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# Size, value, and momentum in emerging market stock returns

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ABSTRACT

In this paper, we examine value and momentum effects in 18 emerging stock markets. Using stock level data from January 1990 to December 2011, we find strong evidence for the value effect in all emerging markets and the momentum effect for all but Eastern Europe. We investigate size patterns in value and momentum. After forming portfolios sorted on size and book-to-market ratio, as well as size and lagged momentum, we use three well-known factor models to explain the returns for these portfolios based on factors constructed using local, U.S., and aggregate global developed stock markets data. Local factors perform much better, suggesting emerging market segmentation.


## 1. Introduction

There is a considerable empirical research identifying value and momentum effects in the U.S. and other developed equity markets. Despite the fact that emerging stock markets constitute an increasing share of the world equity market, there are fewer empirical studies that investigate value and momentum effects in these markets. Until recently, the development of the empirical literature on cross-sections of stock returns in emerging markets has been hampered by the availability of high quality and comprehensive data. Following the pioneering studies in the 1990s by Bekaert and Harvey (1995), Harvey (1995), and Bekaert et al. (1998a,b), several papers have explored various characteristics of emerging stock markets. Studies that have focused and documented the presence of value and momentum effects in emerging equity markets include, for example, those of Fama and French (1998), Griffin et al. (2003), and Rouwenhorst (1999). These studies find that (1) value stocks with higher book equity-to-market equity (B/M) ratios have higher average returns than growth stocks

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which have low B/M ratios and (2) stocks with large cumulative returns over the past year continue to do better. However, these studies provide no details as to the size patterns in value and momentum effects.

The purpose of this paper is twofold. First, we look more closely at the size patterns in value and momentum in the equity market of 18 emerging market countries. Second, we investigate the integration of emerging markets with that of the U.S. equity market. To do so, we try to explain the local cross-sections of value and momentum stock returns using the U.S. factors as well as local factors and compare the performance of local and U.S. factors.

We can summarize our four principal finding as follows. First, we confirm the existence of value and momentum effects in emerging markets, providing fresh "out-of-sample" evidence for the results that have been documented in the literature. Second, for emerging markets we find that the value effect is fairly similar across small and large capitalization stocks (henceforth small and big stocks), a finding that is not consistent with what has been reported in developed markets. In contrast, the momentum effect we find in emerging markets is meaningfully larger for small stocks, a result consistent with the findings for developed markets. Third, in line with the findings in developed markets, our empirical evidence for emerging markets indicates that returns associated with value and momentum are negatively correlated. Lastly, in asset pricing tests explaining the returns of portfolios formed based on value and momentum measures, the economic performance of local factors is significantly better than the U.S. factors, suggesting emerging market segmentation.

Our market integration results add to the literature which focuses on aggregate market returns (see, for example, Bekaert et al., 2002, and Bekaert and Harvey, 2003). To the best of our knowledge, our paper is the first to construct for the emerging markets the B/M ratio and momentum explanatory factors as well as cross-sections of portfolios formed on these characteristics similar to studies focusing on the U.S. and developed markets (see, for example Fama and French, 1993, 2012; Griffin, 2002, and Rouwenhorst, 1998). In what follows, we briefly describe the dataset used in this study and our methodology, then we expand upon each of these four results in some detail.

We use stock level data from 18 emerging countries available from Datastream from January 1990 to December 2011 and group the countries into three emerging regions: Asia, Latin America, and Eastern Europe. In our asset pricing tests, we try to explain the returns of local size and B/M and size and momentum portfolios typical in the literature. We evaluate the performance using three well-known models. To analyze the degree of market integration between emerging equity markets and the U.S. equity market, we estimate separate regressions using local factors as well as the U.S. factors. We also use the factors calculated using the data from global developed stock markets.

The paper is structured as follows. In Section 2 we discuss both our methodology for capturing the expected returns via three widely used asset pricing models and the statistical test that we employ to test for model performance. The data and the variables used are described in Section 3. Our findings are the subject of Section 4 and Section 5 concludes our paper.

