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# The cross-section of emerging market stock returns☆

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ABSTRACT

Using monthly stock returns from 28 emerging market countries and a total sample period of 21 years, we investigate the predictive power of a broad set of factors. We document that the factor definitions of the Fama and French (2015) five-factor model are less robust compared to alternative factor definitions. In contrast, the anomalous returns associated with cash flow-to-price, gross profitability, composite equity issuance, and momentum are pervasive as they show up in equal- and value-weighted portfolio sorts as well as in cross-sectional regressions. In contrast to financial theory and in line with previous findings, we do not find a positive cross-sectional relationship between risk and return. Finally, return forecasts derived from the alternative factor definitions are superior in their out-of-sample predictive ability to the ones derived from the five-factor model.

## 1. Introduction

Patterns in average stock returns are called anomalies because they cannot be explained by factor models such as the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966). Researchers have identified many such patterns for the U.S. stock market. For example, Banz (1981) finds that small stocks (measured by market capitalization) have abnormally high average returns. Similarly, Basu (1977), Rosenberg et al. (1985), and Chan et al. (1991) document that stocks with low prices relative to fundamentals like book value or earnings (value stocks) have higher returns than stocks with high prices relative to these fundamentals (growth stocks). Others show that a stock's average return is also related to the stock's past returns, the firm's accruals, net stock issues, investments, or profitability.[1] Harvey et al. (2016) present an extensive list of 316 different published anomaly variables as potential asset pricing factors, although they admit that some of these factors are highly correlated (i.e., do not contain unique information). Researchers have attempted to shrink this list of anomalies with factor models that only include a small number of characteristic-based factors (e.g., Fama and French, 2015, with the five-factor model). Fama and French (2015) motivate the existence of the anomaly categories valuation, profitability, and investment with a restated version of the dividend discount model, i.e.,

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[1] See e.g., Jegadeesh and Titman (1993), Sloan (1996), Cooper, Gulen, and Schill (2008), Pontiff and Woodgate (2008), and Novy-Marx (2013).

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$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}}{B_t} \tag{1}$$

Eq. (1) says that a lower valuation, a higher expected profitability, or lower expected investments imply, ceteris paribus, higher expected returns. The exact definitions, especially those for expected profitability and investment, remain unclear, and Fama and French (2017) admit that future research will likely refine the definition of these factors.

Although there is some consensus in the research community on those categories,[2] it remains a question as to which variables are the best proxies with the highest predictive power, and whether they differ across markets. For instance, Barillas and Shanken (2018) find that models that include value and profitability factors that are updated monthly (along with a momentum factor) dominate the five-factor model of Fama and French (2015) or the q-factor model of Hou et al. (2015).

The vast majority of empirical asset pricing studies analyze anomalies on the U.S. market. Karolyi (2016, p. 2049) speaks of a U.S. "home bias" in the field of empirical finance as most of those studies cover U.S. markets only, and of a "foreign bias" as some non-U.S. countries are covered more often than others. These non-U.S. countries are mainly developed markets.[3] However, under the hypothesis that developed markets are integrated, the same risk factors should apply to these markets. Therefore, similar results for similar periods are not surprising. Furthermore, criticism regarding data snooping can never be excluded even if t-statistic cutoff points are increased from 2.0 to 3.0, as Harvey et al. (2016) propose.

Emerging market samples, on the other hand, provide an attractive alternative for out-of-sample tests in terms of independent and new samples. Existing studies on emerging markets, such as van der Hart et al. (2003), van der Hart et al. (2005), Cakici et al. (2013), and Hanauer and Linhart (2015) mainly focus on value and momentum or on single emerging countries (e.g., Waszczuk, 2013, examines the Polish market).[4] The limitation of these papers is that they do not cover the more recently discovered anomalies associated with profitability and investments. Furthermore, there is an ongoing discussion as to which variables are the best proxies within the value, profitability, and investment categories (see e.g., Ball et al., 2015). This paper aims to fill this gap by investigating an extensive list of firm-level variables with regard to their return predicting ability in emerging markets. The papers closest to ours in terms of methodology are Fama and French (2008), Hou et al. (2011), and Lewellen (2015). Fama and French (2008) show that some anomalies are dominated by others in a U.S. sample or do not exist across all size groups, whereas Hou et al. (2011) dissect anomaly returns in a global setting. We focus explicitly on emerging markets and analyze a broader set of anomaly variables than both papers. We also give a more generalized view on emerging stock market behavior than Zaremba and Czapkiewicz (2017), for example, who analyze European emerging markets only and examine which of the established factor models best explains the returns of 100 anomalies. They document that the Fama and French (2015) five-factor model outperforms earlier models such as the CAPM, the Fama and French (1993) three-factor, and the Carhart (1997) four-factor model. However, the five-factor model alphas of 27 (8) out of the 32 (20) standalone significant equal-weighted (value-weighted) anomaly returns remain significant. Furthermore, they do not investigate if the significant anomalies (mainly from the groups *value* vs. *growth*, *profitability*, *investment*, and *issuance*) also have the potential to subsume the variables of the five-factor model.

Using monthly stock returns for a total of 28 emerging market countries and a sample period of 21 years, we investigate the predictive power for an extensive set of factors, not only covering the categories valuation, profitability, and investment but also controlling for risk, size, and momentum. We can confirm the results of Fama and French (2015) for the U.S. and Fama and French (2017) for developed markets and find that the categories valuation, profitability, and investment are also priced in emerging markets. However, we document that within the different categories, the factor definitions of the new Fama and French (2015) five-factor model are less robust compared to alternative factor definitions. In contrast, the anomalous returns associated with cash flow-to-price, gross profitability, composite equity issuance, and also momentum are pervasive as they show up in both equal- and value-weighted sorts as well as in cross-sectional regressions. However, in contrast to the prediction of the CAPM and in line with Blitz and van Vliet (2007), we cannot find a positive relationship between risk and return.

Following the methodology of Haugen and Baker (1996) and Lewellen (2015), we further derive out-of-sample return forecasts from current firm characteristics and slopes from past cross-sectional regressions. The return forecasts based on the alternative factor definitions are superior to the ones derived from the five-factor model in both sorts and cross-sectional regressions. Finally, the expected return forecasts can also be employed in mean-variance optimized long-only portfolios. Accounting for transaction costs and limiting investment to big stocks, we demonstrate that the alternative factor definitions lead to a portfolio that dominates value- and equal-weighted portfolios as well as the minimum volatility and an optimized portfolio based on return forecasts derived from the five-factor model.

Thus, our contribution to the existing literature is threefold: First, we determine the magnitude of anomaly variables on the basis of a broad sample of emerging market stocks that were recently discovered in the U.S. and haven't yet been documented for emerging markets. Second, we analyze the incremental power for these anomaly variables (i.e., which variables are priced after controlling for other variables) in Fama and MacBeth (1973) cross-sectional regressions and mean-variance spanning tests. Finally, we investigate the real-time predictive power of return forecasts based on these cross-sectional regressions as shown in Haugen and Baker (1996) and Lewellen (2015) for the U.S. market.

[2] For example, also the q-factor model of Hou, Xue, and Zhang (2015) contains an investment and a profitability factor but these factors are slightly different defined and constructed.

[3] See for example, Griffin (2002), Rouwenhorst (1998), Fama and French (2012), or Fama and French (2017).

[4] de Groot et al. (2012) also document value and momentum effects, as well as a local size effect for frontier emerging markets.

While our results provide strong evidence that the factor definitions of the Fama and French (2015) five-factor model may not be optimal for emerging markets, our results are not only specific for emerging markets. Already, Fama and French (2008) state that asset growth is not a sufficiently robust variable, and Hou et al. (2014) document that the five-factor model cannot explain the composite equity issuance anomaly. Furthermore, Asness and Frazzini (2013) and Barillas and Shanken (2018) document that in combination with momentum, value variables should be better measured with the latest market capitalization. Hou et al. (2011) document that cash flow-to-price is at least as important as book-to-market in describing global stock returns. Finally, also Blitz and van Vliet (2007) and Frazzini and Pedersen (2014) could not document a positive relation between risk (volatility and beta) and return for developed markets. Even Fama and French (2017) admit that future research might further refine their definition of factors in asset pricing models derived from Eq. (1). Therefore, our results are not only relevant for emerging markets but also have implications for developed markets, including the U.S.

The article proceeds as follows. Section 2 describes the data, variables, and research methods. Section 3 presents our empirical results for portfolio sorts, Fama and MacBeth (1973) regressions, as well as ex post mean-variance spanning tests. The out-of-sample predictive ability of return forecasts derived from the cross-sectional regressions is shown in Section 4, and Section 5 concludes.

## 2. Data, variables, and methodology

### 2.1. Data

Our sample comprises data from 28 emerging countries over the July 1995 to June 2016 period. We choose 1995 as start year to ensure the availability of a reasonable number of firms.

To derive our sample of emerging market stocks, we use Thomson Reuters Datastream. We create a multi-level process to identify common stocks and secure data quality. During the first step, we identify stocks by Thomson Reuters Datastream's constituent lists.[5] Following Ince and Porter (2006), Griffin et al. (2010), and Schmidt et al. (2017), we apply static screens, the details of which are presented in Appendix A.1. These screens ensure that our sample comprises exclusively of common stocks.

For the securities that pass our static screens, we obtain return and market capitalization data from Datastream and accounting data from Worldscope. As Ince and Porter (2006) describe, raw return data from Datastream may not be error-free. In a second step and to ensure data quality, we follow Ince and Porter (2006) and Schmidt et al. (2017) and apply dynamic screens to the monthly return data. We calculate returns from the total return index in USD and delete all zero returns (in local currency) from the end of the time series to the first non-zero return.[6] Furthermore, as in Jacobs (2016), we winsorize all returns at the 0.1th and 99.9th percentiles. As a proxy for the risk-free rate, we use the one-month U.S. Treasury bill (T-bill) rate that is obtained from Kenneth French's website.

To qualify for our sample from July of year $y$ to June of year $y + 1$, a security needs a valid value for the market capitalization for June 30 of year $y$ and for December 31 of year $y - 1$, a positive book value, as well as all the fundamental data (i.e., sales, cost of goods sold, earnings, total assets, etc.) required to calculate the anomaly variables as described in the Appendix A.2 at the fiscal year end of year $y - 1$, and valid stock returns and the number of shares outstanding for the last 12 months.

We remove all stocks classified as financial companies. Following the size group methodology of Fama and French (2008) and Fama and French (2012), we assign stocks into three size groups (micro, small, and big) separately for each country. Big stocks are defined as the biggest stocks which together account for 90% of a country's aggregated market capitalization. Small stocks are defined as those stocks that comprise the next 7% of aggregated market capitalization (so that big and small stocks together account for 97% of the aggregated market size of a country). Micro stocks comprise the remaining 3%.[7] Although micro stocks represent only 3% of the total market capitalization of our emerging market universe, they account for 42.85% of the number of stocks. To avoid our results being driven by micro stocks, we follow Hou et al. (2018) and exclude them.

### 2.2. Countries

The country selection follows the composition of the Morgan Stanley Capital International (MSCI) Emerging Markets Index (EMI). We include all countries that, at least at some point during the sample period, are classified as an emerging market.[8] This definition leads to the following preliminary list of 31 countries: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Israel, Jordan, (Republic of) Korea, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Portugal, Qatar, Russia, South Africa, Sri Lanka, Taiwan, Thailand, Turkey, United Arab Emirates, and Venezuela.

The countries are only part of the actual sample in those years in which they were part of the MSCI EMI and for which at least ten

[5] We use Worldscope lists and research lists; moreover, to eliminate the survivorship bias we use dead lists.

[6] In addition, we remove all observations for which the return is greater than 990%, the unadjusted price in local currency is greater than 1,000,000 or the $R_t$ or $R_{t-1}$ is greater than 300%, and $(1 + R_t)(1 + R_{t-1}) - 1$ is smaller than 50%.

[7] To distinguish between these size group, Fama and French (2008) use the 20th and 50th percentiles of end-of-June market cap on NYSE stocks as size breakpoints for the U.S. market, which on average are bigger than AMEX or NASDAQ stocks. However, these breakpoints are applied to all (NYSE, AMEX, and NASDAQ) stocks. For international markets, Fama and French (2012) propose to calculate breakpoints based on aggregated market capitalization, as we do.

