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KEY FINDINGS

- We examine factors in the cross-section of emerging market hard currency corporate bonds and find that the size, value, momentum, and low-risk factors predict future excess returns.
- Factor portfolios yield significant alphas in the Capital Asset Pricing Model, and a multi-factor portfolio that allocates equally to the four factors shows even stronger results, due to the low pairwise correlations among the individual factors.
- Alphas remain significant versus developed market credit factors, and the results hold within countries, sectors, ratings, maturities, and liquid subsamples.

ABSTRACT

We examine factors in a novel dataset on the cross-section of emerging market hard currency corporate bonds. We find that the size, low-risk, value, and momentum factors predict future excess returns. Single-factor and multi-factor portfolios obtain economically and statistically significant premiums. Further, alphas remain significant after controlling for exposures to developed market credit factors. The factor portfolios benefit from bottom-up allocations to countries, sectors, ratings, and maturity segments, as well as from bond selection within these segments. Higher risk-adjusted returns of factor portfolios also can be found within liquid subsamples of the market.

TOPICS

*Fixed income and structured finance, emerging markets, analysis of individual factors/ risk premia, portfolio construction**

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We examine factors in the cross-section of emerging market (EM) hard currency corporate bonds using a novel dataset of about 200,000 bond-month observations over the period 2001–2018. The EM credit market is an economically important asset class that grew from USD $50 billion in 2001 to $1.8 trillion in 2018, surpassing, for example, the developed market (DM) high yield corporate bond market.[1] However, the existing literature on EM credits is still limited and focuses mainly on topics like the interaction between corporate bonds and sovereign bonds (see e.g. Durbin and Ng 2005, Dittmar and Yuan 2008, and Zinna 2014) and the

[1] We calculated the total market value of all bonds in our dataset 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 USD $1.5 trillion at the end of 2018, as measured by the Bloomberg Barclays Global High Yield Corporate DM index.

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 whether factors price the cross-section in this asset class and to investigate the risk and return of factor portfolios. There is a large literature on factor investing in DM equities, although EM equities did receive some attention too: Cakici, Fabozzi, and Tan (2013) and Hanauer and Linhart (2015) documented momentum and value effects, and Blitz, Pang, and Van Vliet (2013) low-risk; Hanauer and Lauterbach (2019) examined a broad set of factors and documented similar results; Fang and Olteanu-Veerman (2020) focused on Chinese A shares and documented size, value, low-risk, and quality effects. Recent studies also documented factor premiums in corporate bonds (see e.g. Houweling and Van Zundert 2017; Israel, Palhares, and Richardson 2018; and Henke et al. 2020 for US investment grade and US high yield, and Bektić et al. 2019 for euro investment grade). However, this literature is restricted to DM credits. Finally, Brooks, Richardson, and Xu (2020) examined factor investing for EM sovereign and quasi-sovereign entities. This study is the first to focus on EM corporate bonds.

As Harvey (2017) pointed out, data mining and p-hacking are big concerns for empirical asset pricing research. To limit these concerns, we examine canonical factors examined before in DM credits. In particular, we use the factor definitions of Houweling and Van Zundert (2017) for four factors: size, low-risk, value, and momentum. One could argue that this study also provides new out-of-sample evidence on the existence of factor premiums.

For our analyses, we use a novel dataset of hard currency bonds issued by EM corporates and agencies that includes almost 200,000 bond-month observations over the period 2001–2018. By running cross-sectional regressions of bond excess returns on lagged factor scores, we show that factors significantly price the cross-section of EM credits. Further, we show that top-quintile factor portfolios generated significantly positive risk-adjusted returns, with Sharpe ratios ranging from 0.57 to 0.85, versus 0.37 for the market. We find economically meaningful and statistically significant CAPM-alphas. Due to the low pairwise correlations among the factors, a multi-factor portfolio that allocates equally to the four single-factor portfolios obtains an information ratio of 1.19, which is larger and has a larger *t*-value than the single-factor portfolios. Importantly, controlling for exposures to DM credit factors, we find that EM factor alphas seem unique to the EM market, even though most EM factors are significantly related to their DM counterparts.

We find that factor premiums exist within, but also across, countries: if we construct country-neutral factor portfolios, we find that Sharpe ratios and alphas generally decline, but remain statistically significant in all cases. In similar analyses, we show the existence of factor premiums within and across sectors, ratings, and maturity-segments. Finally, our results are also present in liquid subsets of our dataset.

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 classified as either 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]

[2] See https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

[3] See https://www.imf.org/en/Publications/WEO.