## 2. Methodology

### 2.1. Models for explaining stock returns

To explain stock returns, we use the three models which we describe in this section. The three models estimated from cross-sectional data are the capital asset pricing model (CAPM) – an equilibrium model that assumes returns depend solely on the market in general (see Lintner, 1965, and Sharpe, 1964) – the Fama–French three-factor model (Fama and French, 1993), and the Carhart four-factor model (Carhart, 1997). The corresponding regression equations are given in Eqs. (1), (2), and (3)below:

$$\text{CAPM}: \quad R_{i,t}-RF_t = a_i + b_i[RM_t-RF_t] + e_{i,t} \tag{1}$$

$$\text{Fama-French Model}: \quad R_{i,t}-RF_t = a_i + b_i[RM_t-RF_t] + s_iSMB_t + h_iHML_t + e_{i,t} \tag{2}$$

$$\text{Carhart Model}: \quad R_{i,t}-RF_t = a_i + b_i[RM_t-RF_t] + s_iSMB_t + h_iHML_t + w_iWML_t + e_{i,t}. \tag{3}$$

In the regression equations, $R_{i,t}$ is the return on portfolio *i* for month *t*; $RF_t$ is the risk-free rate, $RM_t$ is the market return; $SMB_t$ is the difference between returns on diversified portfolios of small stocks and big stocks;

$HML_t$ is the difference between the returns on diversified portfolios of high B/M and low B/M stocks, and; $WML_t$ is the difference between the returns on diversified portfolios of the winners and losers of the past year.

Notice that the CAPM explains returns only using the market return while the other two models include in addition to the market, value measures and size as suggested by Fama and French (1993), and in the case of the four-factor model, momentum as measured by returns on the so-called winner and loser portfolios used in studies of this anomaly (see Jegadeesh and Titman, 1993).

### 2.2. Test of model performance

Following the literature, we utilize the GRS test statistic to evaluate model performance suggested by Gibbons et al. (1989). The statistic is given by

$$GRS = \left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{a}'\hat{\sum}^{-1}\hat{a}}{1+\overline{\mu}'\hat{\Omega}^{-1}\overline{\mu}}\right] \tag{4}$$

where $T$ is the sample size, $N$ is the number of portfolios to be explained, $L$ is the number of explanatory factors, $\hat{a}$ is a vector of regression intercepts, $\hat{\sum}$ is the residual covariance matrix in the sample, and $\hat{\Omega}$ is the sample covariance matrix of the explanatory factors. Under the null hypothesis that all regression intercepts are zero, the GRS test statistic has an $F$ distribution with $N$ and $T–N–L$ degrees of freedom. While convenient to calculate and being an exact distribution for a finite sample, the application requires a strong assumption that errors are independent and identically distributed and follow the normal law.

To address the concern about non-normal and serially autocorrelated errors, we also use a generalized method of moments (GMM)-based test statistic to evaluate the models (see Zhou, 1994). As before, point estimates for the model's parameters are estimated using ordinary least squares regressions. Consider the error vector $g_T$ defined by,

$$g_T = 1/T \times \sum_{t=1}^{T}\begin{bmatrix} e_t \\ e_t.\times[RM_t - RF_t] \\ e_t.\times SMB_t \\ e_t.\times HML_t \\ e_t.\times WML_t \end{bmatrix} = 1/T \times \sum_{t=1}^{T} u_t, \tag{5}$$

where $e_t$ denotes the time-$t$ regression errors stacked into an $N$ by 1 vector, $.\times$ denotes the element by element multiplication, and $u_t$ denotes the GMM residuals. We can construct the Jacobian of the error vector, $D$, where we first differentiate with respect to the $a$'s (from $a_1$ to $a_N$), then similarly the $b$'s, the $s$'s, the $h$'s, and finally the $w$'s. In particular,