[8] See `https://www.msci.com/market-classification` for details.

stocks fulfill our data requirements in a given year.[9] These screens imply that some countries, such as Portugal or Brazil, have a shortened sample period in comparison to MSCI market reclassification. It also implies that some countries (such as Hungary, Sri Lanka, and Venezuela) drop out of the sample entirely because less than ten stocks meet our data criteria even though they were part of the MSCI EMI originally. The Chinese sample includes only stocks that are classified as "B"-shares as well as stocks listed in Hong Kong ("H"-shares), even though Hong Kong is not classified as emerging market, and excludes "A"-shares to proxy the investment universe for an international investor. Table 1 shows descriptive statistics for the stocks that meet our sample-selection criteria for the remaining 28 countries.

### 2.3. Variables

To explain stock returns, we focus on fundamental firm characteristics that have been suggested in the empirical asset pricing literature. Table 2 lists the anomaly variables examined in the study, categorized into the themes risk, value, profitability, and investment. These categories correspond to four of the five factors of the recently proposed Fama and French (2015) five-factor model. We do not list size as a separate category but instead include it as a control variable. We also include momentum in our analysis as it is received as "the premier anomaly" Fama and French (2008, p. 1653). Within the categories, our goal is to be comprehensive in order to offer new insights for emerging markets yet empirically parsimonious to avoid data mining. Therefore, we only include the variables that were already proposed and tested in Fama and French (1996), Fama and French (2008), and Stambaugh et al. (2012).

Fama and French (1996) show that the three-factor model is also able to explain return differences associated with valuation multiples, such as earnings-to-price and cash flow-to-price. Only momentum, the continuation of medium-term past returns, could not be captured.[10] Fama and French (2008) further test asset growth, net stock issues (both related to investments), accruals, and profitability proxied by return on equity (both related to profitability). Stambaugh et al. (2012) propose a mispricing score based on eleven previously documented factors that had anomalous returns relative to the Fama and French (1993) three-factor model. Next to momentum and three of the additional variables in Fama and French (2008), the mispricing score also includes return on assets (Balakrishnan et al., 2010), gross profits-to-assets (Novy-Marx, 2013), net operating assets (Hirshleifer et al., 2004) (all three related to profitability), composite equity issuance (Daniel and Titman, 2006), and investment-to-assets (Lyandres et al., 2008) (both related to investments).[11]

We detail the variable definitions and Worldscope data items in Section A.2 of the Appendix.

### 2.4. Methodology

We investigate the predictive power of these variables for emerging market stock returns with two major methodologies. First, we calculate the returns of one-dimensional portfolio sorts. These sorts provide evidence about average returns of stocks with certain characteristics. Second, we analyze the marginal effects for our anomaly variables (i.e., which variables are priced after controlling for other variables) in Fama and MacBeth (1973) cross-sectional regressions. Subsequently, we apply mean-variance spanning tests to further strengthen and cross-validate our results.

For both the portfolio sorts and the cross-sectional regressions, we follow a similar approach to Fama and French (2008). For all variables except momentum and those value variables using the most recent market capitalization, we sort stocks into five portfolios at the end of June of each year $y$.[12] We calculate the breakpoints for the classification into five quintile portfolios based on big stocks and for each country separately.[13] This leads to country-neutral portfolios precluding that our results are driven by country effects. For value and profitability variables with a profit measure such as earnings, cash flow, or gross profits in the numerator, we exclude negative values for the respective sort as negative values would be hard to interpret.[14] We create two portfolios for each of the negative and positive net stock issues and assign all companies with zero values to the center portfolio (corresponding to the third quintile portfolio). Monthly equal- and value-weighted returns are calculated from July through June of the following year. For momentum and the value variables using the latest market values, the portfolios are updated every month.

Next to the five portfolio returns, we also calculate hedge portfolio returns from long minus short returns of the extreme portfolios from the sorts and report the t-value of a two-sided $t$-test against zero for the respective hedge portfolio returns. For these long minus short hedge returns, we further calculate CAPM alphas $\alpha_i$:

[9] We do this to ensure that each quintile portfolio of our portfolio sorts contains at least two stocks per country on average. Our results remain qualitatively unchanged if we release this constraint and include also those country-year combinations with less than ten stocks at a certain point in time.

[10] We do not include five-year past sales growth and five-year past returns as the associated data requirements would substantially reduce our sample.

[11] We do not include the O-Score bankruptcy probability of Ohlson (1980) and the financial distress measure of Campbell et al. (2008) as these variables are calculated based on models parameterized for the U.S. market (cf. Lu et al., 2017).

[12] This lag should ensure that accounting data for the fiscal year ending in year $y-1$ is known when the portfolios are formed.

[13] As described above, big stocks are defined as the biggest companies, which together account for 90% of the aggregated market capitalization of a country.

[14] For example, a E/P of $-10\%$ because of earnings of $-10$ with a market capitalization of 100 is not necessarily worse than a E/P of $-5\%$ because of earnings of $-10$ and a market capitalization of 200.

**Table 1**
Descriptive statistics.

| | Total no. firms | Min no. firms | Mean no. firms | Max no. firms | Mean size | Median size | Total size | % of total size | Start date | End date |
|---|---|---|---|---|---|---|---|---|---|---|
| Argentina | 24 | 12 | 15 | 19 | 2,640 | 1,340 | 19,706 | 0.61 | 2004/07 | 2009/06 |
| Brazil | 101 | 14 | 49 | 68 | 6,194 | 2,367 | 249,042 | 7.65 | 2005/07 | 2016/06 |
| Chile | 108 | 36 | 54 | 67 | 1,765 | 727 | 99,973 | 3.07 | 1997/07 | 2016/06 |
| China | 126 | 12 | 57 | 92 | 1,338 | 631 | 96,531 | 2.97 | 1997/07 | 2016/06 |
| Colombia | 24 | 10 | 11 | 15 | 4,359 | 2,207 | 41,597 | 1.28 | 1999/07 | 2016/06 |
| Czech Republic | 21 | 10 | 12 | 15 | 4,329 | 1,600 | 21,200 | 0.65 | 1998/07 | 2006/06 |
| Egypt | 60 | 13 | 33 | 45 | 1,115 | 510 | 30,599 | 0.94 | 2004/07 | 2016/06 |
| Greece | 48 | 43 | 44 | 45 | 1,246 | 1,154 | 7,078 | 0.22 | 2014/07 | 2016/06 |
| India | 772 | 94 | 272 | 474 | 1,484 | 357 | 475,534 | 14.61 | 1997/07 | 2016/06 |
| Indonesia | 245 | 42 | 86 | 142 | 1,165 | 328 | 114,316 | 3.51 | 1997/07 | 2016/06 |
| Israel | 139 | 10 | 37 | 97 | 1,193 | 493 | 39,732 | 1.22 | 1995/07 | 2010/06 |
| Jordan | 39 | 24 | 30 | 35 | 405 | 84 | 11,679 | 0.36 | 2007/07 | 2009/06 |
| Korea | 1,428 | 13 | 416 | 894 | 925 | 177 | 405,261 | 12.45 | 1995/07 | 2016/06 |
| Malaysia | 677 | 11 | 261 | 378 | 686 | 168 | 151,040 | 4.64 | 1996/07 | 2016/06 |
| Mexico | 87 | 26 | 41 | 52 | 2,969 | 1,245 | 125,936 | 3.87 | 1995/07 | 2016/06 |
| Morocco | 20 | 10 | 10 | 12 | 2,039 | 670 | 14,799 | 0.45 | 2009/07 | 2013/06 |
| Pakistan | 91 | 11 | 35 | 67 | 266 | 116 | 10,875 | 0.33 | 1995/07 | 2009/06 |
| Peru | 47 | 10 | 22 | 33 | 846 | 524 | 17,848 | 0.55 | 1999/07 | 2016/06 |
| Philippines | 105 | 16 | 39 | 55 | 1,190 | 497 | 53,288 | 1.64 | 1995/07 | 2016/06 |
| Poland | 225 | 12 | 83 | 135 | 764 | 244 | 40,265 | 1.24 | 2002/07 | 2016/06 |
| Portugal | 20 | 20 | 20 | 20 | 889 | 195 | 11,123 | 0.34 | 1997/07 | 1998/06 |
| Qatar | 12 | 11 | 12 | 12 | 5,246 | 3,568 | 59,873 | 1.84 | 2014/07 | 2016/06 |
| Russia | 88 | 12 | 45 | 71 | 13,000 | 4,530 | 339,906 | 10.44 | 2006/07 | 2016/06 |
| South Africa | 176 | 52 | 70 | 82 | 2,538 | 1,038 | 180,520 | 5.55 | 1995/07 | 2016/06 |
| Taiwan | 1,299 | 124 | 521 | 870 | 837 | 231 | 421,933 | 12.96 | 1997/07 | 2016/06 |
| Thailand | 371 | 68 | 136 | 224 | 668 | 153 | 105,036 | 3.23 | 1995/07 | 2016/06 |
| Turkey | 168 | 10 | 89 | 120 | 1,007 | 462 | 63,216 | 1.94 | 2002/07 | 2016/06 |
| United Arab Emirates | 14 | 14 | 14 | 14 | 3,386 | 661 | 46,688 | 1.43 | 2015/07 | 2016/06 |
| ALL | 6,535 | 197 | 2,101 | 3,516 | 1,158 | 244 | 3,254,594 | 100.00 | 1995/07 | 2016/06 |

The table presents summary statistics for the 28 countries of our Datastream and Worldscope sample. Column 1 reports the country names, columns 2, 3, 4, and 5 report the total, minimum, mean, and maximum number of firms per country. Columns 6 and 7 state the average mean and median size per country-month. Column 8 shows the average total size per country-month and column 9 reports these values in percentage of the respective total across countries. Size is measured as market capitalization in million USD. The last two columns report the actual beginning and ending dates during which each country is included in our sample. We require that firms have non-missing values for the variables listed in Table 2. Financial firms are excluded.

$$R_{i,t} = \alpha_i + \beta_i \cdot RMRF_t + \varepsilon_{i,t}. \tag{2}$$

Thereby, $R_{i,\,t}$ is the zero-investment hedge portfolio return and $RMRF_t$ is the excess return of the market portfolio, i.e., a value-weighted return of all stocks in the sample over the risk-free rate, each at time $t$. We calculate robust Newey-West standard errors with automatic lag selection.[15] We specifically use the CAPM as a benchmark and not a three-, four-, or five-factor model as it is our goal to evaluate emerging market returns with a clean slate and without any anticipated bias to a certain variable definition. Therefore, in our sorts, we want to ascertain whether our variables are able to distinct themselves from the theoretically founded CAPM.

While the portfolio sorts give a good impression about the average returns for stocks with certain characteristics, they also have shortcomings. Sorts cannot determine which anomaly variables carry unique information. This is a relevant problem as the variables within our categories rely on the same economic motivation and are usually highly correlated. Therefore, we run cross-sectional regressions as in Fama and MacBeth (1973) to determine which variables are priced once controlling for others. Multiple regression slopes provide direct estimates of marginal effects.

However, also cross-sectional regressions face potential problems. Fama and MacBeth (1973) regressions estimated on all stocks are likely dominated by small stocks. The reasons are similar as for sorts with breakpoints on all stocks and equal-weighting. To account for this, as mentioned above, we exclude micro stocks. Furthermore, we run regressions for big stocks only as an additional check.

Similar to our setup for the sorts, we estimate monthly cross-sectional regressions, but except for momentum and the monthly value variables, the explanatory variables are updated once a year at the end of each June. To limit the effect of outliers, we winsorize all explanatory variables at the 1st and the 99th percentiles. For value and profitability variables with a profit measure such as earnings, cash flow, or gross profits, etc. in the numerator, we set negative values to zero and include a dummy variable, which is one if the variable is negative and zero otherwise. Again, to avoid our results being driven by country effects, we include country

[15] See Newey and West (1987) and Newey and West (1994).

**Table 2**
List of anomaly variables.

| | |
|---|---|
| Panel A: Risk | |
| Beta | systematic risk, among others, Sharpe (1964) |
| Vol | total risk (volatility), Haugen and Heins (1975) |
| Panel B: Value | |
| B/M | Book-to-market equity, Rosenberg et al. (1985) |
| E/P | Earnings-to-price, Basu (1977) |
| CF/P | Cash flow-to-price, Lakonishok et al. (1994) |
| Panel C: Profitability | |
| ROE | Return on equity, Haugen and Baker (1996) |
| ROA | Return on assets, Balakrishnan et al. (2010) |
| GP/A | Gross profits-to-assets, Novy-Marx (2013) |
| OP/BE | Operating profits-to-book equity, Fama and French (2015) |
| OA | Operating accruals value, Sloan (1996) |
| NOA | Net operating assets, Hirshleifer et al. (2004) |
| Panel D: Investment | |
| AG | Assets growth, Cooper et al. (2008) |
| NSI | Net stock issues, Pontiff and Woodgate (2008) |
| CEI | Composite equity issuance, Daniel and Titman (2006) |
| I/A | Investment-to-assets, Lyandres et al. (2008) |
| Panel E: Other variables | |
| Size | Market capitalization, Banz (1981) |
| Mom | Momentum, Jegadeesh and Titman (1993) |

The table lists the variables analyzed in this paper. Panel A lists the variables associated with risk while the anomaly variables are grouped into the three categories value (Panel B), profitability (Panel C), investment (Panel D), and other anomalies (Panel E). For each variable, we list its abbreviation, short description, and source in the academic literature. We detail the variable definitions and Worldscope data items in the Appendix.

dummies.

