-month change in the option-adjusted credit spread for bond *i* in month *t* in each rating category. We look at changes in spread within each rating category to focus on idiosyncratic changes in credit risk, i.e. we subtract the average three-month spread change of the rating category. The residual $\varepsilon_{i,t}$ is the difference between the observed market spread and the estimated spread and can be interpreted as the mispricing.

The value factor top (bottom) portfolio contains the 20% bonds with the largest (smallest) percentage mispricing, i.e. $\varepsilon_{i,t}/OAS_{i,t}$.

[10] We require at least 10 observations per rating category; if less observations are present in a month, we combine bonds of that rating with bonds that are rated one notch higher.

Momentum

The momentum effect, which suggests that assets with high (low) past returns tend to have high (low) future returns, was first documented for equity markets by Jegadeesh and Titman (1993). Research on corporate bond markets found a momentum effect as well, with the strongest results in the high yield segment, see Jostova, Nikolova, Philipov, and Stahel (2013), Houweling and Van Zundert (2017), and Israel et al. (2018).

We define momentum as the past six month cumulative bond excess return with a one month implementation lag. The top (bottom) quintile momentum portfolio contains the 20% bonds with the highest (lowest) past return.

2.3. Other data sources

In the Section 3 below we will not only show the performance of the size, low-risk, value, and momentum factor portfolios in the EM credit universe, but we will also investigate whether their performance can be explained by DM credit factors or by equity market factors. For the DM credit factors, we use the factor portfolios of Houweling and Van Zundert (2017); we download the monthly returns of their study, extended until December 2018, from Robeco's website.[11] We obtain the monthly returns of the Fama-French-Carhart 'international' (i.e. developed market) equity factors and the emerging market equity factors from Kenneth French's website.[12]

3. Results

In this section we discuss our main empirical results. Factor portfolios in the EM credit market generated significantly higher Sharpe ratios than passively investing in the market index and earned statistically significant alphas beyond the market premium. Alphas are generally also significant beyond other EM credit factors, beyond the same factors in the DM credit market and beyond the Fama-French-Carhart equity factors. Factor portfolios created in liquid subsets of the investment universe continue to deliver positive alphas. The factors benefit from country allocation and bond selection within countries, as alphas in country-neutral factor portfolios remain significant but are somewhat lower. Most alphas remain significant within sectors, ratings, investment grade, high yield, bond size quintiles, and maturity quintiles.

[11] See https://www.robeco.com/data

[12] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

3.1. Long-short factor portfolios

First we show CAPM-statistics of the long-short value-weighted factor portfolios over the 2001-2018 sample period; see Panel A of Table 2. The CAPM-alphas and betas of each factor portfolio are estimated by running a time-series regression of its monthly returns on EM credit market returns (labelled DEF). All CAPM-alphas are positive and range from 1.24% for the low-risk factor to 5.30% for the size factor. For the size and value factors the CAPM-alphas are statistically significant. We find that the size and value long-short portfolios have positive CAPM-betas, implying that the bonds in the top portfolio are riskier than in the bottom portfolio. For the momentum factor and especially the low-risk factor, the opposite holds, as their long-short portfolios have a negative CAPM-beta.

To explore potential diversification benefits, Panel B in Table 2 contains pairwise correlations between the CAPM-residuals of the factors. We find that these correlations are either modestly positive or negative, with the strongest negative correlation between value and low risk. These correlations imply that a multi-factor portfolio can benefit from diversification between the individual factors.

The last column of Panel A in Table 2 shows the CAPM-statistics of a multi-factor portfolio that invests 25% in each single-factor portfolio. The CAPM-alpha for the multi-factor portfolio is not as high as that of the highest single factor portfolio, i.e. size, but it does show the highest *t*-value. This shows that by diversifying among the four individual factors, one can achieve a risk-adjusted outperformance that is more stable than if one would focus on a single factor.

3.2. Long-only factor portfolios

In this section, and the sections that follow, we focus on long-only factor portfolios. Many corporate bonds cannot be shorted, and even if this is possible, it can be costly, especially in the EM credit market. Therefore, the results presented above for the long-short portfolios may not paint a realistic picture of the advantages of factor investing. Table 3 shows risk and return and CAPM-statistics of long-only, top quintile factor portfolios. For reference, the table also contains results for the value-weighted market index.

[INSERT TABLE 3 HERE]

We observe in Panel A that all factor portfolios generated significantly higher Sharpe ratios than the market's Sharpe ratio of 0.37. Results range from a Sharpe ratio of 0.57 with a *t*-value of 2.15 for the value factor to a Sharpe ratio of 0.85 with a *t*-value of 4.19 for the low-risk factor. The size, value, and momentum portfolios earned their higher Sharpe ratio by means of a higher return, while the low-risk portfolio mostly benefited from a much lower volatility than the market. In Panel B we see that the outperformance of the low-risk factor portfolio is not significantly different from zero, so that this factor portfolio earned market-like returns. The outperformances of the size, value, and momentum factors, on the other hand, are statistically significant with *t*-values between 2.31 and 3.02. And they are not only statistically significant, but also economically meaningful as these factor portfolios would have made between 1.95% and 5.46% additional annual return compared to the 2.84% annual return of a passive investment in the market index.

Note that the tracking errors indicate that the volatility of the outperformance was substantial, ranging from 3.03% per annum for the momentum portfolio to 6.35% for the size portfolio. These are fairly large compared to the market volatility of 7.62%. Figure 1 plots the cumulative outperformance of each factor versus the market over time. Clearly, in crisis periods and their subsequent recovery, e.g. 2001-2003, 2008-2009 and to a lesser extent 2014-2015, factor portfolios deviated more strongly from the market, as demonstrated by a larger increase or decrease of the cumulative outperformance.[13]

[INSERT FIGURE 1 HERE]

The last column of Table 3 represents the risk and return of a multi-factor portfolio that invests 25% in each single-factor portfolio. The Sharpe ratio of this multi-factor portfolio is not superior to the best single-factor portfolio, but its *t*-value of 5.04 implies significance at a much higher confidence level. Interestingly, the tracking error of the multi-factor portfolio versus the market is lower than of any of the individual factors and its information ratio is the highest. This is a reflection of the low pairwise correlations between the factors.