$$D = \begin{bmatrix} 1 & \overline{f_{1,t}} & \overline{f_{2,t}} & \overline{f_{3,t}} & \overline{f_{4,t}} \\ \overline{f_{1,t}} & \overline{f_{1,t}^2} & \overline{f_{1,t}\times f_{2,t}} & \overline{f_{1,t}\times f_{3,t}} & \overline{f_{1,t}\times f_{4,t}} \\ \overline{f_{2,t}} & \overline{f_{2,t}\times f_{1,t}} & \overline{f_{2,t}^2} & \overline{f_{2,t}\times f_{3,t}} & \overline{f_{2,t}\times f_{4,t}} \\ \overline{f_{3,t}} & \overline{f_{3,t}\times f_{1,t}} & \overline{f_{3,t}\times f_{2,t}} & \overline{f_{3,t}^2} & \overline{f_{3,t}\times f_{4,t}} \\ \overline{f_{4,t}} & \overline{f_{4,t}\times f_{1,t}} & \overline{f_{4,t}\times f_{2,t}} & \overline{f_{4,t}\times f_{3,t}} & \overline{f_{4,t}^2} \end{bmatrix} \otimes I_{N\times N}, \tag{6}$$

where $f_{1,t}$, $f_{2,t}$, $f_{3,t}$, and $f_{4,t}$ correspond to $[RM_t - RF_t]$, $SMB_t$, $HML_t$, and $WML_t$. $\overline{f_{i,t}\times f_{j,t}}$ is simply the sample mean of $f_{i,t} \times f_{j,t}$. $I_{N \times N}$ denotes an $N$ by $N$ identity matrix and $\otimes$ denotes the Kronecker product.

Let $S$ denote the spectral density of the residuals, $u_t$. Then, following the Newey and West (1987) procedure, a sample estimate $\hat{S}$ can be constructed as,

$$\hat{S} = \sum_{j=-k}^{k}\frac{k-|j|}{k}\frac{1}{T}\sum_{t=1}^{T}u_t u'_{t-j}, \tag{7}$$

where $k$ is the number of lags after which the errors are assumed uncorrelated. We can then estimate the covariance matrix of the parameters, $V$, as follows:

$$V = \left(D'\hat{S}^{-1}D\right)^{-1}/T. \tag{8}$$

We can extract a submatrix, denoted by $V_a$, occupying the top left $N$ by $N$ corner of $V$. Under the null hypothesis that all regression intercepts are equal to zero, $a'(V_a)^{-1}a$ is distributed Chi-squared with $N$ degrees of freedom, which we use as our GMM test-statistic for the linear factor model.

A second use for our GMM framework is to test if the means of two excess return series, $R^e_{m,t}$ and $R^e_{n,t}$, are identical. We apply this test to compare the average returns of factors (Market − $R_f$, SMB, HML, and WML) across our emerging regions: Asia, Latin America, and Eastern Europe. We perform the same comparisons for the factors calculated for the U.S. and the Global Developed markets. The procedure is robust to general patterns of correlation and heteroscedasticity in the data.

Consider an error vector, $g_T$, defined as;

$$g_T = 1/T \times \begin{bmatrix} \sum_{t=1}^{T} R^e_{m,t} - \mu_m \\ \sum_{t=1}^{T} R^e_{n,t} - \mu_m \end{bmatrix}, \tag{9}$$

where $\mu_m$ and $\mu_n$ are the respective means of $R^e_{m,t}$ and $R^e_{n,t}$. A covariance matrix of the estimates, $V$, can be constructed by setting $D$ in Eq. (8) to $-I_{2\times 2}$ and by defining the $u_t$ as $[R^e_{m,t},R^e_{n,t}]$' when calculating $\hat{S}$.

## 3. Data

We use monthly stock level data for 18 emerging countries available from Datastream. The sample period is from January 1990 to December 2011. Returns are computed in U.S. dollars; excess returns are calculated relative to the one-month U.S. Treasury bill rate.[1] Fortunately, our data source is not affected by the survivorship bias because the Datastream sample includes not only active firms, but also dead firms.

To ensure a reasonable number of stocks in our portfolios, we combine our 18 emerging countries into the following three regions similar to the Morgan Stanley Capital International (MSCI): (1) Asia (China, India, Indonesia, South Korea, Malaysia, Philippines, Taiwan, and Thailand); (2) Latin America (Argentina, Brazil, Chile, Colombia, and Mexico), and; (3) Eastern Europe (Czech Republic, Hungary, Russia, Poland, and Turkey). We also consider all of the 18 emerging countries together, which we refer to as the "All-Emerging" markets, fully recognizing that there are emerging markets not covered in our study.[2] To test for market integration, we use the U.S. and the Global Developed explanatory factors and cross-sectional portfolio data obtained from Kenneth French's website.[3]