We also apply additional tests. First, we investigate which combination and factor sets of long-short anomaly variables span the highest ex post Sharpe ratios. This mean-variance optimization gives insights for the economic significance of our results (i.e., quantify how much an investor would win or lose by adding certain (theoretical) factors to their investment opportunity set). Second, we calculate out-of-sample expected return estimates derived from the cross-sectional regressions and again apply our two main methods – sorts and Fama and MacBeth (1973) regressions – with expected returns as explanatory variables. Third, to further evaluate these expected return forecasts, we calculate ex ante maximum Sharpe ratio portfolios, allowing only long positions in big stocks and taking reasonable transaction cost into account. We compare the realized performance of these portfolios with alternative investment strategies such as the minimum volatility portfolio and equal- and value-weighted portfolios.

## 3. Empirical results

### 3.1. Sorts

In this section, we clarify which anomaly variables are strong return predicting signals for emerging markets and show robust hedge portfolio returns. Strong signals should not only show a return predictability in equal-weighted sorts, which might be driven by smaller stocks, but also in value-weighted sorts, which on the other hand might be dominated by the largest stocks. Accordingly, both value- and equal-weighted sorts should be considered and we compare both to each other. We calculate the single-sorted portfolio returns based on all-but-micro stocks.

For the equal-weighted portfolio sorts, as presented in Table 3, most quintile returns tend to increase/decrease of returns from portfolio one (smallest values of E/P, OP/BE, etc.) to portfolio five (largest values). Beta and volatility show a reverse relationship, meaning larger values of past beta and volatility, respectively, have lower returns and vice versa, which is in line with the results documented by Blitz et al. (2013) for emerging markets. While the hedge portfolio return of the beta sorted portfolios has a t-value of −1.04, the CAPM alpha has a t-value of −2.56, meaning an equal-weighted low beta minus high beta portfolio would not yield

**Table 3**
Equal-weighted portfolio sorts.

| | 1 | 2 | 3 | 4 | 5 | 5–1 | t(5–1) | Alpha | t($\alpha$) |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Risk | | | | | | | | | |
| Beta | 0.76 | 0.83 | 0.80 | 0.67 | 0.49 | −0.27 | −1.04 | −0.51 | −2.56 |
| Vol | 0.96 | 0.90 | 0.74 | 0.71 | 0.40 | −0.56 | −2.36 | −0.78 | −4.07 |
| Panel B: Value | | | | | | | | | |
| B/M | 0.34 | 0.47 | 0.53 | 0.72 | 1.13 | 0.79 | 4.64 | 0.76 | 4.46 |
| $B/M_m$ | 0.38 | 0.53 | 0.50 | 0.63 | 1.13 | 0.76 | 3.24 | 0.65 | 2.62 |
| E/P | 0.32 | 0.57 | 0.70 | 0.88 | 1.11 | 0.79 | 6.62 | 0.81 | 6.13 |
| $E/P_m$ | 0.36 | 0.63 | 0.67 | 0.85 | 1.06 | 0.71 | 4.25 | 0.65 | 3.17 |
| C/P | 0.32 | 0.53 | 0.98 | 1.02 | 1.28 | 0.96 | 7.70 | 0.96 | 7.38 |
| $C/P_m$ | 0.36 | 0.53 | 0.79 | 1.01 | 1.33 | 0.97 | 5.81 | 0.91 | 4.60 |
| Panel C: Profitability | | | | | | | | | |
| ROE | 0.68 | 0.76 | 0.72 | 0.83 | 0.76 | 0.08 | 0.69 | 0.11 | 1.00 |
| ROA | 0.71 | 0.73 | 0.75 | 0.88 | 0.70 | 0.00 | −0.04 | 0.07 | 0.65 |
| GP/A | 0.50 | 0.66 | 0.76 | 0.76 | 0.98 | 0.48 | 2.71 | 0.62 | 4.15 |
| OP/BE | 0.61 | 0.75 | 0.83 | 0.90 | 0.90 | 0.29 | 2.55 | 0.33 | 2.95 |
| NOA | 0.82 | 0.82 | 0.79 | 0.71 | 0.45 | −0.36 | −3.45 | −0.42 | −3.93 |
| OA | 0.81 | 0.96 | 0.69 | 0.69 | 0.49 | −0.32 | −3.39 | −0.36 | −3.69 |
| Panel D: Investment | | | | | | | | | |
| AG | 0.74 | 0.91 | 0.75 | 0.75 | 0.43 | −0.31 | −2.68 | −0.36 | −3.51 |
| NSI | 0.90 | 0.70 | 0.98 | 0.61 | 0.26 | −0.63 | −2.68 | −0.71 | −2.66 |
| CEI | 1.13 | 0.82 | 0.78 | 0.49 | 0.37 | −0.75 | −5.33 | −0.85 | −5.86 |
| I/A | 0.78 | 0.80 | 0.80 | 0.73 | 0.46 | −0.32 | −3.31 | −0.34 | −4.47 |
| Panel E: Other | | | | | | | | | |
| Size | 0.76 | 0.55 | 0.69 | 0.66 | 0.70 | −0.06 | −0.41 | −0.05 | −0.30 |
| Mom | 0.32 | 0.61 | 0.65 | 0.97 | 1.12 | 0.80 | 2.86 | 0.94 | 2.92 |

The table reports the equal-weighted quintile portfolio sort returns, the long-short portfolio returns, its t-values of a *t*-test against zero, CAPM alphas, and alpha t-values. Abbreviations and definitions of the variables can be found in Appendix A.2. The variables are sorted annually in June of every year, except for $B/M_m$, $E/P_m$, $CF/P_m$, and Mom, which are sorted monthly. The sorting breakpoints are based on big stocks only, which are in the top 90% of the aggregated market capitalization, per country. For value and profitability variables with a profit measure such as earnings, cash flow, or gross profits in the numerator, we exclude negative values for the respective sort as negative values would be hard to interpret. The portfolio return period starts in July 1995 and ends in June 2016 (monthly frequency).

returns significantly different from zero but given its exposure to the market, it would be expected to yield lower returns than it actually does.

For the remaining variables, Size, ROE, and ROA show no clear relationship between characteristic and return. Other than the aforementioned anomalies, all regarded anomalies show an increase or decrease, hedge portfolio returns, and alphas as expected and documented for developed markets (see e.g., Fama and French, 1996; Daniel and Titman, 2006; Fama and French, 2008; Stambaugh et al., 2012). Consequently, all variables of the categories value, profitability, and investment, but also momentum, exhibit t-values of the long-short hedge portfolio returns well above 2 and in many cases even well above 3 in absolute terms, except Size, ROE, and ROA. The value variables show on average higher absolute hedge portfolio returns than the profitability and the investment variables and within the value category, C/P and $C/P_m$ appear strongest with hedge portfolio returns of 0.96% and 0.97%. Within the profitability and investment categories, GP/A and CEI show the highest absolute long-short portfolio returns of 0.48% and − 0.75%, respectively, while OP/BE and AG exhibit only average premiums of 0.29% and − 0.31%. The alphas of the long-short portfolios show similar average values and t-values. Consequently, the CAPM is unable to explain the returns associated with the mentioned characteristics for equal-weighted portfolio sorts in emerging markets and we can confirm the results documented in the literature for developed markets in most cases.

The value-weighted portfolio sort returns, presented in Table 4, reveal that the almost monotonic relationship in returns from the bottom to the top quintile portfolio is often not anymore given when taking company size into account. Consequently, hedge portfolio returns drop substantially, and in many cases, the respective t-value falls below two. This cannot only be observed for volatility in the risk category,[16] but also for both B/M definitions and C/P on an annual basis within the value category as well as for all anomalies for

[16] Please note that the long-short portfolio return and alpha would be more negative if we calculated geometric averages.

**Table 4**
Value-weighted portfolio sorts.

| | 1 | 2 | 3 | 4 | 5 | 5–1 | t(5–1) | Alpha | t(α) |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Risk | | | | | | | | | |
| Beta | 0.51 | 0.76 | 0.52 | 0.57 | 0.39 | −0.12 | −0.42 | −0.34 | −1.25 |
| Vol | 0.67 | 0.53 | 0.62 | 0.32 | 0.44 | −0.23 | −0.79 | −0.46 | −1.81 |
| Panel B: Value | | | | | | | | | |
| B/M | 0.55 | 0.34 | 0.66 | 0.61 | 0.77 | 0.22 | 0.88 | 0.21 | 0.86 |
| $B/M_m$ | 0.49 | 0.33 | 0.56 | 0.74 | 0.81 | 0.32 | 1.25 | 0.29 | 1.04 |
| E/P | 0.24 | 0.62 | 0.42 | 0.70 | 0.95 | 0.70 | 2.83 | 0.71 | 2.54 |
| $E/P_m$ | 0.27 | 0.52 | 0.37 | 0.70 | 1.02 | 0.75 | 2.88 | 0.72 | 2.22 |
| C/P | 0.42 | 0.23 | 0.72 | 0.77 | 0.86 | 0.44 | 1.88 | 0.44 | 1.86 |
| $C/P_m$ | 0.31 | 0.48 | 0.46 | 0.89 | 0.97 | 0.66 | 2.82 | 0.65 | 2.58 |
| Panel C: Profitability | | | | | | | | | |
| ROE | 0.28 | 0.65 | 0.38 | 0.78 | 0.58 | 0.30 | 1.66 | 0.28 | 1.46 |
| ROA | 0.40 | 0.39 | 0.55 | 0.58 | 0.71 | 0.32 | 1.72 | 0.34 | 1.79 |
| GP/A | 0.29 | 0.42 | 0.55 | 0.66 | 0.84 | 0.55 | 2.53 | 0.62 | 2.91 |
| OP/BE | 0.65 | 0.41 | 0.63 | 0.62 | 0.70 | 0.04 | 0.22 | 0.04 | 0.19 |
| NOA | 0.54 | 0.95 | 0.52 | 0.37 | 0.41 | −0.13 | −0.74 | −0.20 | −1.29 |
| OA | 0.44 | 0.73 | 0.40 | 0.70 | 0.56 | 0.12 | 0.63 | 0.10 | 0.52 |
| Panel D: Investment | | | | | | | | | |
| AG | 0.57 | 0.80 | 0.59 | 0.50 | 0.37 | −0.20 | −0.99 | −0.27 | −1.44 |
| NSI | 0.57 | 0.96 | 0.69 | 0.73 | 0.33 | −0.23 | −0.84 | −0.33 | −1.41 |
| CEI | 0.89 | 0.57 | 0.59 | 0.38 | 0.29 | −0.60 | −2.71 | −0.73 | −3.27 |
| I/A | 0.60 | 0.83 | 0.65 | 0.39 | 0.35 | −0.25 | −1.38 | −0.27 | −1.57 |
| Panel E: Other | | | | | | | | | |
| Size | 0.66 | 0.50 | 0.70 | 0.70 | 0.48 | −0.18 | −1.17 | −0.20 | −1.24 |
| Mom | 0.22 | 0.56 | 0.28 | 0.78 | 0.97 | 0.75 | 2.56 | 0.79 | 2.65 |

The table reports the value-weighted quintile portfolio sort returns, the long-short portfolio returns, its t-values of a t-test against zero, CAPM alphas, and alpha t-values. Abbreviations and definitions of the variables can be found in Appendix A.2. The variables are sorted annually in June of every year, except for $B/M_m$, $E/P_m$, $CF/P_m$, and Mom, which are sorted monthly. The sorting breakpoints are based on big stocks only, which are in the top 90% of the aggregated market capitalization, per country. For value and profitability variables with a profit measure such as earnings, cash flow, or gross profits in the numerator, we exclude negative values for the respective sort as negative values would be hard to interpret. The portfolio return period starts in July 1995 and ends in June 2016 (monthly frequency).

the profitability and investment categories except for GP/A and CEI as well as momentum. As the alphas for these three anomalies (with t-values of 2.91, −3.27, and 2.65, respectively) remain high and significant, it is likely that they will dominate the remaining anomaly variables in a Fama and MacBeth (1973) regression. This is not so clear for the value category. On the one hand, $E/P_{(m)}$ and $C/P_m$ remain quite strong despite a value-weighting, while on the other hand, B/M is usually more negatively correlated with profitability variables (see e.g., Novy-Marx, 2013) and might therefore have a high marginal explanatory power.