Panel C of Table 3 shows the CAPM-alphas and betas of each factor portfolio. Consistent with the long-short results of Table 2, the size and value portfolios have more systematic risk than the market with a CAPM-beta above 1, while the betas of the low-risk and momentum factors are below 1. The CAPM-alphas are all statistically significant with *t*-values ranging from 2.49 for value to 4.76 for low risk. The CAPM-alpha of the multi-factor portfolio has the highest *t*-statistic: 4.91.

The results in Table 2 and Table 3 clearly indicate that the main premise of factor investing of earning a higher risk-adjusted return holds just as well for EM credits as for DM credits. These results thus form a successful out-of-sample test of the factor definitions of Houweling and Van Zundert (2017).[14]

[13] Our results are not driven by the 2008-2009 financial crisis. When we exclude the years 2008 and 2009 from our sample, the Sharpe ratios of the single- and multi-factor portfolios remain significantly higher than the Sharpe ratio of the market.

[14] Note that all results in Table 3 are gross of transaction costs. Following Houweling and Van Zundert (2017), we calculate the break-even transaction costs for each factor portfolio, which are defined as the cost level that would reduce its net CAPM-alpha to 0. We find that these break-even costs vary between 2.1% and 4.7%. Unfortunately, we are not aware of any studies on transaction costs in EM credits to benchmark these break-even levels. To offer some level of comparison, we mention the 30 bps realized transaction costs that Mizrach (2015) calculated on the 2003-2015 TRACE database, which contains US dollar-denominated corporate bonds across all ratings of DM and EM issuers. So, the break-even transaction of over 200 bps of the EM credit factor portfolios seem sufficiently high to expect positive after-cost CAPM-alphas.

3.3. Spanning regressions

To test whether the individual factors are indeed distinct factors, we run spanning regressions of each factor on the market portfolio and all other factors. The results in Table 4 show that the returns of the size, low-risk, and momentum factor portfolios cannot be explained by the returns of the other factors, as the alphas remain statistically significant. This is evidence that these factors are distinct phenomena. Although still positive, the alpha of the value factor portfolio loses its significance when we control for size, low risk, and momentum. Even though the loadings on these factors are not statistically significant, these results do show that there is some common component between the value factor on the one hand, and the size, low-risk, and momentum factors on the other hand.

[INSERT TABLE 4 HERE]

3.4. EM credit factors versus DM credit factors

Next, we investigate to which extent factors in the EM credit market are related to factors in the DM credit market and whether these exposures to DM factors can explain the performance of the EM factors. For this analysis we extend the CAPM-regression in Panel C of Table 3 with the four factor portfolios of Houweling and Van Zundert (2017); we will henceforth refer to these five-factor alphas as the HZ-alphas. Table 5 contains the results, where Panel A includes the HZ investment grade factors and Panel B their high yield factors.

[INSERT TABLE 5 HERE]

All EM factors have a positive beta to the same factor in DM. Most of these betas are statistically significant, with the exception of the low-risk and value factors in the investment grade regression of Panel A. The HZ-alphas of the EM size factor drop most (by more than 1%) compared to its CAPM-alpha. After we control for the high yield DM factors in Panel B, the alpha of the size factor even becomes insignificant. This suggests that there is a common component to the size factor in the EM and DM credit markets. Importantly, all other HZ-alphas, including the alphas of the multi-factor portfolio, are statistically significant with *t*-values above 2.5. The EM factor alphas therefore seem unique to the EM market, despite the positive and mostly significant loadings on their DM counterparts.

3.5. EM credit factors versus equity factors

We now turn to the question whether the higher returns of EM credit factors could be attributed to their exposures to equity factors. Therefore, we augment the CAPM-framework with the five Fama-

French-Carhart equity factors: size (SMB), value (HML), profitability (RMW), investments (CMA), and momentum (WML). The results are shown in Table 6; Panel A uses the DM equity factors and Panel B the EM equity factors. Interestingly, the size, value, and momentum factors in the EM credit market have positive betas to their DM and EM equity counterparts, but these are not statistically significant. Also, the adjusted R^2-values in this table are at most 2% higher than in Panel C of Table 2**: Performance statistics of long-short quintile factor portfolios**

A. CAPM-statistics					
	Size	**Low Risk**	**Value**	**Momentum**	**Multi-Factor**
Alpha (%)	5.30**	1.24	2.67*	1.74	2.74**
t-statistic	3.05	1.22	2.13	0.84	4.74
DEF	0.14*	-1.50**	0.59**	-0.63**	-0.35**
t-statistic	2.17	-22.15	9.40	-4.32	-9.43
Adjusted R2	0.02	0.80	0.42	0.30	0.46
B. Correlations					
Size		0.13	0.10	-0.19	
Low Risk	0.13		-0.53	0.33	
Value	0.10	-0.53		-0.32	
Momentum	-0.19	0.33	-0.32		

Notes: This table shows performance statistics of the size, low-risk, value, momentum, and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and market value-weighted short positions in the bottom 20% (for size: the bonds of the 20% largest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest (largest) market value of debt; for value, we select the bonds with the highest (lowest) percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest (lowest) past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade (longest-maturity bonds in high yield). We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. Panel A shows the results of the CAPM-regressions, where the time-series of monthly excess returns of the long-short factor portfolios are regressed on a constant and the EM credit market excess returns (DEF). Panel B shows pairwise correlations between the CAPM-alphas of the factor portfolios. Statistical significance is determined through two-sided tests of whether the CAPM-regression coefficients are different from zero (*t-test* with Newey–West standard errors). * Significant at the 5% level. ** Significant at the 1% level.

, so that the Fama-French-Carhart equity factors do not have a lot of power in explaining the variation in EM credit factor returns. All single-factor alphas remain positive and in six out of eight cases they remain statistically significant. The alphas of the value and momentum factors in Panel B, where we control for exposures to EM equity factors, are the exceptions, suggesting that there may be shared phenomena between EM equity and EM credit markets. Looking at the multi-factor alphas, we find that these remain statistically significant, with a *t*-value of 4.32 (5.01) when controlling for DM (EM) equity factors.