The sample consists of bonds denominated in US dollar, euro, and pound sterling issued by companies and government-related agencies from these countries. We use an issuer's country of risk, provided by Bloomberg Barclays, which is based on issuers' primary source of revenue, operations, or cash flows and their headquarters. 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.[5] Bonds of eligible issuers are included when they have at least one year until maturity and a minimum amount outstanding of 150 million.[6] We exclude bonds for which prices are based on matrix pricing.[7] 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. At every point in time, we apply the inclusion criteria to obtain a cross-section of bonds that comprise our sample. Hence, every month bonds can enter or leave our sample. Whenever a default occurs and a bond is downgraded to D, returns are based on the final traded price of the bond, reflecting the market's expected recovery rate.[8] The next month, we drop the defaulted bond from our sample.

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 at 2%: if the total market value 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.[9] We subsequently use these scaled-down market values in all calculations as if they were the true market values, with one exception: in the construction of the size factor, we use the original market values to sort issuers from small to large.

The dataset is summarized in Exhibit 1. Panel A contains the bond characteristics, Panel B the average composition, and Panel C the average returns and 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 eight years, and a size of USD $625 million. We observe in Panel B that the vast majority of bonds, 89%, are issued in US dollars; 10% are in euros; and only 1% in sterling. About two-thirds have an investment grade rating, mostly BBB, and one-third a high yield rating. 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 indexes, EM issues of all ratings are typically combined in one single universe. Therefore, in our main analyses we consider a combined investment grade and high yield universe. Brazil, Mexico, China, and Chile are the largest countries in the sample, with a combined weight of 50%. Agencies are the largest sector, with 32% of the sample, followed by banking (17%). 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

EXHIBIT 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
Duration-Times-Spread	1847	282	1420	4957
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	Communication	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 Exhibit 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.

return in 2009.[10] The number of bonds in the dataset increased from 132 in 2001

[10] We will show later that our results are robust to excluding the two most volatile years of our sample.

to 2,722 in 2018, with a full-sample average of 917 bonds per month.[11]

FACTOR DEFINITIONS

When defining the size, low-risk, value, and momentum factors, we follow Houweling and Van Zundert (2017). They used relatively straightforward factor definitions that only require bond characteristics, thereby abstaining from other data, such as firm fundamentals and equity market information.[12] We acknowledge that alternative factor definitions potentially can better explain the cross-section of credit returns, as shown by Heckel et al. (2020). Testing such alternative definitions is beyond the scope of this paper. Importantly, by defining the factors consistently with previous studies, we limit concerns of data mining and p-hacking.

Size. Banz (1981) was the first to document that smaller firms outperformed larger firms in the equity market. Evidence on a size premium in corporate bonds is limited. Hottinga, Van Leeuwen, and Van IJserloo (2001) found a positive but insignificant outperformance for bonds of smaller issuers. Houweling and Van Zundert (2017) documented that the size factor portfolio had a higher Sharpe ratio in US investment grade and US high yield. Bektić et al. (2019) showed that bonds of companies with a small equity market value generated significant outperformance for US credits, but not for euro credits. We define the size factor as the total market value of a bond's issuer, where the issuer is identified by its ticker.

Low Risk. Haugen and Heins (1972) and Black, Jensen, and Scholes (1972) were the first to show that risk-sorted portfolios have a flatter risk-return relationship than the CAPM would predict. Newer studies showed that the low-risk effect is also present in corporate bonds (see e.g. Ilmanen et al. 2004, Houweling and Van Zundert 2017, and Israel, Palhares, and Richardson 2018). We define the low-risk factor using both the credit 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.

Value. Basu (1977) first documented that cheap stocks, as identified by a low book-to-price ratio, outperformed expensive stocks. Several studies found evidence of the value effect in the credit market (see e.g. L'Hoir and Boulhabel 2010; Correia, Richardson, and Tuna 2012; Houweling and Van Zundert 2017; and Israel, Palhares, and Richardson 2018). All studies regressed credit spreads on risk measures and used the residuals to identify relative mispricings. The value premium then results from the tendency of credit spreads to revert to their fair spread, i.e., the estimated spread. We estimate fair spreads running the following cross-sectional regression in investment grade and high yield separately, on rating dummies, maturity, and spread change:

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

[11] 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 indexes of two main index providers, specifically the Bloomberg Barclays EM Hard Currency Corp & Quasi Sovereigns index and the JP Morgan CEMBI Broad index. Over the largest overlapping sample period (2004–2018), the average total returns are similar (6.3% vs. 6.0% vs. 6.2%), as are the volatilities (8.2% vs. 9.2% vs. 7.9%). The total return series also show high correlations with these indexes: 97.6% and 97.7%, respectively. For the Bloomberg Barclays index we also have access to excess returns. We find a similar average (2.6% vs. 2.6%) and volatility (7.9% vs. 8.7%) and a high correlation (97.3%) for these excess returns.

[12] Since we do not consider firm fundamentals, we do not distinguish between financial and non-financial firms.