On the one hand, the value-weighted portfolio sorts reveal that many of the anomalies discovered for developed markets are not robust in emerging markets when applied in a value-weighted setting. As emerging markets can be seen as a potential out-of-sample test, we argue that some anomalies fail this out-of-sample test. On the other hand, this setting still does not unveil which anomaly actually carries unique information. As the variables of each category are based on a similar economic motivation, it is reasonable to assume that they might be correlated at least to a certain degree. Pearson correlations, as exhibited in Table 5, support the hypothesis that not all variables carry unique information as especially the value and some of the profitability variables are highly correlated among each other.

In our next test, we investigate in cross-sectional regressions which anomalies carry unique information that cannot be explained by other variables and if the anomalies that see a drop in t-values for value-weighted portfolio sorts are actually dominated by those anomalies that do not see such a drop.

### 3.2. Cross-sectional regressions

We perform cross-sectional Fama and MacBeth (1973) regressions again on the basis of all-but-micro stocks to discover variables with marginal explanatory power for emerging market stock returns. First, we test if the variables of the Fama and French (2015) five-factor model are priced as expected. Then, we compare for each anomaly category the variable definition from the Fama and

**Table 5**
Correlation matrix.

| | Beta | Vol | B/M | B/$M_m$ | E/P | E/$P_m$ | C/P | C/$P_m$ | ROE | ROA | GP/A | OP/BE | NOA | OA | AG | NSI | CEI | I/A | Size |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vol | 0.62 | | | | | | | | | | | | | | | | | | |
| B/M | −0.02 | −0.18 | | | | | | | | | | | | | | | | | |
| B/$M_m$ | 0.06 | −0.18 | 0.79 | | | | | | | | | | | | | | | | |
| E/P | 0.12 | −0.18 | 0.63 | 0.45 | | | | | | | | | | | | | | | |
| E/$P_m$ | 0.24 | −0.14 | 0.55 | 0.72 | 0.70 | | | | | | | | | | | | | | |
| C/P | 0.04 | −0.24 | 0.65 | 0.58 | 0.75 | 0.65 | | | | | | | | | | | | | |
| C/$P_m$ | 0.07 | −0.29 | 0.56 | 0.75 | 0.62 | 0.81 | 0.81 | | | | | | | | | | | | |
| ROE | 0.25 | 0.21 | −0.5 | −0.52 | 0.05 | −0.06 | −0.17 | −0.24 | | | | | | | | | | | |
| ROA | 0.11 | 0.17 | −0.45 | −0.48 | −0.01 | −0.08 | −0.26 | −0.3 | 0.80 | | | | | | | | | | |
| GP/A | −0.06 | −0.06 | −0.67 | 0.64 | −0.23 | −0.32 | −0.31 | −0.35 | 0.55 | 0.62 | | | | | | | | | |
| OP/BE | 0.17 | 0.11 | −0.56 | −0.61 | −0.08 | −0.22 | −0.15 | −0.23 | 0.66 | 0.52 | 0.69 | | | | | | | | |
| NOA | 0.31 | 0.25 | 0.05 | 0.10 | 0.05 | 0.09 | 0.02 | 0.03 | 0.03 | 0.09 | −0.07 | 0.06 | | | | | | | |
| OA | 0.09 | 0.04 | 0.30 | 0.14 | 0.28 | 0.18 | 0.09 | 0.04 | 0.02 | −0.10 | −0.27 | −0.22 | −0.20 | | | | | | |
| AG | 0.46 | 0.23 | −0.11 | −0.16 | 0.15 | 0.08 | −0.04 | −0.06 | 0.39 | 0.24 | 0.08 | 0.32 | 0.34 | 0.20 | | | | | |
| NSI | 0.31 | 0.38 | −0.14 | −0.1 | −0.03 | 0.02 | 0.03 | −0.05 | 0.13 | 0.08 | 0.06 | 0.15 | 0.15 | −0.05 | 0.23 | | | | |
| CEI | 0.53 | 0.64 | −0.3 | −0.31 | −0.25 | −0.28 | −0.32 | −0.37 | 0.26 | 0.14 | 0.14 | 0.30 | 0.18 | 0.07 | 0.45 | 0.45 | | | |
| I/A | 0.22 | 0.14 | −0.18 | −0.21 | 0.03 | 0.07 | 0.01 | −0.08 | 0.19 | 0.22 | 0.25 | 0.36 | 0.44 | −0.24 | 0.48 | 0.10 | 0.22 | | |
| Size | 0.19 | 0.15 | −0.51 | −0.54 | −0.27 | −0.35 | −0.35 | −0.41 | 0.34 | 0.33 | 0.45 | 0.46 | 0.07 | −0.23 | 0.14 | 0.10 | 0.20 | 0.22 | |
| Mom | −0.23 | −0.11 | −0.02 | −0.43 | 0.08 | −0.41 | 0.04 | −0.32 | 0.04 | 0.05 | 0.13 | 0.12 | −0.11 | 0.16 | −0.06 | −0.06 | −0.06 | 0.02 | 0.16 |

The table reports correlations for the value-weighted long-short portfolio returns. Abbreviations and definitions of the variables can be found in Appendix A.2. The variables are sorted annually in June of every year, except for B/$M_m$, E/$P_m$, CF/$P_m$, and Mom, which are sorted monthly. The sorting breakpoints are based on big stocks only, which are in the top 90% of the aggregated market capitalization, per country. For value and profitability variables with a profit measure such as earnings, cash flow, or gross profits in the numerator, we exclude negative values for the respective sort as negative values would be hard to interpret. The portfolio return period starts in July 1995 and ends in June 2016 (monthly frequency).

**Table 6**
Fama and MacBeth (1973) regressions.

| Model | Beta | B/M | B/$M_m$ | E/$P_m$ | C/$P_m$ | GP/A | OP/BE | NOA | OA | AG | NSI | CEI | I/A | Size | Mom |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Five-Factor Model Variables | | | | | | | | | | | | | | | |
| (1) | −26.33 | 57.98 | | | | | 93.50 | | | −16.03 | | | | 4.09 | |
| | (−1.37) | (7.39) | | | | | (6.38) | | | (−1.60) | | | | (0.92) | |
| Panel B: Six-Factor Model Variables | | | | | | | | | | | | | | | |
| (2) | −31.79 | 54.61 | | | | | 89.58 | | | −15.19 | | | | 3.92 | 28.00 |
| | (−1.81) | (6.94) | | | | | (6.00) | | | (−1.55) | | | | (0.90) | (1.29) |
| Panel C: Comparison Value Variables | | | | | | | | | | | | | | | |
| (3) | −32.87 | 24.92 | 31.28 | | | | 83.92 | | | −17.25 | | | | 5.42 | 55.65 |
| | (−1.91) | (2.49) | (2.98) | | | | (5.75) | | | (−1.77) | | | | (1.29) | (2.94) |
| (4) | −32.93 | | 41.89 | 134.37 | 67.27 | | 46.86 | | | −16.29 | | | | 3.35 | 66.93 |
| | (−1.96) | | (5.38) | (2.88) | (3.26) | | (3.34) | | | (−1.70) | | | | (0.79) | (3.53) |
| Panel D: Comparison Profitability Variables | | | | | | | | | | | | | | | |
| (5) | −30.00 | | 50.32 | 95.16 | 70.99 | 171.89 | 4.49 | −41.19 | −25.04 | 10.39 | | | | 4.85 | 65.16 |
| | (−1.79) | | (6.42) | (2.00) | (3.26) | (4.79) | (0.33) | (−2.93) | (−0.56) | (0.81) | | | | (1.15) | (3.45) |
| Panel E: Comparison Investment Variables | | | | | | | | | | | | | | | |
| (6) | −24.24 | | 47.70 | 55.63 | 75.20 | 171.16 | | −43.49 | | 6.48 | 265.99 | −344.20 | 12.17 | 4.69 | 61.90 |
| | (−1.45) | | (6.20) | (1.13) | (3.69) | (4.82) | | (−3.02) | | (0.42) | (4.05) | (−5.36) | (0.71) | (1.11) | (3.32) |
| Panel F: Strongest EM Variables | | | | | | | | | | | | | | | |
| (7) | −27.77 | | 48.12 | | 82.31 | 181.56 | | −23.81 | | | | −101.95 | | 4.68 | 60.11 |
| | (−1.62) | | (6.27) | | (3.99) | (5.19) | | (−2.37) | | | | (−5.05) | | (1.12) | (3.14) |
| Panel G: Strongest EM vs. Five-Factor Model Variables Model | | | | | | | | | | | | | | | |
| (8) | −27.04 | 30.35 | 28.73 | | 60.66 | 178.79 | 20.06 | −51.85 | | 26.12 | | −95.14 | | 6.28 | 53.64 |
| | (−1.60) | (3.00) | (2.67) | | (3.10) | (5.11) | (1.37) | (−3.74) | | (2.07) | | (−4.56) | | (1.50) | (2.88) |
| Panel H: Only big stocks | | | | | | | | | | | | | | | |
| (9) | −26.36 | 50.97 | | | | | 66.30 | | | −12.85 | | | | 10.90 | |
| | (−1.25) | (5.73) | | | | | (4.23) | | | (−1.09) | | | | (2.02) | |
| (10) | −31.56 | | 52.11 | | 80.86 | 164.94 | | −7.86 | | | | −124.08 | | 12.29 | 47.95 |
| | (−1.70) | | (5.18) | | (3.28) | (4.46) | | (−0.53) | | | | (−4.71) | | (2.31) | (2.16) |
| (11) | −31.49 | 27.50 | 29.20 | | 63.41 | 174.73 | 2.79 | −28.70 | | 19.85 | | −120.00 | | 14.60 | 38.38 |
| | (−1.73) | (2.48) | (2.11) | | (2.58) | (4.53) | (0.18) | (−1.63) | | (1.48) | | (−4.55) | | (2.71) | (1.84) |

The table presents cross-sectional regressions with monthly returns as dependent variables and company characteristic as indicated as independent variables. Abbreviations and definitions of the variables can be found in Appendix A.2. The regressions are estimated monthly, but the variables are updated only once a year in June, except for B/$M_m$, E/$P_m$, CF/$P_m$, and Mom, which are updated monthly. For value and profitability variables with a profit measure such as earnings, cash flow, or gross profits in the numerator, negative values are set to zero and a dummy variable is included, which is one if the value was negative and zero otherwise (not shown). We include country dummies and a constant (not shown). The cross-sectional regressions start in July 1995 and end in June 2016 (monthly frequency).

French (2015) five-factor model to various alternative definitions. Further, we test the strongest return predicting variables for emerging markets jointly with the established factors. Finally, we check the robustness by repeating the most important cross-sectional regressions for the subsample of big stocks.

Table 6 exhibits the results of the cross-sectional regressions. In Panel A, it can be seen that the average regression slopes on B/M and OP/BE have the expected signs and are significantly different from zero, whereas the average slope on AG is insignificant, although the algebraic sign points to the right direction. When adding Mom in Panel B, it seems that momentum is not priced. However, when additionally including B/$M_m$ (i.e., the book value of equity to market value of equity based on the most recent market value available), Mom becomes highly significant, as can be seen in Panel C. This is in line with the results of Asness and Frazzini (2013) and Barillas and Shanken (2018) suggesting that, in combination with momentum, value variables should be better measured with the latest market capitalization. We therefore conclude that to disentangle the value from the momentum effect, using value measures with the most recent market value is recommendable. We decide to drop B/M to mitigate multicollinearity concerns and as $B/M_m$ – besides its ability to disentangle value and momentum – shows a higher average regression coefficient and t-value than B/M. When comparing $B/M_m$, $E/P_m$, and $C/P_m$, we find that all three variables show significant coefficients, indicating that each of them carries unique information.

Panel D exhibits a comparison of various profitability measures, namely GP/A, OP/BE, NOA, and OA.[17] We find that GP/A and NOA are superior not only to OA, but also to OP/BE, which represents the profitability definition in the Fama and French (2015) five-factor model. The investment variable comparison in Panel E confirms the impression of the value-weighted sorts (i.e., CEI remains the only relevant variable). The t-value of 4.05 for the average NSI slope should not be confused with a robust return predictability of NSI as a lower net share issuance usually predicts higher returns (cf. also Tables 3 and 4) and not vice versa. Accordingly, we drop NSI. Interestingly, $E/P_m$ loses its significance once stronger investment variables than AG are included into the model. In portfolio sorts, $E/P_{(m)}$ seems to have a similar or even better return predictive power as $B/M_{(m)}$ and $C/P_{(m)}$. In the cross-sectional setting, it becomes apparent that $E/P_m$ has little marginal ability to predict returns after controlling for other strong variables. Therefore, we decide to drop $E/P_m$.