[INSERT TABLE 6 HERE]

3.6. Liquidity effects

Corporate bonds tend to be less liquid than stocks and this may be more pronounced in EM than in DM. We examine whether factor portfolios in EM credit markets still deliver statistically significant risk-adjusted returns in liquid subsamples of our dataset. We construct liquid subsamples in three ways, using bond age and/or bond size as liquidity proxies. In the first method, we only consider the youngest 50% of the bonds in each month to construct the factor portfolios. Likewise, the second method only considers the largest 50% of the bonds. Since both methods cut the cross-section of bonds in half, which by itself lowers performance expectations (as per the Fundamental Law of Active Management of Grinold and Kahn, 1995), we consider a third method. This method, following Houweling and Van Zundert (2017), selects the most liquid bond per company, thus preserving the number of companies in the cross-section. Each month:

1. We limit the set of bonds of the company to bonds with an age of at most two years. If no bonds are younger than two years, we limit the set to bonds with an age of at most four years. If no such bonds are found, we select all bonds of the company.
2. Within the age-restricted set of bonds, we select the largest bond.

Table 7 shows the results of constructing the factor portfolios on the three liquid subsamples, alongside the original results on the full dataset. All factors show weaker performance statistics in the first two methods of creating liquid subsamples, which was expected due to the smaller sample size, but all HZ-alphas[15] remain positive. The size factor is most affected, as its HZ-alpha is no longer significant in both the youngest and largest subsamples. For the low-risk and value factors, only one subsample gives a significant HZ-alpha. The momentum factor and the multi-factor portfolio retain their significance in both subsamples. For all factors, we find significant alphas and Sharpe ratios in the third method, which preserves the cross-sectional breadth in the issuer dimension. These results indicate that factor premia are not just concentrated in less liquid segments of the EM credit market, but that higher risk-adjusted returns can also be generated in liquid subsamples of bonds, though it is fair to say that statistical significance is lower in smaller cross-sections.

[INSERT TABLE 7 HERE]

In an alternative (unreported) robustness check for liquidity effects we applied a 1-month implementation lag to allow for the possibility that bonds may not be tradeable at the end-of-month index price due to stale pricing. Instead of the base case-setup, where we construct factor portfolios at the end of month *t* with factor scores at the end of that same month *t*, we now use factor scores from the previous month, *t* -1. Reassuringly, the results with this implementation lag are very similar to the

[15] In this analysis, and in the analyses that follow below, we report the alphas versus the investment grade factors of Houweling and Van Zundert (2017), because Table 1 shows that the majority of the bonds in the EM credit market has an investment grade credit rating.

base case without lag. The exception is the size factor, for which we do observe worse performance statistics, e.g. the HZ-alpha drops from 3.46% to 2.82% and its *t*-value from 2.64 to 2.47. Even though the size factor's preference for smaller issuers and smaller bonds exposes it most to liquidity effects, the HZ-alpha remains significant. For the other factor portfolios, the Sharpe ratios, HZ-alphas, and their statistical significance are robust to this delayed implementation.

3.7. Country effects

Emerging market economies are well-known for their boom-bust cycles, such as in Latin America in the 1980s, in Asia in the 1990s, or, to give a more recent example, Turkey in 2018. One may wonder whether the factors studied in this paper worked in spite of, or perhaps because of, such country-specific effects. For instance, the momentum factor populates the portfolio with bonds that recently did well, even if that means allocating more to some countries, and less to others. To explore such country allocation effects, we construct a 'country-neutral' portfolio for each factor as follows:

1. For each country, we rank bonds of companies domiciled in that country on their factor score.
2. We select the 20% best bonds for each country.[16]
3. We construct the market value-weighted portfolio of all selected bonds.

The portfolio thus constructed has the same proportion of bonds in each country as the market. Table 8 shows the results of these country-neutral portfolios, and, for ease of comparison, also the base case results without controlling for country allocation effects. We observe that all Sharpe ratios and HZ-alphas are lower compared to the base results, as are most *t*-values. These weaker results for the country-neutral factor portfolios suggest that the original portfolios without country-neutrality generated part of their added value by their bottom-up preferences to particular countries. Preventing country allocation worsens the results, as evidenced by the lower returns of the size, value, and momentum factors, and the higher volatility of the low-risk factor. Reassuringly, most single-factor results are still statistically significant, with the exception of the Sharpe ratio of the value factor. The Sharpe ratio and HZ-alpha of the multi-factor portfolio also retain their significance with *t*-values above 4.

[INSERT TABLE 8 HERE]

[16] We require countries to have at least 5 bonds in the particular month. Countries with less observations are combined into an 'other' category in that month.

3.8. Other neutralities

Broadening the country analysis of the previous section, Table 9 shows results for factor portfolios constructed with various other neutralities to control for allocations to sectors, ratings, investment grade vs. high yield (labelled IG/HY), bond size (measured by its amount outstanding) quintiles, and maturity quintiles. The portfolio construction proceeds as described above in Section 3.7: we first sort bonds on a factor within their group (e.g. a rating category), then we select the best 20% of each group, and finally we construct the market value-weighted portfolio of all selected bonds. For the low-risk factor we do not create rating-neutral, IG/HY-neutral, or maturity-neutral portfolios, because these characteristics are an integral part of the factor definition. Likewise, for the size factor we do not construct bond size-neutral portfolios as bond size is closely related to company size.

[INSERT TABLE 9 HERE]

With a few exceptions, imposing a neutrality during the construction of a factor portfolio generally lowers the return, Sharpe ratio, HZ-alpha, and their associated *t*-values. So, similar to what we concluded on country allocation above, factors have some skill to successfully allocate to sectors, ratings, IG vs. HY segments, bond size segments, and maturity segments. Sector-neutrality is often the exception to this general finding, as it improves some of the statistics for the size, low-risk, value, and multi-factor portfolios. Also, IG/HY-neutrality improves Sharpe ratios, alphas, and *t*-values for the size and value factors.

Virtually all *t*-values for the Sharpe ratios and alphas of the single-factor portfolios, and all *t*-values for the multi-factor portfolio, continue to point at statistical significance. Therefore, the factors generate most of their ability to predict bond returns from selection within groups (sectors, ratings, etc.) and not from allocation to groups.