For bond i in month t, $OAS_{i,t}$ is the observed option-adjusted credit spread; $I^r_{i,t}$ is 1 if the bond has rating r (ranging from AAA, AA+, AA, etc. to C),[13] and 0 otherwise; $M_{i,t}$ is the time to maturity; $\Delta OAS_{i,t}$ is the past three-month credit spread change, where we focus on idiosyncratic risk by subtracting the average within each rating category. The residual $\varepsilon_{i,t}$ is the difference between the observed spread and the estimated spread and can be interpreted as the mispricing. We define value as the percentage mispricing, that is, $\varepsilon_{i,t}/OAS_{i,t}$.

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 bonds found a momentum effect as well, with the strongest results in the high yield segment (see Jostova et al. 2013, Houweling and Van Zundert 2017, and Israel, Palhares, and Richardson (2018). We define momentum as the past six month cumulative bond excess return with a one month implementation lag.

RESULTS

Predictive Regressions

Before forming factor portfolios, we first test whether the factor scores have the ability to price the cross-section of next-month excess returns. In each month, we compute z-scores for each factor by subtracting the cross-sectional mean from the individual bonds' factor scores, after which we divide by the cross-sectional standard deviation and cap the z-scores at –3 and 3. High z-scores correspond to bonds from small issuers for the size factor, to bonds with large mispricings for the value factor, and to bonds with large past returns for the momentum factor.[14] For the low-risk factor, we combine rating and maturity z-scores, so that shorter-dated, higher-rated bonds have higher z-scores.[15] In each month, we run a separate cross-sectional regression of excess returns on lagged z-scores. We include the z-score of Duration Times Spread (DTS) (Ben Dor et al. 2007) and seven credit rating dummies to control for risk exposures.

Exhibit 2 shows the time-series averages of the coefficients with their corresponding t-statistics. It follows that higher z-scores of size, low risk, and value lead to significantly higher next-month excess returns at the 5% significance level.[16] For momentum, we find a positive coefficient as well, but it is only significant at the 10% level. Overall, these results imply that bonds with higher factor scores tend to earn higher future excess returns, after controlling for DTS and credit rating.[17] In our subsequent analyses, we test whether this predictability can be exploited by constructing factor portfolios.

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[13] 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.

[14] We take the logarithm of the total market value for each issuer, and the credit momentum factor.

[15] Specifically, we first transform credit ratings to a numerical scale such that a high numerical value corresponds to a high credit rating. We then take the sum of the z-score of this numerical rating and the z-score of the logarithm of the time to maturity.

[16] In unreported results, we regress next-month excess returns on the DTS z-score, an investment-grade dummy, and the z-score of the logarithm of time to maturity, thereby splitting low risk into its rating and maturity components. We find that after controlling for DTS and maturity, investment grade bonds earn higher excess returns than high yield bonds, although this difference is statistically insignificant. The z-score of log maturity does obtain a significant coefficient, indicating that after controlling for DTS and the investment-grade dummy, bonds with shorter maturities earn significantly higher excess returns.

[17] The results are qualitatively similar when we omit the rating dummies. Factor coefficients remain positive and are significant at the 5% and 10% level.

EXHIBIT 2

Predictive Regressions of Excess Returns on Factor z-scores

	Size	Low Risk	Value	Momentum
Constant	0.0029	0.0012	0.0019	0.0028
***t*-Statistic**	1.40	0.56	0.96	1.31
DTS Coefficient	0.0037**	0.0051**	0.0032*	0.0048**
***t*-Statistic**	2.61	2.88	2.37	2.71
Factor Coefficient	0.0006*	0.0036*	0.0019*	0.0019
***t*-Statistic**	2.52	2.22	2.50	1.72
Rating Dummies	Yes	Yes	Yes	Yes
Mean Observations	917	917	856	841
Mean Adjusted R^2	0.20	0.21	0.21	0.23

NOTES: This exhibit contains the results of regressing monthly excess returns on lagged z-scores of size, low risk, value, and momentum. We take the logarithm of size and momentum. We compute z-scores by subtracting the cross-sectional mean from the individual bonds' factor scores, after which we divide by the cross-sectional standard deviation and cap the z-scores at –3 and 3. For low risk, we first transform credit ratings to a numerical scale, such that a high numerical value corresponds to a high credit rating. We then take the sum of the z-score of this numerical rating and the z-score of the logarithm of the time to maturity. For size and the logarithm of maturity, we flipped the sign of the z-scores. This way, bonds from small issuers have a high z-score on size, short investment-grade bonds have a high z-score on low risk, bonds with a high relative mispricing have a high z-score on value, and bonds with high past cumulative excess returns have a high z-score on momentum. We control for market exposure by including the z-score of duration-times-spread (DTS) as an additional independent variable. Moreover, we control for rating by adding seven rating dummies for bonds with ratings AA, A, BBB, BB, B, CCC, and bonds rated < CCC, where we require at least 10 observations per dummy. The dependent variable is the excess return over duration-matched US Treasuries, German Bunds, and UK Gilts for US dollar, euro, and sterling denominated bonds, respectively. We run this regression for each month separately and report the time-series averages of the coefficient estimates with their corresponding *t*-statistics based on Newey-West (1987) standard errors. Statistical significance is determined through two-sided tests of whether the regression coefficients are different from zero. * Significant at the 5% level.
** Significant at the 1% level.