This choice leads to our preliminary final model, shown in Panel F. The average regression slopes for all variables are highly significant different from zero, except the ones for Beta and Size (we keep both variables as control variables). When comparing the variables of our final emerging markets model with the factors of the Fama and French (2015) five-factor model in Panel G, we document that the profitability definition of Fama and French (2015) becomes insignificant compared to GP/A and NOA. Even more extreme, the investment definition of the five-factor model sees a change in the algebraic sign (as did NSI before). As already seen, B/M is significant along with $B/M_m$ but we still drop it for the reasons mentioned above. To mitigate concerns that the results might be driven by small stocks, a robustness check using only big stocks is presented in Panel H. The main results for big stocks are very similar to the results for small stocks with one major difference: the average slope for NOA is not significantly different from zero anymore. Together with the inconclusive result of the value-weighted sorts and a preference for parsimonious variable sets, we decide to drop NOA. Therefore, our final model consists of $B/M_m$, $C/P_m$, GP/A, CEI, along with Size and Mom.

### 3.3. Mean-variance spanning tests

To substantiate our results, we conduct mean-variance spanning tests for different factor sets as in Ball et al. (2016). For this purpose, we use the long-short returns of the value-weighted portfolio sorts (5-1 for B/M, $B/M_m$, $C/P_m$, GP/A, OP/BE, and Mom, while 1-5 for AG, CEI, and Size) and compute ex post maximum Sharpe ratios associated with various factor combinations from the viewpoint of an investor trading in these factors. The lower bound for the weights is zero and the sum of the weights has to add up to 1. Table 7 exhibits the weights of each factor for the respective tangency portfolio and the corresponding Sharpe ratios. Differences in the Sharpe ratios quantify how much investors would win or lose by adding certain (theoretical) factors to their investment opportunity set.

The annualized Sharpe ratio of the market portfolio is 0.29, which can be increased to 0.41 when adding the classic value (B/M) and Size long-short portfolios. Further, adding momentum to this combination substantially increases the Sharpe ratio to 0.77, which is also substantially higher than the maximum Sharpe ratio that can be achieved by the long-short portfolios associated with the Fama and French (2015) five-factor model (0.59).

The Sharpe ratio of 1.68 for the factor set comprising our suggested emerging market variables from the cross-sectional regressions above is considerably higher than the Sharpe ratio of the Fama and French (2015) five-factor model, even when extended by the momentum variable (0.84). Comparing our model to the five-factor model yields two insights: first, the Sharpe ratio does not increase any further when adding the factors of the five-factor model, and second, all of our selected variables are better choices to maximize the Sharpe ratio than those of the five-factor model variables. This goes as far as that no weight is assigned to the classic variable definitions. This is not only the case for the profitability and investment variables but also for the value variables, where no weight is assigned to the returns of the classic B/M definition. We conclude that the Fama and French (2015) factors do not add any additional performance enhancement nor a substantial risk reduction to a mean-variance optimized portfolio consisting of our proposed factors. We therefore see our results strengthened by this additional test.

## 4. Expected return forecasts

In this section, we investigate the out-of-sample predictive power of expected return estimates derived from Fama and MacBeth (1973) cross-sectional regressions. Similar to Haugen and Baker (1996) and Lewellen (2015), we estimate expected returns based on the average historic Fama and MacBeth (1973) coefficients and the latest company characteristics.

To determine the expected return for each stock, we calculate the average Fama and MacBeth (1973) coefficients of the previous 36 months for the classic Fama and French (2015) five-factor model as well as for our proposed model, including the strongest emerging market factors.[18] For each firm, we then multiply the average Fama and MacBeth (1973) coefficients with the current

[17] For brevity, we do not include ROE and ROA as they show no return predicting power in the single sorted portfolios. In unreported results, we also find no return predicting power in cross-sectional regressions.

[18] We always use the Fama and MacBeth (1973) coefficients of regressions based on all-but-micro stocks no matter if we further analyze the all-but-micro sample or big-stocks-only sample. All results hold when using big-stocks-only Fama and MacBeth (1973) coefficients to determine big-stocks-only expected returns.

**Table 7**
Maximum ex post Sharpe ratios.

| | RMRF | B/M | B/M$_m$ | C/P$_m$ | GP/A | OP/BE | AG | CEI | Size | Mom | SR |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1FM | 1.00 | | | | | | | | | | 0.29 |
| 3FM | 0.29 | 0.09 | | | | | | | 0.63 | | 0.41 |
| 4FM | 0.17 | 0.00 | | | | | | | 0.44 | 0.39 | 0.77 |
| 5FM | 0.12 | 0.11 | | | | 0.28 | 0.24 | | 0.26 | | 0.59 |
| 6FM | 0.12 | 0.05 | | | | 0.18 | 0.17 | | 0.28 | 0.21 | 0.84 |
| EMFM | 0.10 | | 0.15 | 0.05 | 0.31 | | | 0.13 | 0.12 | 0.14 | 1.68 |
| 5FM vs. EMFM | 0.10 | 0.00 | 0.15 | 0.05 | 0.31 | 0.00 | 0.00 | 0.13 | 0.12 | 0.14 | 1.68 |

The table presents the maximum ex post Sharpe ratios that can be achieved by using different combinations of long-short portfolios and the weights on each long-short portfolio required to achieve the maximum Sharpe ratio. Abbreviations and definitions of the variables can be found in Appendix A.2. The variables are sorted annually in June of every year, except for B/M$_m$, CF/P$_m$, and Mom, which are sorted monthly. The sorting breakpoints are based on big stocks only, which are in the top 90% of the aggregated market capitalization, per country. For value and profitability variables with a profit measure such as cash flow or gross profits in the numerator, we exclude negative values for the respective sort as negative values would be hard to interpret. The portfolio return period starts in July 1995 and ends in June 2016 (monthly frequency).

**Table 8**
Portfolio sorts based on expected returns.

| | 1 | 2 | 3 | 4 | 5 | 5–1 | t(5–1) | Alpha | t($\alpha$) |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Equal-weighted | | | | | | | | | |
| FF5FM | 0.67 | 1.02 | 1.31 | 1.44 | 1.69 | 1.02 | 5.94 | 1.06 | 5.25 |
| EMFM | 0.39 | 0.97 | 1.21 | 1.51 | 2.10 | 1.71 | 10.22 | 1.69 | 9.15 |
| Panel B: Value-weighted | | | | | | | | | |
| FF5FM | 0.64 | 0.81 | 0.94 | 1.07 | 1.39 | 0.75 | 3.01 | 0.81 | 2.69 |
| EMFM | 0.34 | 0.68 | 0.88 | 1.45 | 1.33 | 0.98 | 4.29 | 1.01 | 4.59 |

The table reports equal- and value-weighted quintile portfolio sort returns, the long-short portfolio returns, its t-values of a t-test against zero, CAPM alphas, and alpha t-values. The expected returns are calculated based on the Fama and French (2015) five-factor model (FF5FM) and the strongest emerging market variables (EMFM). The sorts are done monthly. The sorting breakpoints are based on big stocks only, which are in the top 90% of the aggregated market capitalization, per country. The portfolio return period starts in July 1998 and ends in June 2016 (monthly frequency).

company characteristics of the respective variables. This results in a total evaluation period from July 1998 to June 2016 in which expected returns are available.

We evaluate the derived return forecasts again with our two main methods – sorts and Fama and MacBeth (1973) regressions – with expected returns as return predicting signal. Furthermore, we calculate ex ante maximum Sharpe ratio portfolios, allowing only long positions in big stocks and taking reasonable transaction cost into account. We compare the realized performance of these portfolios with alternative investment strategies such as minimum volatility as well as equal- and value-weighted portfolios.

### *4.1. Sorts and cross-sectional regressions based on expected return forecasts*

We repeat our initial analysis and sort all non-micro stocks into five quintile portfolios, but instead of using company characteristics, we use expected return forecasts. Again, quintile breakpoints are based on big stocks per country, and we calculate equal- and value-weighted realized returns for each portfolio. Table 8 exhibits the quintile portfolio returns, the long-short hedge portfolio returns, their t-values, as well as CAPM alphas and corresponding t-values, each for portfolios based on return forecasts using the five-factor model and our suggested model.

Return forecasts show a nearly monotonic increase in average realized returns for both models and for both weighting methods. However, return forecasts from our emerging market model lead to a larger dispersion in realized returns, resulting in a larger average return of the long-short portfolios. For the equal-weighted portfolios, as shown in Panel A, the classic five-factor model yields an average monthly long-short return of 1.02%, while the emerging market factor model yields a return of 1.71%. Both long-short portfolio returns are highly economically and statistically significantly different from zero, the five-factor model with a t-value of 5.94, our emerging market model with a t-value of 10.22. The CAPM alphas and t-values show analogous numbers. A similar picture can be seen for the value-weighted portfolios (Panel B) with generally lower spreads but still with a clear trend. The emerging market model yields a higher long-short return and CAPM alpha with higher respective t-values than the classic five-factor model albeit the model of Fama and French (2015) also yields significant results.

Next, we investigate the expected return forecasts derived from the two models in Fama and MacBeth (1973) regressions. Table 9 shows the results for all-but-micro stocks as well as for big stocks. Again, we include country dummies. Unbiased return forecasts should predict subsequent realized returns with a slope of one (cf. Lewellen, 2015). Both models show highly significant average regression slopes for both samples in univariate regressions, ranging from 0.51 for the five-factor model forecasts in the big stock

**Table 9**
Fama and MacBeth (1973) regressions based on expected returns.

| | all-but-micro micro | | | big stocks only | | |
|---|---|---|---|---|---|---|
| Expected return model | (1) | (2) | (3) | (4) | (5) | (6) |
| FF5FM | 0.63 | | 0.27 | 0.51 | | 0.16 |
| | (7.11) | | (2.54) | (5.10) | | (1.26) |
| EMFM | | 0.65 | 0.58 | | 0.63 | 0.60 |
| | | (9.25) | (6.98) | | (7.53) | (6.05) |

The table presents cross-sectional regressions with monthly returns as dependent variables and expected returns of the same month as independent variables. The expected returns are calculated based on the Fama and French (2015) five-factor model (FF5FM) and the strongest emerging market variables (EMFM). T-values are given in parentheses below the coefficients. Models 1 to 3 refer to all-but-micro micro stocks, models 4 to 6 refer to big stocks only. We include country dummies and a constant (not shown). The cross-sectional regressions start in July 1998 and end in June 2016 (monthly frequency).

universe to 0.65 for our emerging market model in the all-but-micro-stocks universe. These estimates are very similar to the ones for "All-but-tiny stocks" and "Large stocks" in Lewellen (2015) and imply that the expected return forecasts have strong predictive power for subsequent realized returns. However, the expected return forecasts would need to be shrunk toward the cross-sectional mean by about 35% to 50% (one minus regression coefficient) to result in unbiased return forecasts. Another implication is that the cross-sectional out-of-sample return estimates provide a reliable way to forecast subsequent returns. This finding is in contrast to the results for time-series predictive regressions (cf. Welch and Goyal, 2008).

For a direct comparison between the two forecasting models, we also perform multivariate regressions. The average coefficient of the returns estimated with our proposed emerging market model is not only higher but also exhibits higher t-values. For the sample comprising only big stocks the t-value for the coefficient of the expected returns estimated using the classic five-factor model even drops to 1.26. The coefficient for the emerging market factor model expected returns remains at 0.60 and still has a t-value of 6.05. We therefore conclude that the model consisting of the strongest emerging market factors clearly outperforms the model of Fama and French (2015) in terms of cross-sectional return predictability.

### 4.2. Simulating the investment performance of expected return forecasts

A common feature of the tests presented above is that they are based on theoretical "zero-investment" long-short portfolio returns (sorts) or represent average regression coefficients that can be interpreted as the returns for one unit exposure to this factor but are orthogonal to all other factors included in the model (cross-sectional regressions). However, it is questionable whether these returns can be realized in practice, as short-selling constraints may prevent the implementation of long-short strategies and transaction costs may erode the factor strategy profits. These constraints are particularly relevant for emerging markets (see e.g., Roon et al., 2001). Therefore, in this section, we focus on long-only portfolios of big stocks and take reasonable transaction costs into account.[19] We compare the realized performance of these portfolios with alternative investment strategies such as the minimum volatility portfolio as well as equal- and value-weighted portfolios. We follow van der Hart et al. (2003) and incorporate transaction cost estimates of 100 basis points per single-trip transaction.