3.9. Other robustness checks

Panel A of Table 10 shows results for equally-weighted factor portfolios. Compared to a value-weighted portfolio, an equally-weighted portfolio benefits from exposure to the size factor, as smaller companies see their portfolio weights increase and larger companies decrease. For most factors, an equally-weighted portfolio indeed generated better investment results, as evidenced by the higher alphas and their *t*-statistics. The exception is the low-risk factor, for which results deteriorate somewhat, which can be understood by the higher risk of smaller companies, see Panel A of Table 2**:**
Performance statistics of long-short quintile factor portfolios

A. CAPM-statistics					
	Size	**Low Risk**	**Value**	**Momentum**	**Multi-Factor**
Alpha (%)	5.30**	1.24	2.67*	1.74	2.74**

t-statistic	3.05	1.22	2.13	0.84	4.74
DEF	0.14*	-1.50**	0.59**	-0.63**	-0.35**
t-statistic	2.17	-22.15	9.40	-4.32	-9.43
Adjusted R2	0.02	0.80	0.42	0.30	0.46
B. Correlations					
Size		0.13	0.10	-0.19	
Low Risk	0.13		-0.53	0.33	
Value	0.10	-0.53		-0.32	
Momentum	-0.19	0.33	-0.32		

Notes: This table shows performance statistics of the size, low-risk, value, momentum, and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and market value-weighted short positions in the bottom 20% (for size: the bonds of the 20% largest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest (largest) market value of debt; for value, we select the bonds with the highest (lowest) percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest (lowest) past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade (longest-maturity bonds in high yield). We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. Panel A shows the results of the CAPM-regressions, where the time-series of monthly excess returns of the long-short factor portfolios are regressed on a constant and the EM credit market excess returns (DEF). Panel B shows pairwise correlations between the CAPM-alphas of the factor portfolios. Statistical significance is determined through two-sided tests of whether the CAPM-regression coefficients are different from zero (*t-test* with Newey–West standard errors). * Significant at the 5% level. ** Significant at the 1% level.

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Panel B of Table 10 evaluates the factor portfolios over a holding period of one month instead of one year as in the base case. Alphas and *t*-values are lower than in the base case. The HZ-alphas for the size, low-risk, and multi-factor portfolios remain significant over this shorter holding period. Especially momentum seems to suffer from this shorter holding period, where the alpha and *t*-value are close to zero.

4. Conclusion

In this paper, we extend the notion of factor investing to the EM hard currency credit market. We find that allocating to size, low-risk, value, and momentum factor portfolios yields higher risk-adjusted returns than passively investing in the market value-weighted index, with Sharpe ratios ranging from 0.57 to 0.85 versus 0.37 for the market. All four single-factor portfolios obtain positive and statistically significantly CAPM-alphas, which generally remain significant after controlling for DM credit factors or equity factors. The factors have low pairwise correlations. An equally-weighted combination of the four single-factor portfolios into a multi-factor portfolio leads to a higher information ratio, higher *t*-values for the Sharpe ratio and alpha, and consistent significance in all robustness tests.

The results in this paper form new out-of-sample evidence and show that factors that are well-known in the equity market, and increasingly known in the DM credit market, also yield higher risk-adjusted returns in the EM credit market. To the best of our knowledge, we are the first to examine factor investing in EM credits, thereby filling a gap in the empirical asset pricing literature. By successfully out-of-sample testing the factor definitions of Houweling and Van Zundert (2017), the results of our study also strengthen the confidence in previously found results in other markets.

At the same time, our results can provide guidance for investors in EM credits. We show that systematically allocating to factors can help them to achieve higher risk-adjusted returns and to more efficiently allocate capital. Moreover, factors can be used to analyze the performance of active managers and evaluate the uniqueness of their skills. We leave these topics for future research.

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Table 1: Descriptive statistics

A. Bond characteristics

	Mean	**5%**	**50%**	**95%**
Monthly excess return (%)	0.33%	-3.63%	0.21%	4.50%
Time to maturity (years)	7.96	1.71	5.94	25.83
Credit spread (bps)	370	116	276	1313
Spread-duration (years)	5.11	1.45	4.60	11.56
Market value ($ millions)	625	225	501	1377
Age (years)	3.10	0.28	2.49	8.00
Number of issuers	269			

B. Universe composition

	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**CC-C**
Rating	0.73%	4.62%	19.10%	44.42%	16.19%	11.94%	2.01%	1.00%
	USD	**EUR**	**GBP**					
Currency	89.18%	9.69%	1.13%					
	Brazil	**Mexico**	**China**	**Chile**	**UAE**	**Malaysia**	**Kazakhstan**	**Other**
Country	14.97%	13.15%	12.86%	9.11%	5.38%	4.65%	3.94%	35.95%
	Agencies	**Banking**	**Commu-nication**	**Basic Industry**	**Energy**	**Capital Goods**	**Electric**	**Other**
Sector	31.93%	16.59%	11.20%	9.23%	8.87%	4.45%	4.56%	13.18%

C. Calendar years

	total return	**excess return**	**number of bonds**		**total return**	**excess return**	**number of bonds**
2001	5.31%	-1.84%	132	2010	12.13%	6.58%	574
2002	9.95%	-2.35%	116	2011	4.29%	-5.27%	747
2003	20.50%	15.61%	121	2012	15.26%	12.47%	1054
2004	11.35%	6.85%	163	2013	-1.73%	0.97%	1698
2005	5.43%	4.13%	225	2014	4.77%	0.78%	2017
2006	7.37%	3.39%	224	2015	-1.73%	-2.29%	2105
2007	4.59%	-5.61%	285	2016	8.92%	7.90%	2329
2008	-20.48%	-31.88%	261	2017	7.80%	5.40%	2576
2009	31.90%	32.92%	364	2018	-1.25%	-2.10%	2722

Notes: This table shows summary statistics for all constituents of our EM hard currency dataset over the 2001-2018 sample period. Panel A reports the time-series average of the equally weighted cross-sectional mean and percentile statistics of several bond characteristics. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. The time to maturity is the number of years until the bond expires. The credit spread is the option-adjusted yield of the bond in excess of the yield of the duration-matched government bond in basis points. Spread-duration is the option-adjusted spread-duration in years. Market value is the market value of the bond in million US dollars. Age is the time in years since the bond's issue date. Panel B reports the time series average of the market value weights in different credit ratings, currencies, countries, and sectors. The market value weights per issuer are capped at 2% at each point in time. Credit rating is the middle credit rating of the rating agencies S&P, Moody's, and Fitch (worst rating in case of two ratings). Currency is the currency denomination of the corporate bond. Country is the issuer's country of domicile. Sector is the Bloomberg Barclays Class 3 sector classification. Panel C reports statistics per calendar year. The total return and excess return over duration-matched government bonds are first calculated as the market value-weighted average over all bonds in each month, and then the compounded cumulative return in the year is calculated. The number of bonds is calculated at the end of each calendar year.