Long-Short Portfolios

We construct long-short portfolios per factor by sorting bonds on that factor and taking long (short) positions in the top (bottom) 20% of bonds. For size, the long (short) portfolio contains the bonds of the 20% smallest (largest) issuers. For low risk, the long portfolio consists of the 20% shortest-dated investment grade bonds, and the short portfolio contains the 20% longest-dated high yield bonds. The value long (short) portfolio contains the 20% bonds with the largest (smallest) mispricing. Finally, the top (bottom) momentum portfolio contains the 20% bonds with the highest (lowest) past return. We calculate market value (instead of equally) weighted returns to limit the exposure to smaller, less liquid bonds. We hold bonds for 12 months using the overlapping portfolios methodology of Jegadeesh and Titman (1993).

We show CAPM-statistics of the long-short factor portfolios over the 2001–2018 sample period; see Panel A of Exhibit 3. We estimate the CAPM-alphas and betas of each factor portfolio 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; their CAPM-betas are positive, implying that the bonds in the top portfolio are riskier than those 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.[18]

[18] In unreported results, we create long-short tercile factor portfolios within the IG-universe to ensure that alphas are not driven by exposures toward riskier HY bonds. Despite the smaller cross-section and partitioning it in three instead of five groups, all factors obtain positive alphas. Alphas are statistically

EXHIBIT 3

Performance Statistics of Long-Short Quintile Factor Portfolios

	Size	Low Risk	Value	Momentum
A. CAPM-statistics				
Alpha (%)	5.30**	1.24	2.67*	1.74
t-Statistic	3.05	1.22	2.13	0.84
DEF	0.14*	–1.50**	0.59**	–0.63**
t-Statistic	2.17	–22.15	9.40	–4.32
Adjusted R^2	0.02	0.80	0.42	0.30
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 exhibit shows performance statistics of the size, low-risk, value, and momentum 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.

Panel B contains pairwise correlations between the CAPM-residuals of the factors. We find that these correlations are 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 among the individual factors.

Long-Only Portfolios

From here onwards, we focus on long-only portfolios. Many corporate bonds cannot be shorted, and even if this is possible, it can be costly, especially for EM credits. Therefore, long-short portfolios may not paint a realistic picture. Exhibit 4 shows risk and return and CAPM-statistics of long-only, top-quintile factor portfolios and of the value-weighted market index.

We observe in Panel A that all factor portfolios generated significantly higher Sharpe ratios than the market. Size, value, and momentum realized this due to a higher return, while low-risk mostly benefited from its lower volatility. In Panel B we see that the outperformance of the low-risk factor portfolio is not significantly different from zero, so that it 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. They are also economically meaningful, as these portfolios would have made between 1.95% and 5.46% additional annual return versus the 2.84% return of a passive investment in the market index.

The last column of Exhibit 4 contains the risk and return of a multi-factor portfolio that invests 25% in each single-factor portfolio. We opt for the mixing of four sub-portfolios, rather than constructing a multi-factor portfolio based on the integration of the four factors into a multi-factor score. As pointed out by Chow, Li, and Shim (2018), the mixing approach is more transparent and allows for easier interpretation of results. While the integration approach tends to offer higher in-sample performance, we use the conservative mixing approach which provides more diversification and requires less turnover and implementation costs. The Sharpe ratio of the 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 any of the individual factors and its information ratio of 1.19 is the highest. This is a reflection of the low pairwise correlations between the factors.

Panel C shows the CAPM-alphas and betas. Consistent with the long-short results of Exhibit 3, size and value have more systematic risk than the market with a beta

significant at the 5% level for size and low-risk, and at the 10% level for value.

EXHIBIT 4

Performance Statistics of Top Quintile Factor Portfolios

	Market	Size	Low Risk	Value	Momentum	Multi-Factor
A. Return Statistics						
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						
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						
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
D. Characteristics						
Time to Maturity (years)	7.9	4.9	2.6	8.0	8.4	6.0
Credit Spread (bps)	355	675	214	503	432	473
Spread Duration (years)	5.2	3.5	2.3	5.0	5.0	4.0
Duration-Times-Spread	1797	2275	522	2439	2083	1830
Average Rating	BBB/BBB–	BB+/BB	A–/BBB+	BBB/BBB–	BB+/BB	BBB–/BB+
E. Turnover and Break-Even Transaction Costs						
Turnover 1-Sided (%)		108	62	92	106	83
Break-Even Transaction Costs (%)		4.65	2.33	2.65	2.10	3.37