We form these portfolios at the end of each quarter and not at the end of each month to limit portfolio turnover. On each portfolio formation date, we calculate the portfolio weights that maximize the ex ante Sharpe ratio:

$$\max_{\overrightarrow{w}_{MSR}} \frac{\overrightarrow{\mu}^T \overrightarrow{w}_{MSR}}{\sqrt{\overrightarrow{w}^T_{MSR} \Omega \overrightarrow{w}_{MSR}}} \tag{3}$$

where $\overrightarrow{w}_{MSR}$ is the vector containing the optimal weights, $\overrightarrow{\mu}$ is the vector of our expected return measure (we calculate expected returns again based on the classic Fama and French, 2015, five-factor model and on the strongest emerging market signals), and $\Omega$ is the expected covariance matrix of the stock returns. We estimate the covariance matrix by using the latest 36 months of returns and shrink it following the approach of Ledoit and Wolf (2004), as there are more constituents in the portfolio than estimation months available. To prohibit all expected returns from being negative at a certain date, which could cause problems in the optimization, we normalize the expected returns to a median of 0.5% by subtracting the median of expected returns at a rebalancing date and adding 0.5% afterwards.

As in Chow et al. (2016), we further set the constraints for the portfolio weights in the optimization to zero as the lower bound and to the minimum of 1.5% and 20 times the stock's weight in the market value-weighted portfolio as upper bound. The sum of the weights has to add up to one. Similar to Chow et al. (2016) and as in Bielstein and Hanauer (2018), we set weights below 0.01% to zero.

We compare the maximum Sharpe ratio portfolios against the equal- and value-weighted portfolios of all big stocks and a minimum volatility strategy. For the minimum volatility portfolio, we apply the same constraints but do not include the expected

[19] We assume that an international investor who wants to invest in an optimized portfolio of emerging market companies, would most likely choose only big companies as investable universe.

**Table 10**
Investability indicators.

| | Turnover | # of Stocks | Effective N | Weight in Top 10 |
|---|---|---|---|---|
| VW | 0.06 | 876 | 151 | 0.19 |
| EW | 0.11 | 1156 | 1156 | 0.01 |
| MinVol | 0.21 | 144 | 89 | 0.15 |
| $MaxSR_{5FM}$ | 0.25 | 139 | 89 | 0.15 |
| $MaxSR_{EMFM}$ | 0.30 | 141 | 89 | 0.15 |

The table shows investability indicators for the main strategies tested in our study. Turnover is the average one-way portfolio turnover at each portfolio formation date. # of Stocks is the average number of stocks in the respective portfolio at each portfolio formation date. Effective N is the average reciprocal of the Hirshman-Herfindahl index of portfolio weights. Weight in Top 10 is the average sum of the weights of the ten largest portfolio positions. The rows display the investment strategies. VW is the market value-weighted, EW the equal-weighted, and MinVol the minimum volatility portfolio. MaxSR5FM and MaxSREMFM are the maximum Sharpe ratio portfolios using the Fama and French (2015) five-factor model and our proposed emerging markets model to forecast expected stock returns. The portfolio return period starts in July 1998 and ends in June 2016 (monthly frequency).

**Table 11**
Portfolio performance and risk.

| | SR | Return % | SD % | MD % | TE % | IR |
|---|---|---|---|---|---|---|
| VW | 0.39 | 10.75 | 22.75 | 60.34 | 0.00 | |
| EW | 0.51 | 13.29 | 22.22 | 59.35 | 5.85 | 0.43 |
| MinVol | 0.69 | 11.18 | 13.49 | 40.36 | 13.03 | 0.03 |
| $MaxSR_{5FM}$ | 0.78 | 15.66 | 17.72 | 48.79 | 9.49 | 0.52 |
| $MaxSR_{EMFM}$ | 0.95 | 18.64 | 17.59 | 50.52 | 9.71 | 0.81 |

The table presents performance and risk metrics for the all investment strategies tested in our study. SR indicates the (annualized) Sharpe Ratio. Return % is the average arithmetic return (annualized) as a percentage. SD % is the standard deviation (annualized) as a percentage. MD % stands for the maximum drawdown as a percentage. TE % represents the tracking error to the value-weighted portfolio as a percentage. IR is the information ratio with respect to the value-weighted portfolio. The rows display the investment strategies. VW is the market value-weighted, EW the equal-weighted, and MinVol the minimum volatility portfolio. MaxSR5FM and MaxSREMFM are the maximum Sharpe ratio portfolios using the Fama and French (2015) five-factor model and our proposed emerging markets model to forecast expected stock returns. The portfolio return period starts in July 1998 and ends in June 2016 (monthly frequency). We assume one-way transaction costs of 100 basis points following van der Hart et al. (2003).

return forecasts:

$$\min_{\vec{w}_{MVP}} \sqrt{\vec{w}_{MVP}^{T}\Omega\vec{w}_{MVP}} \tag{4}$$

Table 10 exhibits the portfolio characteristics for the value-, equal-, and minimum volatility weighted portfolios, as well as the maximum Sharpe ratio portfolios based on the Fama and French (2015) variables and the strongest emerging market variables, as identified in the Fama and MacBeth (1973) regressions over the full sample in Section 3.2.

As the value-weighted portfolio only causes turnover when the constituents are changing (e.g., due to a reclassification of big stocks), it is not surprising that its turnover is the lowest of all strategies. As very small weights are cut off, it does not contain all the big stocks that are available, as does the equal-weighted portfolio. The diversification of the value-weighted portfolio – measured by the effective N – is between the diversification of the equal-weighted and the optimized portfolios. The weight of the ten largest stocks is highest for the value-weighted portfolio. For the optimized portfolios, by contrast, the maximum weight for each stock is limited at 1.5%. Of the optimized portfolios, turnover is the lowest for the minimum volatility portfolio (21%) but is only slightly higher for the maximum Sharpe ratio portfolios (5FM: 25%. EMFM: 30%). All three show an effective N of 89.

Table 11 shows portfolio Sharpe ratios, arithmetic mean returns, standard deviations, tracking errors, and information ratios. As expected, the minimum volatility portfolio exhibits the lowest volatility (13.49%) and lowest maximum drawdown (40.36%) while earning an average return of 11.18%, which is slightly higher than that of the value-weighted portfolio (10.75%).[20] The Sharpe ratio maximized portfolios show the highest mean returns (5FM: 15.66%, EMFM: 18.64%), information ratios (5FM: 0.52, EMFM: 0.81), and Sharpe ratios (5FM: 0.78, EMFM: 0.95) with volatilities still below the value- and equal-weighted portfolios. As the emerging market factor model portfolio not only shows a higher mean return than the five-factor model portfolio but also a slightly lower volatility (5FM: 17.72%, EMFM: 17.59%), we conclude that our emerging market factors are also superior to the Fama and French (2015) variables for optimized long-only portfolios.

Fig. 1 finally visualizes the cumulated performance of the investment strategies.

[20] Please note that the minimum volatility portfolio would exhibit an even higher outperformance if we used geometric returns.

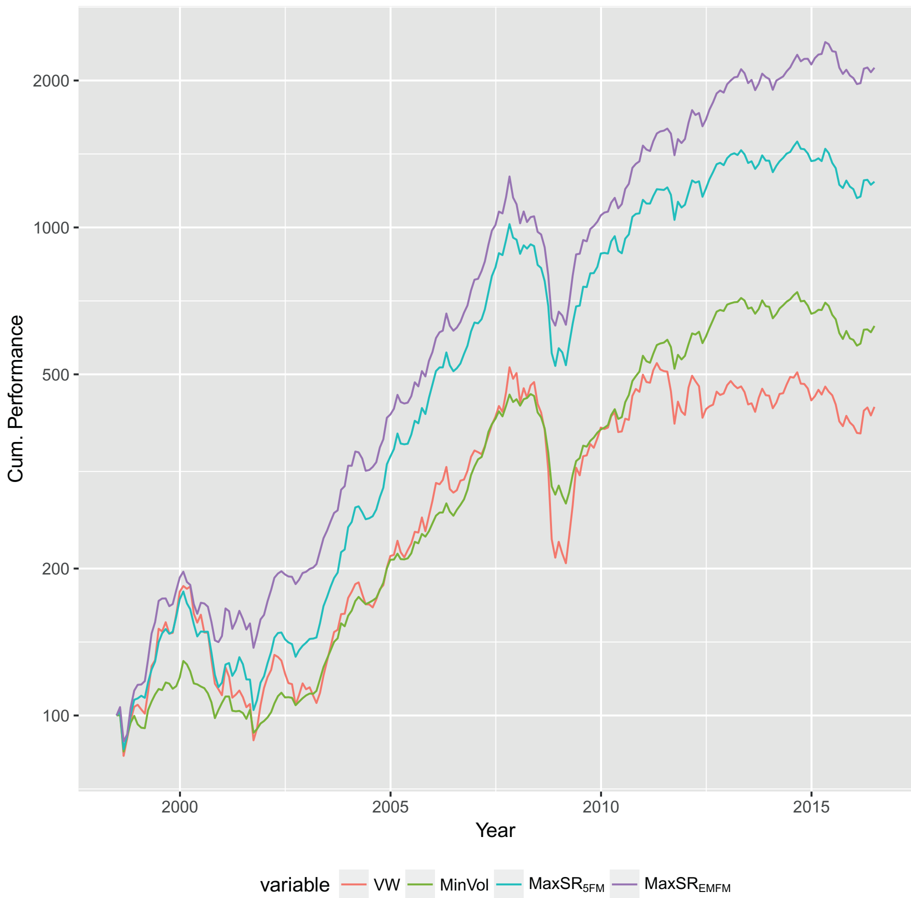


**Fig. 1.** Cumulative performance of the investment strategies.
This figure displays the hypothetical development of a 100 USD investment in each of the investment strategies. VW is the market value-weighted portfolio. MinVol is the minimum variance portfolio. $MaxSR_{5FM}$ and $MaxSR_{EMFM}$ are the maximum Sharpe Ratio portfolios using the Fama and French (2015) five-factor model and our proposed emerging markets model, respectively, to forecast expected stock returns. The portfolio return period starts in July 1998 and ends in June 2016 (monthly frequency). We assume one-way transaction costs of 100 basis points following van der Hart et al. (2003).

### *4.3. Robustness: performance of expected returns for different regions*

To show that the superior performance of our emerging market factors is, despite country-neutrality, not driven by a single region, we provide regional results as a robustness check. We divide the countries of our full sample into three regions: Central and Latin America (AMER); Europe, Middle East, and Africa (EMEA); and Asia (ASIA). We test the return predictability of our emerging markets model for these three regions and compare it with the five-factor model. As in Section 4.1, we calculate equal- and value-weighted sorts as well as cross-sectional regressions based on expected returns, which are calculated from the latest company characteristics and historic average cross-sectional coefficients of the two models.

Table 12 exhibits quintile portfolio returns, long-short returns, CAPM alphas, as well as the corresponding t-values for both weighting schemes. Panel A shows the results for Central and Latin America. The Fama and French (2015) five-factor model is not able to forecast significant long-short returns or a CAPM alpha, neither for the equal- nor for the value-weighting. Compared to that, our proposed emerging market model yields monthly average long-short returns of 0.84% (t-value: 2.93) for equal- and 1.36% (t-value: 2.48) for value-weighting. The CAPM alphas show similar results. For Europe, Middle East, and Africa (Panel B), we find similar but even more robust results for our model and slightly significant results for the five-factor model in case of equal-weighted portfolios (5–1 return of 0.46%, t-value of 1.74 and CAPM alpha of 0.49%, t-value of 1.66) but again insignificant long-short returns in case of value-weighted portfolios. For Asia (Panel C), we find significant long-short returns for both expected return models; for the value-weighting, the results are similar, and for the equal-weighting, we again find a substantially stronger performance for our proposed model than for the five-factor model.