Table 2: Performance statistics of long-short quintile factor portfolios

A. CAPM-statistics	Size	Low Risk	Value	Momentum	Multi-Factor
Alpha (%)	5.30**	1.24	2.67*	1.74	2.74**
t-statistic	3.05	1.22	2.13	0.84	4.74
DEF	0.14*	-1.50**	0.59**	-0.63**	-0.35**
t-statistic	2.17	-22.15	9.40	-4.32	-9.43
Adjusted R^2	0.02	0.80	0.42	0.30	0.46
B. Correlations					
Size		0.13	0.10	-0.19	
Low Risk	0.13		-0.53	0.33	
Value	0.10	-0.53		-0.32	
Momentum	-0.19	0.33	-0.32		

Notes: This table shows performance statistics of the size, low-risk, value, momentum, and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and market value-weighted short positions in the bottom 20% (for size: the bonds of the 20% largest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest (largest) market value of debt; for value, we select the bonds with the highest (lowest) percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest (lowest) past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade (longest-maturity bonds in high yield). We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. Panel A shows the results of the CAPM-regressions, where the time-series of monthly excess returns of the long-short factor portfolios are regressed on a constant and the EM credit market excess returns (DEF). Panel B shows pairwise correlations between the CAPM-alphas of the factor portfolios. Statistical significance is determined through two-sided tests of whether the CAPM-regression coefficients are different from zero (*t*-test with Newey–West standard errors). * Significant at the 5% level. ** Significant at the 1% level.

Table 3: Performance statistics of top quintile factor portfolios

A. Return statistics

	Market	**Size**	**Low Risk**	**Value**	**Momentum**	**Multi-Factor**
Mean (%)	2.84	8.30	2.40	6.30	4.79	5.45
Volatility (%)	7.62	10.78	2.82	11.15	7.46	7.45
Sharpe ratio	0.37	0.77**	0.85**	0.57*	0.64**	0.73**
t-statistic		2.72	4.19	2.15	2.79	5.04

B. Outperformance statistics

	Size	**Low Risk**	**Value**	**Momentum**	**Multi-Factor**
Outperformance (%)	5.46**	-0.45	3.46*	1.95*	2.60**
t-statistic	3.02	-0.30	2.42	2.31	4.50
Tracking error (%)	6.35	5.27	4.93	3.03	2.19
Information ratio	0.86	-0.09	0.70	0.64	1.19

C. CAPM-statistics

	Size	**Low Risk**	**Value**	**Momentum**	**Multi-Factor**
Alpha (%)	5.03**	1.46**	2.43*	2.23**	2.79**
t-statistic	3.18	4.76	2.49	2.71	4.91
DEF	1.15**	0.33**	1.36**	0.90**	0.94**
t-statistic	18.77	9.10	30.59	9.88	42.93
Adjusted R^2	0.66	0.79	0.86	0.84	0.92

Notes: This table shows performance statistics of the size, low-risk, value, momentum, and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest market value of debt; for value, we select the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. Panel A shows the annualized mean and standard deviation of the monthly excess returns and Sharpe ratios. Panel B shows the annualized outperformance with respect to the market return, the tracking error, calculated as the annualized volatility of the outperformance, and the information ratio. Panel C shows the results of the CAPM-regressions, where the time-series of monthly excess returns of the factor portfolios are regressed on a constant and the EM credit market excess returns (DEF). Statistical significance is determined through two-sided tests of whether (1) the Sharpe ratio is different from the Sharpe ratio of the market (Panel A; Jobson and Korkie, 1981), (2) the outperformance is different from zero (Panel B; *t*-test with Newey–West standard errors), (3) the CAPM-regression coefficients are different from zero (Panel C; *t*-test with Newey–West standard errors). * Significant at the 5% level. ** Significant at the 1% level.

Table 4: Factor spanning regressions

	Size	Low Risk	Value	Momentum
Alpha (%)	4.17*	1.56**	1.56	2.87**
t-statistic	2.28	6.35	1.69	3.91
DEF	0.83	0.40**	1.08**	0.96**
t-statistic	1.97	5.17	3.43	6.52
Size		0.02	0.13	-0.07*
t-statistic		0.86	0.96	-2.02
Low Risk	0.55		-0.19	-0.39
t-statistic	0.87		-0.61	-1.81
Value	0.30	-0.02		0.11
t-statistic	1.08	-0.67		1.27
Momentum	-0.31	-0.08	0.22	
t-statistic	-1.43	-1.91	1.20	
adjusted R^2	0.68	0.80	0.87	0.85

Notes: This table shows time-series regressions of the size, low-risk, value, momentum and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and held for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest market value of debt; for value, we select the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. The table shows the results of the spanning regressions where the time-series of monthly excess returns of the factor portfolios are regressed on a constant, the EM credit market excess return (DEF) and all other EM factor portfolio monthly excess returns. Statistical significance is determined through two-sided tests of whether the coefficient is different from zero (*t*-test with Newey–West standard errors). Alphas are annualized by multiplying the constant by 12. * Significant at the 5% level. ** Significant at the 1% level.