Our data appear to provide a comprehensive coverage of the stock universes in these regions. Table 1 provides summary information. As can be seen, the mean sample size (across the years) includes more than 4000 firms in our Asian sample, close to 800 in our Latin American sample, and more than 400 in our

[1] Throughout the paper, we always work with returns expressed in U.S. dollars. This is a potential issue for our results, which the paper shares with the related literature focusing on asset pricing in developed markets, especially if the purchasing power parity does not hold or if in fact the portfolio returns to be explained are correlated with the exchange-rate risks (see, for example, Dumas and Solnik, 1995; Solnik, 1974). See Zhang (2006) for an explicit incorporation of exchange-rate risk into asset pricing tests. The paper evaluates the cross-sectional performance of several international asset pricing models allowing for exchange-rate premia in the local returns for the UK and Japanese stocks.

[2] The emerging countries in our study differ from the countries included in the MSCI index in the following ways. We excluded Peru because of limited data availability (particularly early in the study period) in Datastream. Argentina is not in the MSCI index but we added that country because we had a reasonable number of firms as early as the beginning of our sample period. Because we wanted to have multiple countries in a region rather than only one, we did not include Africa. Although there were three potential candidate countries to include from this region, South Africa, Egypt, and Morocco, the latter two countries had very limited data available. We have the same countries in our Asian sample as included in the MSCI index.

[3] U.S. and the Global Developed factor and portfolio data are used in Fama and French (2012). Twenty-three developed countries are included in the Global Developed region: U.S., Canada, Japan, Australia, New Zealand, Hong Kong, Singapore, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

**Table 1**
Firm characteristics in Asia, Latin America, and Eastern Europe emerging markets. The table provides the annual size and book equity-to-market equity ratios (B/M), as well as the number of firms for the three regions in our Datastream sample. Countries in each region are given in Section 3 of the paper. The first momentum sort absorbs a year of data, so the mean values are reported across the years from 1991 to 2011. Annual values are the median of the monthly values in that year.

| | Asia | | | Latin America | | | Eastern Europe | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | Size ($) | B/M | Firms | Size($) | B/M | Firms | Size ($) | B/M | Firms |
| 1991 | 105.30 | 0.60 | 555 | 279.00 | 0.60 | 104 | 141.80 | 0.63 | 27 |
| 1992 | 99.70 | 0.50 | 841 | 196.60 | 0.70 | 176 | 54.25 | 1.19 | 46 |
| 1993 | 197.00 | 0.40 | 1077 | 234.00 | 0.40 | 237 | 173.24 | 0.27 | 69 |
| 1994 | 208.10 | 0.50 | 1258 | 179.40 | 0.50 | 472 | 95.90 | 0.41 | 72 |
| 1995 | 158.80 | 0.60 | 1724 | 118.30 | 0.60 | 533 | 72.75 | 0.69 | 110 |
| 1996 | 170.30 | 0.60 | 1918 | 147.20 | 0.60 | 584 | 108.40 | 0.57 | 181 |
| 1997 | 55.20 | 1.20 | 1914 | 185.50 | 0.60 | 596 | 101.17 | 0.50 | 206 |
| 1998 | 64.50 | 1.10 | 1931 | 89.20 | 1.00 | 733 | 55.26 | 1.04 | 252 |
| 1999 | 133.00 | 0.70 | 3058 | 55.60 | 0.80 | 1055 | 95.29 | 0.57 | 292 |
| 2000 | 74.70 | 1.00 | 3757 | 43.70 | 1.00 | 1097 | 62.20 | 0.78 | 343 |
| 2001 | 76.60 | 0.90 | 4206 | 38.70 | 1.00 | 1047 | 50.24 | 0.79 | 354 |
| 2002 | 79.50 | 0.80 | 4486 | 27.20 | 1.10 | 1029 | 40.35 | 1.04 | 386 |
| 2003 | 98.20 | 0.70 | 4799 | 48.70 | 0.80 | 982 | 60.01 | 0.87 | 437 |
| 2004 | 90.90 | 0.70 | 5166 | 73.90 | 0.60 | 952 | 89.70 | 0.81 | 501 |
| 2005 | 82.60 | 0.80 | 5804 | 85.00 | 0.70 | 989 | 79.33 | 0.63 | 677 |
| 2006 | 79.10 | 0.70 | 7078 | 133.70 | 0.60 | 988 | 96.19 | 0.51 | 760 |
| 2007 | 116.50 | 0.50 | 7542 | 257.50 | 0.50 | 1034 | 129.42 | 0.51 | 877 |
| 2008 | 47.40 | 1.20 | 7664 | 123.40 | 0.90 | 1007 | 45.97 | 1.33 | 974 |
| 2009 | 92.30 | 0.70 | 7869 | 245.80 | 0.70 | 996 | 86.61 | 0.83 | 957 |
| 2010 | 129.00 | 0.70 | 8251 | 368.50 | 0.60 | 994 | 98.16 | 0.69 | 834 |
| 2011 | 106.40 | 0.80 | 8116 | 533.60 | 0.70 | 756 | 63.06 | 1.03 | 800 |
| Average | 107.86 | 0.75 | 4239 | 164.98 | 0.71 | 779 | 85.68 | 0.75 | 436 |