Finally, Table 13 shows a region-specific comparison of the two models in a cross-sectional regression setting. The results confirm the impression of the regional sorts: for Central and Latin America, our model can explain realized returns while the five-factor model

**Table 12**
Portfolio sorts based on expected returns for different regions

| | 1 | 2 | 3 | 4 | 5 | 5–1 | t-val(5–1) | Alpha | t-val($\alpha$) |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Central and Latin America | | | | | | | | | |
| $FF5FM_{EW}$ | 0.77 | 1.25 | 1.34 | 0.99 | 1.06 | 0.29 | 1.05 | 0.39 | 1.21 |
| $FF5FM_{VW}$ | 0.95 | 0.77 | 1.29 | 1.30 | 0.84 | −0.11 | −0.19 | 0.22 | 0.40 |
| $EMFM_{EW}$ | 0.99 | 1.07 | 1.17 | 1.47 | 1.83 | 0.84 | 2.93 | 0.94 | 2.80 |
| $EMFM_{VW}$ | 0.46 | 0.91 | 1.37 | 1.57 | 1.82 | 1.36 | 2.48 | 1.42 | 2.48 |
| Panel B: Europe, Middle East, and Africa | | | | | | | | | |
| $FF5FM_{EW}$ | 1.01 | 1.15 | 1.36 | 1.11 | 1.47 | 0.46 | 1.74 | 0.49 | 1.66 |
| $FF5FM_{VW}$ | 0.73 | 1.00 | 1.15 | 0.89 | 1.27 | 0.54 | 1.54 | 0.51 | 1.28 |
| $EMFM_{EW}$ | 0.73 | 1.11 | 1.20 | 1.55 | 2.05 | 1.32 | 5.33 | 1.30 | 4.42 |
| $EMFM_{VW}$ | 0.55 | 1.02 | 0.90 | 1.15 | 1.82 | 1.27 | 3.66 | 1.21 | 3.41 |
| Panel C: Asia | | | | | | | | | |
| $FF5FM_{EW}$ | 0.56 | 1.00 | 1.36 | 1.57 | 1.72 | 1.16 | 6.11 | 1.16 | 5.38 |
| $FF5FM_{VW}$ | 0.46 | 0.80 | 1.06 | 1.29 | 1.55 | 1.09 | 3.93 | 1.18 | 3.51 |
| $EMFM_{EW}$ | 0.36 | 0.93 | 1.25 | 1.54 | 2.18 | 1.83 | 9.86 | 1.80 | 10.00 |
| $EMFM_{VW}$ | 0.34 | 0.63 | 1.18 | 1.32 | 1.45 | 1.11 | 3.99 | 1.19 | 4.43 |

The table reports equal- and value-weighted quintile portfolio sort returns, the long-short portfolio returns, its t-values of a *t*-test against zero, CAPM alphas, and alpha t-values for each region. The expected returns are calculated based on the Fama and French (2015) five-factor model (FF5FM) and the strongest emerging market variables (EMFM). The subscripts EW and VW stand for equally and value-weighted. The sorts are done monthly. The sorting breakpoints are based on big stocks only, which are in the top 90% of the aggregated market capitalization, per country. The portfolio return period starts in July 1998 and ends in June 2016 (monthly frequency).

**Table 13**
Fama and MacBeth (1973) regressions based on expected returns for different regions.

| Expected return model | AMER | | | EMEA | | | ASIA | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| FF5FM | 0.11 | | −0.17 | 0.29 | | −0.24 | 0.61 | | 0.26 |
| | (0.54) | | (−0.81) | (1.68) | | (−1.32) | (6.71) | | (2.32) |
| EMFM | | 0.30 | 0.31 | | 0.61 | 0.68 | | 0.68 | 0.60 |
| | | (2.89) | (2.97) | | (6.52) | (7.05) | | (9.06) | (6.81) |

The table presents cross-sectional regressions with monthly returns as dependent variables and expected returns of the same month as independent variables. The expected returns are calculated based on the Fama and French (2015) five-factor model (FF5FM) and the strongest emerging market variables (EMFM). T-values are given in parentheses below the coefficients. Models 1 to 3 refer to emerging market countries of Central and Latin America (AMER), models 4 to 6 refer those of Europe, Middle East, and Africa (EMEA), and models 7 to 9 refer to Asian emerging market countries. Regressions are based on all-but-micro stocks. We include country dummies and a constant (not shown). The cross-sectional regressions start in July 1998, and end in June 2016 (monthly frequency).

cannot. For Europe, Middle East, and Africa, the five-factor model can explain the realized returns with an average regression slope of 0.29 and an associated t-value of 1.68 while our model shows an average coefficient of 0.61 and a t-value of 6.52. When comparing both models in a multivariate regression, the coefficient on expected returns derived from the five-factor model is negative and insignificant, but the slope on the expected returns derived from the emerging markets model becomes even larger and remains significant. For Asia, both return forecasts are highly significant in univariate regressions, but when comparing them in a multivariate setting, it becomes apparent that the expected return forecasts based on the emerging markets model still have a higher explanatory power (coefficient: 0.60, t-value: 6.81) than the ones based on the five-factor model (coefficient: 0.26, t-value: 2.32). Therefore, we conclude that our main results are confirmed by the analyses based on different regions.

## 5. Conclusion

Although the importance of emerging market economies and stock markets is constantly rising, few studies have investigated anomalous stock return patterns for emerging markets. The purpose of examining emerging market stock returns in this study is threefold. First, we determine the magnitude of anomaly variables on the basis of a broad sample of emerging market stocks that were recently discovered in the U.S. and have not yet been documented for emerging markets. Second, using Fama and MacBeth (1973) cross-sectional regressions and mean-variance spanning tests, we analyze the incremental power for these anomaly variables (i.e., which variables are priced after controlling for other variables). Finally, we investigate the real-time predictive power of return forecasts based on these Fama and MacBeth (1973) regressions, as shown in Haugen and Baker (1996) and Lewellen (2015) for the U.S. market.

Using monthly stock returns for a total of 28 emerging market countries and a sample period of 21 years, we can confirm the results of Fama and French (2015) for the U.S. and Fama and French (2017) for developed markets and find that the categories valuation, profitability, and investment are also priced in emerging markets. However, we document that within the different categories, the factor definitions of the new Fama and French (2015) five-factor model are less robust compared to alternative factor definitions. In contrast, the anomalous returns associated with cash flow-to-price, gross profitability, composite equity issuance, and momentum are pervasive as they show up in both equal- and value-weighted sorts as well as in cross-sectional regressions. However, in contrast to the prediction of the CAPM and in line with Blitz et al. (2013), we cannot find a positive relationship between risk and return.

Following the methodology of Haugen and Baker (1996) and Lewellen (2015), we further derive out-of-sample return forecasts from current firm characteristics and slopes from past cross-sectional regressions. The return forecasts based on the alternative factor definitions are superior to the ones derived from the five-factor model in both sorts and cross-sectional regressions. We also apply the expected return forecasts in mean-variance optimized long-only portfolios. Accounting for transaction costs and limiting the investment universe to big stocks, we demonstrate that the alternative factor definitions lead to a portfolio that dominates value- and equal-weighted strategies as well as the minimum volatility and an optimized portfolio based on return forecasts derived from the five-factor model. Finally, we show that our results also hold for the emerging market regions Central and Latin America; Europe, Middle East, and Africa; and Asia.

Although there is some consensus in the research community that the categories value, profitability, and investments are priced, it remains a question as to which variables are the best proxies for these categories. Also, Fama and French (2017) admit that future research might further refine the definition of factors in asset pricing models such as the Fama and French (2015) five-factor model. Therefore, our results not only provide strong evidence that the factor definitions of the Fama and French (2015) five-factor model may not be optimal for emerging markets, but also confirm individual findings for developed markets, including the U.S. market in previous studies. Already Fama and French (2008) state that asset growth is not a sufficiently robust variable, and Hou et al. (2014) document that the five-factor model cannot explain the composite equity issuance anomaly. Furthermore, Asness and Frazzini (2013) and Barillas and Shanken (2018) document that in combination with momentum, value variables should be better measured with the latest market capitalization. Hou et al. (2011) document that cash flow-to-price is at least as important as book-to-market in describing global stock returns. Finally, Blitz and van Vliet (2007) and Frazzini and Pedersen (2014) could not document a positive relation between risk (volatility and beta) and return for developed markets.

## Appendix A

### A.1. Static screens

During the first step, we identify stocks by Datastream's constituent lists and follow the suggestions of Ince and Porter (2006), Griffin et al. (2010), Hanauer and Linhart (2015), and Schmidt et al. (2017). To avoid a survivorship bias, we use the intersection of Datastream research lists, Worldscope lists, and dead lists for each of the 31 regarded countries. Table A.1 presents the utilized constituents lists for emerging market countries.

We restrict our sample to stocks of type equity; companies and securities located or listed in the domestic country; the primary quotation of a security; and the (major) security with the biggest market capitalization and liquidity for companies with more than one equity security. Furthermore, we exclude securities with quoted currency and ISIN country code other than the domestic country. Exemptions are Russia, where we also allow for US-Dollar listings, the Czech Republic, where we allow not only for GGISN “CZ” but also for “CS”, as well as China, where we exclude shares with share class “A” which would fulfill all requirements but were not accessible for international investors.

To eliminate non-common equity stocks, we search similar to Griffin et al. (2010) for suspicious words in the company name, indicating that the security is a duplicate, preferred stock, dept., etc. Generic keywords for all countries are listed in Table A.2. If a part of a security's name is matched to a generic keyword, the security should better be classified to the category listed in the first column of Table A.2 and not as common equity. The keywords of Table A.3 are country-specific and only the names of the stocks of the corresponding country are matched to these keywords.[21] After a manual review, the identified securities are excluded from the sample.

[21] The determination of the keywords is also a gradual process. Copying them from Ince and Porter (2006) and Griffin et al. (2010) does not work, as many regular common stocks would also be eliminated. Based on our actual output of securities from Thomson Reuters Datastream, we refine the keywords repeatedly to come to our final exclusion keywords. A good example is the general-filter keyword “UT”, which indicates that a security is a Unit Trust. But using “UT” would also eliminate securities with the element “SOUTH” in their name. With the knowledge of the output names, the keyword is further developed to “UT “.

Table A.1
Constituent lists: Emerging markets.

| Country | Lists | Country | Lists |
|---|---|---|---|
| Argentina | DEADAR | Morocco | DEADMOR |
| | WSCOPEAR | | WSCOPEMC |
| | FPARGA | | FMOR |
| Brazil | DEADBRA | Pakistan | DEADPA |
| | WSCOPEBR | | WSCOPEPK |
| | FBRA | | FPAK |
| Chile | DEADCHI | Peru | DEADPE |
| | WSCOPECL | | WSCOPEPE |
| | FCHILE | | FPERU |
| China | DEADCH | Philippines | DEADPH |
| | WSCOPECH | | WSCOPEPH |
| | FCHINA | | FPHIQ |
| | DEADHK | Poland | DEADPO |
| | WSCOPEHK | | WSCOPEPO |
| | FHKQ | | FPOL |
| Colombia | DEADCO | Portugal | DEADPT |
| | WSCOPECB | | WSCOPEPT |
| | FCOL | | FPOR |
| Czech Republic | DEADCZ | Qatar | DEADQT |
| | WSCOPECZ | | WSCOPEQA |
| | FCZECH | | FQATAR |
| Egypt | DEADEGY | Russia | DEADRU |
| | WSCOPEEY | | WSCOPERS |
| | FEGYPT | | FRUS |
| Greece | DEADGR | South Africa | DEADSAF |
| | WSCOPEGR | | WSCOPESA |
| | FGREE | | FSAF |
| Hungary | DEADHU | South Korea | DEADKO |
| | WSCOPEHN | | WSCOPEKO |
| | FHUN | | FKOR |
| India | DEADIND | Sri Lanka | DEADSL |
| | WSCOPEIN | | WSCOPECY |
| | FINDIA | | FSRILA |
| Indonesia | DEADIDN | Taiwan | DEADTW |
| | WSCOPEID | | WSCOPETA |
| | FINO | | FTAIQ |
| Israel | DEADIS | Thailand | DEADTH |
| | WSCOPEIS | | WSCOPETH |
| | FISR | | FTHAQ |
| Jordan | DEADJO | Turkey | DEADTK |
| | WSCOPEJO | | WSCOPETK |
| | FJORD | | FTURK |
| Malaysia | DEADMY | United Arab Emirates | DEADAB |
| | WSCOPEMY | | WSCOPEAE |
| | FMALQ | | FABUD |
| Mexico | DEADME | Venezuela | DEADVE |
| | WSCOPEMX | | WSCOPEVE |
| | FMEX | | FVENZ |

We use Thomson Reuters Datastream's constituent lists to build our sample of common stocks. To avoid a survivorship bias, we use the intersection of Datastream research lists, Worldscope lists, and dead lists for each of the initially 31 regarded countries. The table presents the identifiers of the constituent lists of the 31 emerging market countries.