Table 5: Developed market credit factor time-series regressions

	Size	Low Risk	Value	Momentum	Multi-Factor
A. Investment grade DM					
Alpha (%)	3.46**	1.10**	2.33*	2.89**	2.45**
t-statistic	2.64	4.33	2.50	5.32	4.81
DEF DM IG	1.13**	0.34**	1.51**	0.80**	0.94**
t-statistic	6.82	5.53	12.90	10.30	18.59
Size DM IG	1.03**	0.25**	-0.05	-0.36**	0.22**
t-statistic	4.25	3.51	-0.33	-2.87	2.64
Low-risk DM IG	0.23	0.02	0.23	-0.17	0.08
t-statistic	0.96	0.22	1.61	-0.85	1.15
Value DM IG	-0.25	-0.08	0.02	-0.09	-0.10
t-statistic	-1.35	-1.03	0.16	-0.85	-1.46
Momentum DM IG	-0.46	-0.10	-0.38**	0.68**	-0.07
t-statistic	-1.75	-1.75	-2.74	7.23	-0.78
Adjusted R^2	0.69	0.82	0.87	0.89	0.92
B. High yield DM					
Alpha (%)	3.23	1.31**	2.54**	3.09**	2.54**
t-statistic	1.58	4.62	2.70	4.75	4.09
DEF DM HY	1.16**	0.36**	1.46**	0.82**	0.95**
t-statistic	6.43	7.03	23.09	11.12	20.92
Size DM HY	0.33**	0.01	0.01	-0.12**	0.06*
t-statistic	3.70	0.63	0.14	-2.84	2.41
Low-risk DM HY	0.05	0.09**	-0.22**	-0.19*	-0.07
t-statistic	0.25	3.27	-2.82	-2.42	-1.15
Value DM HY	-0.22	-0.04	0.36**	0.03	0.03
t-statistic	-1.39	-1.43	3.08	0.82	0.67
Momentum DM HY	-0.07	-0.04	-0.45**	0.25**	-0.08
t-statistic	-0.40	-1.83	-3.76	5.11	-1.71
Adjusted R^2	0.69	0.81	0.89	0.88	0.92

Notes: This table shows time-series regressions of the size, low-risk, value, momentum, and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest market value of debt; for value, we select the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. The table shows regression results of factor portfolio excess returns on the EM market excess return (DEF) and the factor portfolios for US investment grade (Panel A) or US high yield (Panel B) of Houweling and Van Zundert (2017). Statistical significance is determined through two-sided tests of whether the coefficient is different from zero (*t*-test with Newey–West standard errors). Alphas are annualized by multiplying the regression intercept by 12. * Significant at the 5% level. ** Significant at the 1% level.

Table 6: Fama-French-Carhart time-series regressions

	Size	Low Risk	Value	Momentum	Multi-Factor
A. DM equity factors					
Alpha (%)	4.15**	1.31**	1.89*	2.26**	2.40**
t-statistic	2.72	4.18	2.11	2.82	4.32
DEF	1.17**	0.33**	1.35**	0.94**	0.95**
t-statistic	14.47	8.42	34.10	11.02	31.89
SMB	0.06	0.03*	0.02	0.00	0.03
t-statistic	0.55	2.28	0.40	0.10	0.93
HML	-0.01	-0.04	0.12	-0.06	0.00
t-statistic	-0.06	-1.75	1.78	-1.45	0.16
RMW	0.22*	0.04	0.03	-0.18**	0.03
t-statistic	2.12	1.84	0.61	-2.97	1.07
CMA	-0.15	0.03	0.00	0.16**	0.01
t-statistic	-0.96	1.25	0.03	3.43	0.26
WML	0.04	-0.02*	-0.01	0.04	0.02
t-statistic	0.68	-2.12	-0.19	1.27	0.85
Adjusted R^2	0.67	0.80	0.87	0.86	0.92
B. EM equity factors					
Alpha (%)	5.60**	1.71**	1.71	1.42	2.61**
t-statistic	3.98	4.28	1.84	1.21	5.01
DEF	1.09**	0.34**	1.38**	0.92**	0.93**
t-statistic	16.23	8.52	22.76	10.28	29.40
SMB	0.14*	0.01	0.03	-0.03	0.03*
t-statistic	2.43	0.96	0.65	-1.14	2.28
HML	0.03	-0.03	0.05	0.04	0.02
t-statistic	0.40	-1.29	0.99	1.05	0.81
RMW	0.01	0.01	0.04	-0.07	-0.00
t-statistic	0.07	0.36	0.58	-1.12	-0.02
CMA	-0.17	0.02	0.13	0.08	0.02
t-statistic	-1.59	1.34	1.60	0.99	0.33
WML	-0.01	-0.02	-0.04	0.04	-0.01
t-statistic	-0.28	-1.48	-1.11	0.77	-0.50
Adjusted R^2	0.66	0.79	0.87	0.85	0.92

Notes: This table shows time-series regressions of the size, low-risk, value, momentum and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest market value of debt; for value, we select the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. The table shows the results of the Fama-French-Carhart regressions where the time-series of monthly excess returns of the EM credit factor portfolios are regressed on a constant, the EM credit market excess returns (DEF), and the equity factors size (SMB), value (HML), profitability (RMW), investments (CMA), and momentum (WML). Panel A uses developed market equity factors and Panel B emerging market equity factors. Statistical significance is determined through two-sided tests of whether the coefficient is different from zero (*t*-test with Newey–West standard errors). Alphas are annualized by multiplying the regression intercept by 12. * Significant at the 5% level. ** Significant at the 1% level.

Table 7: Performance statistics of top quintile factor portfolios in liquid subsets

		Mean (%)	Volatility (%)	Sharpe ratio	*t*-statistic	HZ-alpha (%)	*t*-statistic
Size	Base case	8.30	10.78	0.77**	2.72	3.46**	2.64
	Youngest half	7.79	15.18	0.51	1.56	2.76	1.88
	Largest half	7.10	16.71	0.42	0.43	1.73	0.75
	1 bond per issuer	10.61	11.95	0.89**	3.22	5.54**	2.88
Low Risk	Base case	2.40	2.82	0.85**	4.19	1.10**	4.33
	Youngest half	2.83	4.33	0.65*	2.20	1.00*	2.33
	Largest half	2.61	4.67	0.56	1.43	0.92	1.73
	1 bond per issuer	2.44	2.91	0.84**	3.96	1.15**	4.78
Value	Base case	6.30	11.15	0.57*	2.15	2.33*	2.50
	Youngest half	5.46	14.09	0.39	0.30	0.96	0.76
	Largest half	5.27	11.30	0.47	1.03	1.96*	2.28
	1 bond per issuer	7.52	11.79	0.64*	2.36	3.64**	2.86
Momentum	Base case	4.79	7.46	0.64**	2.79	2.89**	5.32
	Youngest half	4.53	9.79	0.46	0.82	2.56**	2.89
	Largest half	5.41	9.17	0.59*	2.01	3.07**	4.06
	1 bond per issuer	5.58	7.97	0.70**	3.11	3.62**	5.36
Multi-Factor	Base case	5.45	7.45	0.73**	5.04	2.45**	4.81
	Youngest half	5.15	9.74	0.53*	2.24	1.82**	3.17
	Largest half	5.10	9.35	0.55*	2.22	1.92**	3.12
	1 bond per issuer	6.54	7.86	0.83**	5.28	3.49**	4.64