Eastern Europe sample. The mean firm size is close to $108 million dollars in Asia, $165 million in Latin America, and about $86 million in Eastern Europe. The mean B/M ratio is about 0.70 regardless of the region. Our sample gets considerably larger in the latter part of our sample period.

### *3.1. Calculation of asset pricing factors*

We consider four factors which we use as explanatory variables in our asset pricing regressions as given in Eqs. (1), (2), and (3). These factors are the market factor, the small minus big (SMB) factor, the high minus low (HML) factor, and the momentum (WML) factor. We described each of these factors in Section 2.1. We calculate the factors for each of the three regions as well as the All-Emerging markets. This requires us to double sort on size and the B/M ratio and to do the same for size and momentum. Following the literature, we always use the 6-month lagged value of the B/M ratio to make sure that the accounting information is available to the investor at the time of the portfolio sort. For all three regions the market factor is simply the value-weighted average of the returns of all stocks in the region. For All-Emerging markets, the market factor is calculated in the same way.

Next, we detail the calculations of SMB, HML, and WML which closely follow Fama and French (2012). For Asia, Latin America, and Eastern Europe, we form six portfolios to calculate the regional SMB and HML factors. We first classify the largest market capitalization stocks which constitute the 90% of the region's total market capitalization as big stocks. All remaining stocks in the region are classified as small stocks. Then, for the region's big stocks, we determine the usual bottom 30% (growth), middle 40% (neutral), and top 30% (value) breakpoints for the B/M ratio and apply these breakpoints to big and small stocks. These classifications allow us to form the six value-weighted portfolios which we denote by SG, SN, SV, BG, BN, and BV, where S and B indicate small or big, and G, N, and V indicate growth, neutral, and value. The size factor, SMB, is the equal-weighted average of the returns for the three small stock portfolios minus the average of the returns for the three big stock portfolios. We construct value minus growth returns for small and big stocks, $HML_S$ = SV minus SG and $HML_B$ = BV minus BG, and HML is the equal-weighted average of $HML_S$ and $HML_B$.

The calculation of the WML factor is identical to the calculation of the HML factor except that the second sort at time $t$ is made not on the stock's B/M ratio but on the prior year's return (excluding the last month, $t-1$). For portfolios formed at the end of month $t$, the prior year's return (lagged momentum) is a stock's cumulative return from $t-2$ to $t-12$, where the last month is omitted. The intersection of the independent size and lagged momentum sorts results in six value-weight portfolios, SL, SN, SW, BL, BN, and BW, where S and B indicate small or big, and L, N, and W indicate losers, neutral, and winners (bottom 30%, middle 40% and top 30% of lagged momentum, respectively). We form winner minus loser returns of small and big stocks, $WML_S = SW - SL$ and $WML_B = BW - BL$, and WML is the equal-weighted average of $WML_S$ and $WML_B$. The reason why the B/M or momentum breakpoints come from the region's big stock universe is to prevent the sorts from being driven by the characteristics of stocks of small capitalization firms.