Table A.2
Generic filter rules to exclude non-common equity securities.

| Non-common equity | Keywords |
|---|---|
| Duplicates | “DUPLICATE” “DUPL” “DUP.” “DUPE” “DULP” “DUPLI” “1000DUPL” “XSQ” “XETa” “DUP ““DUPL “ |
| Depository Receipts | “ADR” “GDR” |
| Preferred Stock | “Stock” “PREFERRED” “PF.” “PFD” “PFD.” “PREF” “‘PF’” “PRF” |
| Warrants | “WARRANT” “.WARRANT” “WARRANTS” “WTS” “.WTS” “WTS2” “WARRT” |
| Debt | “DEB ““DB” “DCB” “DEBT ““DEBENTURES” “DEBENTURE” “%” |
| Unit Trusts (2 words) | “RLST IT” “INVESTMENT TRUST” “INV TST” “UNIT TRUST” “UNT TST” “TRUST UNITS” “TST UNITS” “TRUST UNIT” “TST UNIT” |
| Unit Trusts (1 word) | “UT ““.IT” |
| ETF | “ETF” “ISHARES” “INAV” “X-TR” “LYXOR” “JUNGE” “AMUNDI” |

(*continued on next page*)

Table A.2 (*continued*)

| Non-common equity | Keywords |
|---|---|
| Ince and Porter (2006) | "500" "BOND ""DEFER" "DEP ""DEPY" ".DEPY." "ELKS" "ETF" "FUND" "FD" "FD." ".FD." ".FUND" "FUND." ".GDR" "IDX" ".IDX" "IDX." "INDEX" "MIPS" "MITS" "MITS." "MITT ""MITT." "NIKKEI" "NOTE." "NOTE ""PERQS" "PINES ""PINES." "PRTF" "PTNS" "PTSHP" "QUIBS" "QUIDS" "RATE" "RCPTS" "RECEIPTS" "REIT" ".REIT" "RETUR" "SCORE" "SPDR" "STRYPES" "TOPRS" "WTS" "XXXXX" "YIELD" "YLD" ".YLD" "QUIDS" |
| Expired securities | "EXPIRED" "EXPD" "EXPIRY" "EXPY" |

The table lists generic keywords for all regions, which serve as indicators that a Datastream security is, in contrast to its stock classification in Datastream, not common equity. If a part of a security's name matches a generic keyword, the security is better classified to the category listed in the first column of the same row and not as common equity. After a manual review, the identified securities are removed from the sample.

Table A.3
Country-specific filter rules to exclude non-common equity securities.

| Country | Keywords |
|---|---|
| Emerging Markets | |
| Brazil | "PN" "PNA" "PNB" "PNC" "PNC" "PNE" "PNF" "PNG" "RCSA" "RCTB" "PNDEAD" "PNADEAD" "PNBDEAD" "PNCDEAD" "PNDDEAD" "PNEDEAD" "PNFDEAD" "PNGDEAD" |
| China | "A" |
| Colombia | "PFCL" "PRIVILEGIADAS" "PRVLG" |
| Greece | "PR" "PB" "PR." ".PR" |
| Hungary | "törzsrészvény" "osztalékelsbbségi" |
| India | "XNH" |
| Indonesia | "FB" "FBDEAD" "RTS" "RIGHTS" "RIGHTS" |
| Israel | "P1" |
| Malaysia | "A ""'A'" "FB" "(XCO)" "XCODEAD" "SES" "(SES)" "RIGHTS" |
| Mexico | "ACP" "BCP" "'C'" "'L'" "CPO" "O ""'O'" "C ""L " |
| Peru | "INVERSION" "INVN" "INV" |
| Philippines | "PDR" |
| Portugal | "R" "'R'" |
| South Africa | "'N'" "CPF" "OPTS" "OPTS" |
| South Korea | "1P" "2P" "3P" "1 PB" "1 PB" "3 PB" "4 PB" "5 PB" "6 PB" "1PFD" "1PF" "PF2" "2PF" |
| Sri Lanka | "RTS" "RIGHTS" "NON VTG" |
| Taiwan | "TDR" "'TDR'" |
| Thailand | "FB" "FBDEAD" |

The table lists country-specific keywords, which serve as indicators, that a Datastream security is, in contrast to its stock classification in Datastream, not common equity. If a part of the security's name matches one of its country-specific keywords from the second column, the security is better classified not as common equity. After a manual review, the identified securities are removed from the sample.

### *A.2. Variable definitions*

For each variable, we describe the detailed variable definition and used Worldscope items:

*A.2.1. Risk variablesA.2.1.1. Beta: systematic risk.*. We estimate a stock's beta versus the respective MSCI country index over the last 36 months in local currency. We require a minimum of 12 monthly returns. To make our systematic risk measure comparable to other mostly annually updated variables, we update it in June of each year $y$.A.2.1.2. Vol: total risk (volatility). We measure a stock's volatility as the standard deviation of its monthly returns over the last 36 months in local currency. We require a minimum of 12 monthly returns. To make our total risk measure comparable to other mostly annually updated variables, we update it in June of each year $y$.

#### *A.2.2. Value variables*

The denominator of all value variables is market capitalization (Datastream item MV). Book equity, earnings, and cash flow are for the fiscal year ending in calendar year $y-1$. Value variables without the subscript $m$ (e.g., B/M) use market capitalization as measured at the end of December of year $y-1$ to predict returns from July of year $y$ to June of year $y+1$. Value variables with the subscript $m$ (e.g., B/M$_m$) use the most recent market capitalization (cf. Asness and Frazzini, 2013).A.2.2.1. B/M: Book-to-market equity. Book equity is defined as common equity (Worldscope item WC03501) plus deferred taxes (WC03263), if available.A.2.2.2. E/P: Earnings-to-price. Earnings are measured before extraordinary items (WC01551).A.2.2.3. C/P: Cash flow-to-price. Cash flow is defined as operating cash flow (WC04860).

#### *A.2.3. Profitability variables*

All profitability variables are solely based on values from the balance sheet, the income statement, and the statement of cash flows. For the portfolios formed in June of year $y$, earnings, sales, the different cost components, assets and book equity are from the fiscal year ending in calendar year $y-1$.A.2.3.1. ROE: Return on equity. We measure return on equity as earnings before extraordinary items (WC01551) divided by book equity. Book equity is defined as common equity (WC03501) plus deferred taxes (WC03263), if available.A.2.3.2. ROA: Return on assets. Return on assets is defined as earnings before extraordinary items (WC01551) divided by total assets (WC02999).A.2.3.3. GP/A: Gross profits-to-assets. As in Novy-Marx (2013), gross profits-to-assets is net sales or revenues (WC01001) minus cost of goods sold (WC01501) both divided by total assets (WC02999).A.2.3.4. OP/BE: Operating profits-to-book equity. We measure operating profits-to-book equity as in Fama and French (2015) as sales or revenues (WC01001) minus cost of goods sold (WC01051), minus selling, general, and administrative expenses (WC01101), minus interest expense (WC01251); all divided by book equity. To have a valid value, at least one of cost components *cost of goods sold*, *selling, general and administrative expenses*, or *interest expense* must be non-missing. Book equity is defined as common equity (WC03501) plus deferred taxes (WC03263), if available.A.2.3.5. OA: Operating accruals. Following Sloan (1996), we define operating accruals as the change in operating working capital minus depreciation, depletion, and amortization (WC01151, zero if missing); all deflated by total assets (WC02999). Change in operating working capital is the change in current assets (WC02201) minus change in cash and short-term investments (WC02001), minus change in current liabilities (WC03101), plus change in debt in current liabilities (WC03051), plus change in income taxes payable (WC03063, zero if missing). Operating accruals in June of year $y$ are measured from fiscal year ending in calendar year $y-2$ to fiscal year ending in calendar year $y-1$.A.2.3.6. NOA: Net operating assets. As in Hirshleifer et al. (2004), net operating assets in June of year $y$ are defined as operating assets minus operating liabilities for the fiscal year ending in calendar year $y-1$; all deflated by total assets (WC02999) for the fiscal year ending in calendar year $y-2$. Operating assets is total assets (WC02999) minus cash and short-term investment (WC02001). Operating liabilities is total assets minus short-term and long-term debt (WC03255), minus minority interest (WC03426), minus preferred stock and common equity (WC03995).

*A.2.4. Investment variablesA.2.4.1. AG: Asset growth.* As in Cooper et al. (2008), we measure asset growth in June of year $y$ as the percentage change in total assets (WC02999) from fiscal year ending in calendar year $y-2$ to fiscal year ending in calendar year $y-1$.A.2.4.2. NSI: Net stock issues. Following Pontiff and Woodgate (2008), we measure net stock issues as the difference in the natural logs of split-adjusted shares outstanding in June of year $y$ and year $y-1$. Split-adjusted shares outstanding are calculated as shares outstanding (Datastream item NOSH) divided by the adjustment factor (Datastream item AF). We update this variable each June to make it comparable to the yearly updated asset growth variable.A.2.4.3. CEI: Composite equity issuance. Similar to Daniel and Titman (2006), composite equity issuance is defined as the growth rate in the market capitalization not attributable to the total stock return $R$: $log(MC_y/MC_{y-1}) - R_{(y-1,y)}$. For the portfolio formation at the end of June of year $y$, $R_{(y-1,y)}$ is the cumulative log return (calculated via the total return index, Datastream item RI) from June of year $y-1$ to June of year $y$ and $MC_y$ is the market capitalization (Datastream item MV) from June of year $y$. Equity issuance such as stock issues, stock option plans, and share-based compensations and acquisitions increase the composite equity issuance, whereas share repurchases or cash dividends reduce the composite equity issuance. We apply a one-year lookback window and also update this variable only each June to make it comparable to the yearly updated asset growth and net stock issuance variables.A.2.4.4. I/A: Investment-to-assets. As in Lyandres et al. (2008), we measure investment-to-assets in June of year $y$ as the change in gross property, plant, and equipment (WC02301) plus the annual change in inventories (WC02101) (both from fiscal year ending in calendar year $y-2$ to fiscal year ending in calendar year $y-1$) all divided by total assets (WC02999) of year $y-2$.

*A.2.5. Other variablesA.2.5.1. Size: Market capitalization.* Market capitalization (Datastream item MV) is price times number of shares outstanding. To make the size measure comparable to other mostly annually updated variables, we update it at the end of June of each year $y$. At these points in time, market capitalization is also used to sort the stocks into size groups for the subsequent year.A.2.5.2. Mom: Momentum. As in Fama and French (2008) and similar to Jegadeesh and Titman (1993), we measure momentum as the cumulated total stock return (calculated via the total return index, Datastream item RI) from month $t-12$ to month $t-2$, where $t$ is the month of the forecasted return. Skipping the last month is standard in the momentum literature to avoid an overlapping with the short-term reversal effect as documented by Jegadeesh (1990). We measure the momentum variable monthly.

### *A.3. Portfolio descriptive measures*

This section gives an overview of portfolio descriptive measures used in the paper.

#### *A.3.1. Turnover*

We calculate the average one-way turnover according to DeMiguel et al. (2009):

$$\text{Turnover}_i = \frac{1}{2}\frac{1}{T}\sum_{t=1}^{T}\sum_{n=1}^{N}(\mid w_{n,t+1,i} - w_{n,t,i}\mid) \tag{5}$$

where $w_{n,\ t,\ i}$ is the weight of stock $n$ at time $t$ of strategy $i$.

#### *A.3.2. Effective N*

We determine the average effective number of stocks in the portfolio, calculated as the reciprocal of the Hirshman-Herfindahl index of portfolio weights Chow et al. (2016):

$$\text{EffectiveN}_i = \frac{1}{T}\sum_{t=1}^{T}\left(\sum_{n=1}^{N} w_{n,t,i}^2\right)^{-1} \tag{6}$$

where Effective $N_i$ is the average effective number of stocks of strategy $i$ and $w_{n,\ t,\ i}$ is the weight of stock $n$ at time $t$ of strategy $i$.

### A.3.3. Maximum drawdown

We compute the maximum drawdown Grossman and Zhou (1993) as the highest total decrease in price from a high to a low in the sample for each portfolio:

$$\text{MD}_i = -\min(r_{i,loc_{peak}-loc_{min}}) \tag{7}$$

where $\text{MD}_i$ is the maximum drawdown for strategy $i$ and $r_{i,\ loc_{peak}-loc_{min}}$ is the return from a local price high to a local price low of strategy $i$. Of all price decreases we take the most negative one and switch the sign.

### A.3.4. Tracking error

The tracking error is calculated as the standard deviation of the portfolio's active return, which is the portfolio's return minus the return of the value-weighted portfolio.

### A.3.5. Information ratio

The information ratio is calculated as the portfolio's average active return divided by its tracking error.

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