Notes: This table shows performance statistics for the size, low-risk, value, momentum, and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period using all bonds ('base case'), only the youngest 50% of the bonds in each month ('youngest half'), only the largest 50% of the bonds in each month ('largest half'), or the most liquid bond per issuer ('1 bond per issuer'). The most liquid bond per issuer is determined in two steps: (1) Limit the set of bonds to bonds with an age of at most two years; if no such bonds are found, restrict to an age of at most four years; if still no bonds are found, select all bonds; (2) within the age-restricted set of bonds, select the bond with the largest amount outstanding. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest market value of debt; for value, we select the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. The mean and standard deviation of the monthly excess returns and Sharpe ratios are annualized. The HZ-alpha is the annualized alpha in the 5-factor regression using the EM credit market and the size, low risk, value, and momentum factor portfolios from US investment grade factor portfolios of Houweling and Van Zundert (2017). Statistical significance is determined through two-sided tests of whether (1) the Sharpe ratio is different from the Sharpe ratio of the corporate bond market (Jobson and Korkie, 1981), (2) the alpha is different from zero (*t*-test with Newey–West standard errors). Alphas are annualized by multiplying the regression intercept by 12. * Significant at the 5% level. ** Significant at the 1% level.

Table 8: Performance statistics of country-neutral top quintile factor portfolios

		Mean (%)	Volatility (%)	Sharpe ratio	*t*-statistic	HZ-alpha (%)	*t*-statistic
Size	Base case	8.30	10.78	0.77**	2.72	3.46**	2.64
	Country neutral	7.36	10.04	0.73**	2.65	3.12**	3.34
Low Risk	Base case	2.40	2.82	0.85**	4.19	1.10**	4.33
	Country neutral	2.96	3.65	0.81**	3.64	1.42**	3.07
Value	Base case	6.30	11.15	0.57*	2.15	2.33*	2.50
	Country neutral	4.63	9.36	0.49	1.95	1.13*	2.45
Momentum	Base case	4.79	7.46	0.64**	2.79	2.89**	5.32
	Country neutral	3.84	7.04	0.55*	2.24	1.70**	4.09
Multi-Factor	Base case	5.45	7.45	0.73**	5.04	2.45**	4.81
	Country neutral	4.70	7.08	0.66**	4.51	1.84**	4.97

Notes: This table shows performance statistics of the base case and country-neutral size, low-risk, value, momentum, and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. The country-neutral portfolios are formed by first selecting the 20% best bonds per country and then market value-weighting all selected bonds to form the final factor portfolio. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest market value of debt; for value, we select the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. The mean and standard deviation of the monthly excess returns and Sharpe ratios are annualized. The HZ-alpha is the annualized alpha in the 5-factor regression using the EM credit market and the size, low risk, value, and momentum factor portfolios from US investment grade factor portfolios of Houweling and Van Zundert (2017). Statistical significance is determined through two-sided tests of whether (1) the Sharpe ratio is different from the Sharpe ratio of the corporate bond market (Jobson and Korkie, 1981), (2) the alpha is different from zero (*t*-test with Newey–West standard errors). Alphas are annualized by multiplying the regression intercept by 12. * Significant at the 5% level. ** Significant at the 1% level.

Table 9: Performance statistics of top quintile factor portfolios controlled for sector, rating, IG/HY, amount outstanding, or maturity effects

		Mean (%)	Volatility (%)	Sharpe ratio	*t*-statistic	HZ-alpha (%)	*t*-statistic
Size	Base case	8.30	10.78	0.77**	2.72	3.46**	2.64
	Sector-neutral	7.02	8.25	0.85**	2.76	3.50**	2.69
	Rating-neutral	5.07	6.54	0.77*	2.39	2.18*	2.34
	IG/HY-neutral	6.84	6.45	1.06**	4.36	3.73**	4.47
	Maturity-neutral	7.51	10.34	0.73*	2.44	2.95*	2.23
Low Risk	Base case	2.40	2.82	0.85**	4.19	1.10**	4.33
	Sector-neutral	2.54	3.06	0.83**	4.27	1.10**	3.85
	Amount outstanding-neutral	2.28	3.27	0.70**	3.00	0.72*	2.33
Value	Base case	6.30	11.15	0.57*	2.15	2.33*	2.50
	Sector-neutral	5.62	10.15	0.55*	2.36	2.09**	2.61
	Rating-neutral	5.83	10.64	0.55*	2.08	2.10*	2.47
	IG/HY-neutral	6.31	10.60	0.60*	2.56	2.54**	2.91
	Amount outstanding-neutral	6.23	11.30	0.55	1.94	2.23*	2.29
	Maturity-neutral	6.07	10.91	0.56*	2.21	2.15*	2.55
Momentum	Base case	4.79	7.46	0.64**	2.79	2.89**	5.32
	Sector-neutral	4.41	7.11	0.62**	2.64	2.46**	5.04
	Rating-neutral	4.10	6.96	0.59**	2.71	2.13**	4.82
	IG/HY-neutral	4.41	6.89	0.64**	3.14	2.43**	4.97
	Amount outstanding-neutral	4.55	7.45	0.61*	2.52	2.55**	4.95
	Maturity-neutral	4.88	7.75	0.63**	3.09	2.64**	5.58
Multi-Factor	Base case	5.45	7.45	0.73**	5.04	2.45**	4.81
	Sector-neutral	4.90	6.56	0.75**	5.13	2.29**	4.98
	Rating-neutral	4.40	6.62	0.67**	4.70	1.80**	4.65
	IG/HY-neutral	4.99	6.76	0.74**	5.33	2.26**	4.70
	Amount outstanding-neutral	5.03	8.30	0.61*	2.48	1.86*	2.19
	Maturity-neutral	5.34	7.95	0.67**	4.56	2.18**	4.26