NOTES: This exhibit 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). Panel D shows the time-series average of the dollar-weighted characteristics. Panel E shows the average annualized one-sided turnover of the combination of the 12 overlapping portfolios; the break-even transaction costs are the cost level that would reduce its net CAPM-alpha to 0. 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.

above 1, while low-risk and momentum have betas below 1. The CAPM-alphas are all statistically significant with *t*-values ranging from 2.49 to 4.76. The CAPM-alpha of the multi-factor portfolio has the highest *t*-statistic: 4.91.[19]

[19] Similar as for the long-short portfolios, in unreported results we restrict our bond universe to IG bonds and repeat the analysis from Exhibit 4. With the exception of momentum, all factor portfolios

Panel D shows portfolio characteristics. The size factor has a lower time to maturity and spread duration than the market, but a substantially higher credit spread on average. The higher credit spread may reflect the riskiness of the issuer, as the average rating of the size factor portfolio is indeed lower than the market, but it can also be a sign of a size or illiquidity premium. Exhibit 2 provided empirical support for the size factor being distinct from rating and DTS. The low risk factor selects safer bonds with shorter remaining maturities by construction. The value factor selects bonds with similar maturities, spread durations, and ratings as the market. These results provide supporting evidence of the effectiveness of the value regression. The average credit spread is slightly higher, since it selects bonds with a higher credit spread than justified by their rating, maturity, and past three-month spread change. In contrast to what one would expect based on the ex-post credit volatility in Panel A, the momentum factor tends to select bonds that are deemed riskier when evaluated on credit spread or rating. These results support the finding from Gebhardt, Hvidkjaer, and Swaminathan (2005) that positive past returns coincide with lower future risks, which are not yet fully reflected in the current credit spread and rating.

Note that all results above are gross of transaction costs. We mainly focused on the question of whether factors are able to predict returns instead of testing a profitable trading strategy. Still, it is interesting to evaluate the factor portfolios' turnover and compare the magnitude of the CAPM-alphas with transaction costs. First, Panel E in Exhibit 4 shows the average annualized one-sided turnover. Low-risk stands out as the lowest turnover factor, followed by value and momentum. The size factor shows to be the highest turnover factor.[20] Next, 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. Panel E of Exhibit 4 shows that these break-even costs vary between 2.1% and 4.7%. To offer a level of comparison, Dekker and De Jong (2021) documented average effective bid-ask spreads of 51 bps for a 2005–2017 sample of dollar-denominated EM corporate bonds covered by the TRACE database. This number rose to 1.1% during the financial crisis. Mizrach (2015) found 30 bps on the 2003–2015 TRACE database across all ratings of DM and EM issuers. So, the break-even transaction of over 200 bps of the EM credit factor portfolios seems sufficiently high to expect positive after-cost CAPM-alphas.

Exhibit 5 plots the cumulative outperformance of each factor versus the market. Clearly, in crisis periods and their subsequent recovery, for example, 2001–2003, 2008–2009, and 2014–2015, factor portfolios deviated more strongly from the market, as demonstrated by a larger increase or decrease of the cumulative outperformance.[21]

Spanning Regressions

To test whether the individual factors are distinct phenomena, we run spanning regressions of each factor on the market portfolio and all other factors. The results in

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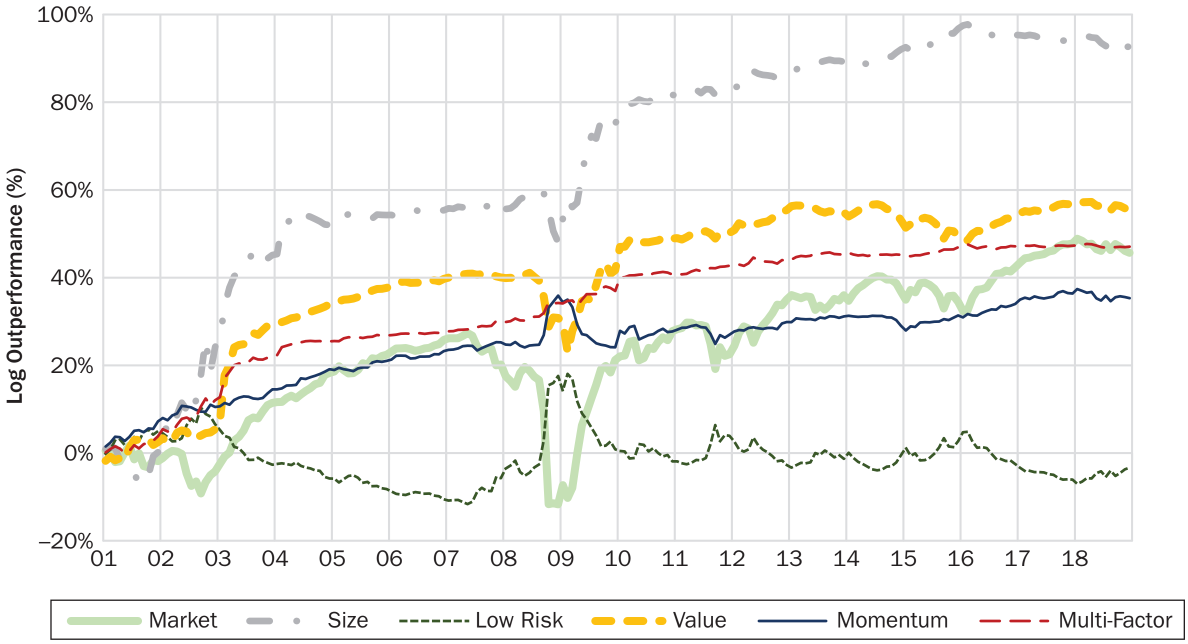
have Sharpe ratios that are significantly higher than the market and significantly positive CAPM alphas. Hence, the results in Exhibit 4 are unlikely to be driven by exposures toward riskier HY bonds.

[20] This is an artifact of the construction of the size quintile portfolios to contain the same number of issuers: since smaller issuers have less bonds outstanding than larger issuers, the top quintile portfolio contains less bonds, thereby inflating the turnover figure. In unreported results, we form size quintile portfolios to contain the same number of bonds instead of issuers; in this alternative size factor portfolio, the turnover declines to 84%, while the CAPM-alpha remains significant at the 1% level.

[21] Our results are not driven by the 2008–2009 financial crisis. If 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 market.

EXHIBIT 5

Cumulative Performance of Market Index and Cumulative Outperformance of Top Quintile Factor Portfolios



NOTES: This exhibit shows the cumulative excess return of the market index 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%.

Exhibit 6 show that size, low-risk, and momentum cannot be explained by the other factors, as the alphas remain statistically significant. Although still positive, the alpha of the value factor loses its significance when we control for size, low risk, and momentum. Even though the loadings on these factors are not statistically significant, they 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.

EM Credit Factors Versus DM Credit Factors

Next, we investigate the extent to which EM credit factors are related to DM credit factors. For this analysis we extend the CAPM-regression in Panel C of Exhibit 4 with the four factor portfolios of Houweling and Van Zundert (2017); we will henceforth

EXHIBIT 6
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 exhibit 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, we proportionally scale down the market values of its bonds 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.

refer to these five-factor alphas as the HZ-alphas.[22] Exhibit 7 contains the results, where Panel A includes the HZ investment grade factors and Panel B the high yield factors.

All EM factors have a positive beta to the same factor in DM. Most of these betas are statistically significant, with the exception of low-risk and value in investment grade. The HZ-alphas of the size factor drop most (by more than 1%) compared to its CAPM-alpha. And if we control for the high yield DM factors, the alpha of the size factor even becomes insignificant. This suggests that there is a common component to the size factor in EM and DM credits. 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.

Liquidity Effects

Liquidity in corporate bonds tends to be lower than in equities. Therefore, we examine whether EM credit factor portfolios still deliver statistically significant risk-adjusted returns in liquid subsamples of our dataset. We construct three liquid subsamples using bond age and/or bond size as liquidity proxies. In the first, we select the youngest 50% of the bonds in each month and in the second subsample the largest 50%. 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 sampling 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.

Exhibit 8 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 subsamples, which was expected due to the smaller sample. The size factor is most affected, as its HZ-alpha is no longer significant in both the youngest and largest subsamples. For low-risk and value, only one subsample gives no significant HZ-alpha.[23] The momentum portfolio and the multi-factor portfolio retain their significance in all three subsamples. For all factors, we find significant alphas

[22] We download the monthly returns of the Houweling and Van Zundert (2017) factor portfolios, extended until December 2018, from Robeco's website: https://www.robeco.com/data.

[23] In this and subsequent analyses, we report the alphas versus the investment grade factors of Houweling and Van Zundert (2017), because Exhibit 1 shows that the majority of EM credits has an investment grade rating.

EXHIBIT 7

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 exhibit 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, we proportionally scale down the market values of its bonds 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.

EXHIBIT 8

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 exhibit 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, we proportionally scaled down the market values of its bonds 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 five-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). We determined statistical significance 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.

and Sharpe ratios in the third method, which preserves the cross-sectional breadth. These results indicate that factor premiums 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.[24]

Allocation Effects

Emerging market economies are well-known for their boom-bust cycles. One may wonder whether factors 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. More generally, factor portfolios may result in bottom-up allocations to sectors, ratings, etc. To explore these allocation effects, we construct various “neutral” portfolios, in which we control for allocations to countries, sectors, ratings, investment grade vs. high yield (labelled IG/HY), bond size quintiles (amount outstanding), or maturity quintiles. A neutral portfolio is constructed to have the same proportion of bonds in each group as the market:

1. Within each group (e.g. country), rank bonds on their factor score.
2. Select the 20% highest-ranked bonds in each group.[25]
3. Construct the market value-weighted portfolio of all selected bonds.