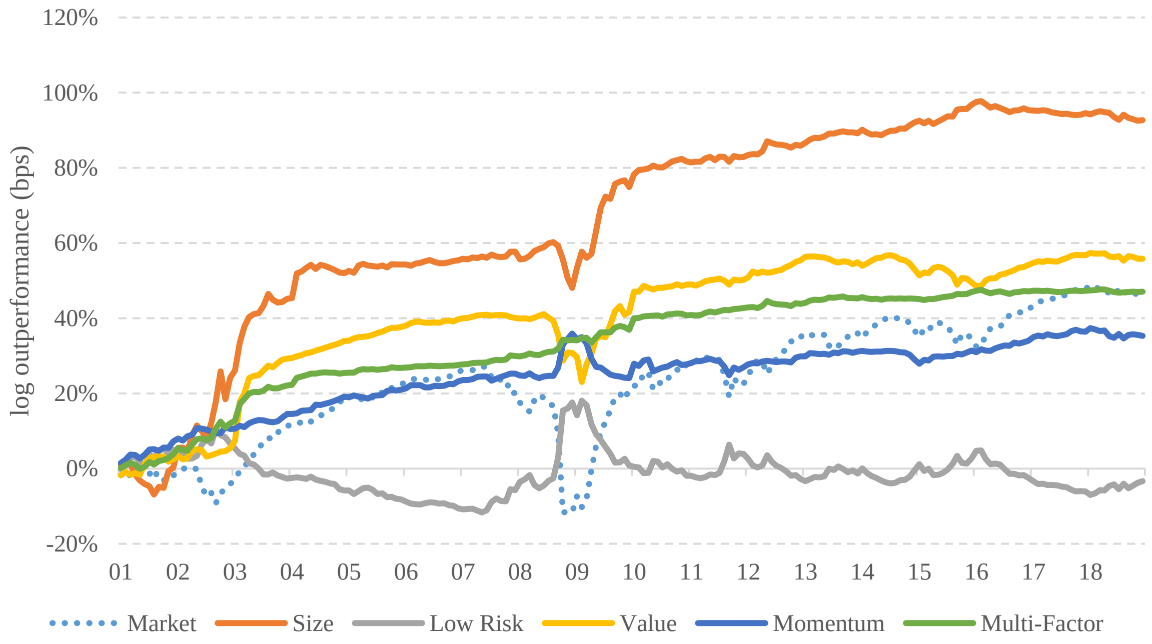
Notes: This table shows performance statistics of the base case and sector-neutral, rating-neutral, IG/HY-neutral, amount outstanding-neutral, and maturity-neutral size, low-risk, value, momentum, and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. The neutral portfolios are formed by first selecting the 20% best bonds per sector (Bloomberg Barclays class 3 classification), rating (AAA-A, BBB, BB, B, CCC-C), market segment (investment grade, high yield), amount outstanding (five equal-sized groups), maturity (five equal-sized groups) and then market value-weighting all selected bonds to form the final factor portfolio. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest market value of debt; for value, we select the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. The mean and standard deviation of the monthly excess returns and Sharpe ratios are annualized. The HZ-alpha is the annualized alpha in the 5-factor regression using the EM credit market and the size, low risk, value, and momentum factor portfolios from US investment grade factor portfolios of Houweling and Van Zundert (2017). Statistical significance is determined through two-sided tests of whether (1) the Sharpe ratio is different from the Sharpe ratio of the corporate bond market (Jobson and Korkie, 1981), (2) the alpha is different from zero (*t*-test with Newey–West standard errors). Alphas are annualized by multiplying the regression intercept by 12. * Significant at the 5% level. ** Significant at the 1% level.

Table 10: Performance statistics of equally-weighted portfolios and of 1-month holding period

	Mean (%)	Volatility (%)	Sharpe ratio	*t*-statistic	HZ-alpha (%)	*t*-statistic
A. Equally-weighted, 12 month holding period						
Size	10.99	11.68	0.94**	3.49	5.90**	3.45
Low-risk	2.34	2.90	0.81**	3.71	0.99**	3.57
Value	7.90	11.29	0.70**	3.24	3.86**	3.24
Momentum	5.49	7.18	0.76**	4.14	3.68**	6.08
Multi-factor	6.68	7.60	0.88**	5.58	3.61**	4.97
B. Market value-weighted, 1 month holding period						
Size	7.60	11.78	0.64	1.78	3.05*	2.16
Low-risk	2.14	3.13	0.68**	2.79	0.72*	2.36
Value	5.63	11.25	0.50	1.59	1.26	1.48
Momentum	3.20	9.67	0.33	-0.37	-0.13	-0.10
Multi-factor	4.64	8.23	0.56*	2.54	1.23*	2.23

Notes: This table shows performance statistics of the size, low-risk, value, momentum, and multi-factor portfolios for EM hard currency corporate bonds over the 2001-2018 sample period. Each month, (1) the low-risk, value, and momentum factor portfolios take equally-weighted long positions in the top 20% of the bonds and the size factor portfolio takes equally-weighted long positions in the 20% smallest issuers and weights bonds within an issuer according to their market values; positions are held for 12 months, leading to 12 overlapping portfolios (Panel A); or (2) a factor portfolio takes market value-weighted long positions in the top 20% of the bonds and holds them for 1 month (Panel B). For size, we select the issuers with the smallest market value of debt; for value, we select the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%. The mean and standard deviation of the monthly excess returns and Sharpe ratios are annualized. The HZ-alpha is the annualized alpha in the 5-factor regression using the EM credit market and the size, low risk, value, and momentum factor portfolios from US investment grade factor portfolios of Houweling and Van Zundert (2017). Statistical significance is determined through two-sided tests of whether (1) the Sharpe ratio is different from the Sharpe ratio of the corporate bond market (Jobson and Korkie, 1981), (2) the alpha is different from zero (*t*-test with Newey–West standard errors). Alphas are annualized by multiplying the regression intercept by 12. * Significant at the 5% level. ** Significant at the 1% level.

Figure 1: Cumulative performance of market index and cumulative outperformance of top quintile factor portfolios



Notes: This figure shows the cumulative excess return of the market index (dotted line) and the cumulative difference versus the market index of the excess return of the size, low-risk, value, momentum single-factor portfolios and the multi-factor portfolio for EM hard currency corporate bonds over the 2001-2018 sample period. Each month, a factor portfolio takes market value-weighted long positions in the top 20% of the bonds (for size: the bonds of the 20% smallest issuers) and holds them for 12 months, leading to 12 overlapping portfolios. For size, we select the issuers with the smallest market value of debt; for value, we select the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, we select the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, we select short-maturity bonds in investment grade. We use excess returns over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. If an issuer has more than 2% market value-weight in the index in a month, the market values of its bonds are proportionally scaled down to cap the issuer weight at 2%.