For the low-risk factor, we do not create neutral portfolios on ratings, IG/HY, or maturities, 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.

Exhibit 9 shows the results of these neutral portfolios, and also the base case results without controlling for allocation effects. Virtually all *t*-values for the Sharpe ratios and alphas of the single-factor portfolios, and all *t*-values for the multi-factor portfolio, suggest statistical significance. Even though the factors sometimes benefit from bottom-up preferences to particular groups, the factors generate most of their ability to predict bond returns from selection within groups (countries, sectors, etc.).

CONCLUSIONS

In this article, we test factors in the cross-section of EM hard currency credits. To limit data mining and p-hacking concerns, we use size, low-risk, value, and momentum factor definitions as previously documented for DM credits. By running cross-sectional regressions, we find that factors are significantly priced in the cross-section. Further, factor portfolios have higher Sharpe ratios than passively investing in the

[24] We performed two additional analyses on liquidity. In the first, we apply a one-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. Except for the size factor, the Sharpe ratios, HZ-alphas, and their statistical significance are robust to this delayed implementation. For the size factor, we observe worse performance statistics, for example, the HZ-alpha drops from 3.46% to 2.82% and its t-value from 2.64 to 2.47. In the second analysis, following Goldstein, Jiang, and Ng (2017), we use the VIX index and the three-month TED spread as market-wide liquidity proxies and use these to split our sample in two equally sized subsamples. We create subsamples based on VIX, where the first (second) subsample contains the months with an above (below) median VIX and market liquidity is expected to be low (high). Likewise, we create subsamples based on the TED spread. We find that in both the high-liquidity and low-liquidity subsamples, the Sharpe ratios of the factor portfolios are higher than the market and that all HZ-alphas remain positive. For the multi-factor portfolio, HZ-alphas are significant in all four subsamples.

EXHIBIT 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
	Country-Neutral	7.36	10.04	0.73**	2.65	3.12**	3.34
	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
	Country-Neutral	2.96	3.65	0.81**	3.64	1.42**	3.07
	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
	Country-Neutral	4.63	9.36	0.49	1.95	1.13*	2.45
	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
	Country-Neutral	3.84	7.04	0.55*	2.24	1.70**	4.09
	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
	Country-Neutral	4.70	7.08	0.66**	4.51	1.84**	4.97
	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 exhibit 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 five-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.

market value-weighted index. All CAPM-alphas are positive and statistically significant and remain significant after controlling for DM credit 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 show that factors that are well-known in equities, and increasingly known in DM credits, are also priced and yield higher risk-adjusted returns in EM credits. To the best of our knowledge, we are the first to examine factors in EM credits, thereby filling a gap in the empirical asset pricing literature. By successfully out-of-sample testing DM credit factor definitions on a novel dataset of EM credits, our study also strengthens the confidence in results previously found 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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REFERENCES

Banz, R. W. 1981. "The Relationship between Return and Market Value of Common Stocks." *Journal of Financial Economics* 9 (1): 3–18.

Basu, S. 1977. "Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis." *The Journal of Finance* 32 (3): 663–682.

Bektić, D., J.-S. Wenzler, M. Wegener, D. Schiereck, and T. Spielmann. 2019. "Extending Fama–French Factors to Corporate Bond Markets." *The Journal of Portfolio Management* 45 (3): 141–158.

Ben Dor, A., L. Dynkin, J. Hyman, P. Houweling, E. van Leeuwen, and O. Penninga. 2007. "DTS (Duration Times Spread)." *The Journal of Portfolio Management* 33 (2): 77–100.

Black, F., M. Jensen, and M. Scholes. 1972. "The Capital Asset Pricing Model: Some Empirical Tests." In *Studies in the Theory of Capital Markets*, edited by M. C. Jensen, 79–121. New York: Praeger.

Blitz, D., J. Pang, and P. Van Vliet. 2013. "The Volatility Effect in Emerging Markets." *Emerging Markets Review* 16: 31–45.

Brooks, J., S. Richardson, and Z. Xu. 2020. ("Systematic) Investing in Emerging Market Debt." *The Journal of Fixed Income* 30 (2): 44–61.

Cakici, N., F. Fabozzi, and S. Tan. 2013. "Size, Value, and Momentum in Emerging Market Stock Returns." *Emerging Markets Review* 16: 46–65.

Cavallo, E., and P. Valenzuela. 2010. "The Determinants of Corporate Risk in Emerging Markets: An Option-Adjusted Spread Analysis." *International Journal of Finance & Economics* 15 (1): 59–74.

Chow, T.-M., F. Li, and Y. Shim. 2018. "Smart Beta Multifactor Construction Methodology: Mixing Versus Integrating." *The Journal of Index Investing* 8 (4): 47–60.

Correia, M., S. Richardson, and I. Tuna. 2012. "Value Investing in Credit Markets." *Review of Accounting Studies* 17 (3): 572–609.

Dekker, L., and F. De Jong. 2021. "Liquidity Pricing in Emerging Market Corporate Bonds." Retrieved from SSRN: https://ssrn.com/abstract=3493243.

Dittmar, R., and K. Yuan. 2008. "Do Sovereign Bonds Benefit Corporate Bonds in Emerging Markets?" *The Review of Financial Studies* 21 (5): 1983–2014.

Durbin, E., and D. Ng. 2005. "The Sovereign Ceiling and Emerging Market Corporate Bond Spreads." *Journal of International Money and Finance* 24 (4): 631–649.

Fang, D., and D. Olteanu-Veerman. 2020. "The Case for Factor Investing in China A Shares." *The Journal of Index Investing* 11 (2): 76–91.

Garay, U., M. González, and J. Rosso. 2019. "Country and Industry Effects in Corporate Bond Spreads in Emerging Markets." *Journal of Business Research* 102: 191–200.

Gebhardt, W., S. Hvidkjaer, and B. Swaminathan. 2005. "Stock and Bond Market Interaction: Does Momentum Spill Over?" *Journal of Financial Economics* 75 (3): 651–690.

Goldstein, I., H. Jiang, and D. T. Ng. 2017. "Investor Flows and Fragility in Corporate Bond Funds." *Journal of Financial Economics* 126 (3): 592–613.

Grinold, R., and R. Kahn. 1995. *Active Portfolio Management: Quantitative Theory and Applications.* Chicago: Irwin.

Hanauer, M. X., and J. G. Lauterbach. 2019. "The Cross-section of Emerging Market Stock Returns." *Emerging Markets Review* 38: 265–286.

Hanauer, M. X., and M. Linhart. 2015. "Size, Value, and Momentum in Emerging Market Stock Returns: Integrated or Segmented Pricing?" *Asia-Pacific Journal of Financial* Studies 44 (2): 175–214.

Harvey, C. 2017. "Presidential Address: The Scientific Outlook in Financial Economics." *The Journal of Finance* 72 (4): 1399–1440.

Haugen, R., and A. Heins. 1972. "On the Evidence Supporting the Existence of Risk Premiums in the Capital Market." Available at SSRN: https://ssrn.com/abstract=1783797 or http://dx.doi.org/10.2139/ssrn.1783797.

Heckel, T., Z. Amghar, I. Haik, O. Laplénie, and R. Leote de Carvalho. 2020. "Factor Investing in Corporate Bond Markets: Enhancing Efficacy through Diversification and Purification!" *The Journal of Fixed Income* 29 (3): 6–21.

Henke, H., H. Kaufmann, P. Messow, and J. Fang-Klingler. 2020. "Factor Investing in Credit." *The Journal of Index Investing* 11 (1): 33–51.

Hottinga, J., E. Van Leeuwen, and J. Van IJserloo. 2001. "Successful Factors to Select Outperforming Corporate Bonds." *The Journal of Portfolio Management* 28 (1): 88–101.

Houweling, P., and J. Van Zundert. 2017. "Factor Investing in the Corporate Bond Market." *Financial Analysts Journal* 73 (2): 100–115.

Ilmanen, A., R. Byrne, H. Gunasekera, and R. Minikin. 2004. "Which Risks Have Been Best Rewarded?" *The Journal of Portfolio Management* 30 (2): 53–57.

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

Jegadeesh, N., and S. Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *The Journal of Finance* 48 (1): 65–91.

Jobson, J., and B. M. Korkie. 1981. "Performance Hypothesis Testing with the Sharpe and Treynor Measure." *The Journal of Finance* 36 (4): 889–908.

Jostova, G., S. Nikolova, A. Philipov, and C. Stahel. 2013. "Momentum in Corporate Bond Returns." *The Review of Financial Studies* 26 (7): 1649–1693.

L'Hoir, M., and M. Boulhabel. 2010. "A Bond-picking Model for Corporate Bond Allocation." *The Journal of Portfolio Management* 36 (3): 131–139.

Mizrach, B. 2015. *Analysis of Corporate Bond Liquidity.* Retrieved from FINRA Office of the Chief Economist: www.finra.org/sites/default/files/OCE_researchnote_liquidity_2015_12.pdf.

Newey, W. K., and K. D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55 (3): 703–708.

Zinna, G. 2014. "Identifying Risks in Emerging Market Sovereign and Corporate Bond Spreads." *Emerging Markets Review* 20: 1–22.