For All-Emerging markets, the factors are calculated in the same way as described above, but using the same methodology as Fama and French (2012), the B/M ratio or momentum breakpoints are calculated separately for each region to mitigate any effects of differences in accounting rules across the three regions. In particular, all stocks included in the entire set of 18 countries are sorted by market capitalization and then the largest market capitalization stocks which constitute 90% of the total market capitalization are classified as big stocks. The remaining stocks are small stocks.

To classify stocks into value, neutral, or growth categories, we use the same classification that would result from the procedure described for calculating factors for individual regions. In particular, focusing on the region's largest stocks constituting 90% of the region's total market capitalization, we determine the usual bottom 30% (growth), middle 40% (neutral), and top 30% (value) breakpoints for the B/M ratio and apply these breakpoints to all of the region's stocks. Intersecting the size classification, which is made for all the three regions combined, with the B/M ratio classification that is made region-specific, allows us to sort the entire universe of emerging market stocks into six value-weighted portfolios which we denote by SG, SN, SV, BG, BN, and BV. These six portfolios are then used to calculate the HML factor for All-Emerging markets. Calculation of the WML factor for All-Emerging markets is identical to the HML factor calculation, except that B/M ratio is used in lieu of the prior year's return.

### 3.2. Formation of size and B/M ratio, and size and momentum sorted portfolios

We work with 25 portfolios based on $5 \times 5$ sorts on size and B/M as well as size and momentum, calculated separately for each of the three regions, and All-Emerging markets. Then, using our asset pricing models we try to explain the returns of these portfolios. Following the literature, the B/M ratio sorts are made based on the ratio's value six months before the date of the portfolio sorts. The momentum sorts are based on the cumulative returns between $t-12$ and $t-2$.

The portfolio formation process follows Fama and French (2012) closely with only one slight modification. The modification is necessary in order to adapt the procedure they describe for developed markets to the case of emerging markets where the market capitalizations are significantly smaller. Fama and French make sure that for the developed markets that they consider, the size breakpoints roughly correspond to the quintile values of the NYSE component stocks. For emerging markets, the NYSE size quintile values are simply too large, leaving only a very small number of firms in the top size quintile. To deal with this issue, we adopt a market share based approach. The objective of this approach is to make sure that for each month, our five size groups in a region have approximately the same shares of the total regional market capitalization as the U.S. (NYSE, AMEX, and NASDAQ stocks) size groups do based on sorts by applying the NYSE quintile size breakpoints as described in Fama and French (1993, 1996). We define our target quintile weights as the monthly market shares of U.S. size quintiles based on the NYSE size breakpoints.

For each of the three regions, we sort stocks based on market capitalization and then choose the breakpoints such that the market shares of each size quintile are closest to the month's target quintile weights. Next, based on the region's big stocks, we calculate the 20, 40, 60, and 80 percentile B/M ratio breakpoints. Big stocks are defined to be the region's largest market capitalization stocks which constitute a certain share of the region's total market capitalization. The share is the same as the market share of U.S. stocks exceeding the NYSE median in total US market capitalization for that month. The two independent sorts, allow us to place all stocks in the region into one of 25 value-weighted size-B/M portfolios. Formation of the 25 size-momentum portfolios is identical, except that lagged momentum return is used in lieu of the B/M ratio.

For All-Emerging markets, when forming the size quintiles, we follow the same procedure as the individual regions. In particular, we sort the entire set of stocks in all of the 18 countries based on market capitalization and choose the breakpoints such that the market shares of each size quintile are closest to the month's target quintile weights. However, because the B/M ratio and momentum breakpoints are region specific, in order to calculate region specific B/M ratio breakpoints, we calculate the 20%, 40%, 60%, and 80% percentile values of B/M ratio for the largest regional stocks constituting a certain share of the regional market. The share is the same as the market share of U.S. stocks larger than the NYSE median in total U.S. market capitalization for that month. Intersecting the size sorts that come from all 18 countries taken together, and the B/M ratio sorts that are region specific, we place all stocks in the 18 countries into one of the 25 value-weighted size-B/M portfolios. Formation of the 25 size-momentum portfolios is identical, except that prior year's return is used instead of the B/M ratio.

## 4. Results

In this section we present our empirical results.

### *4.1. Factor returns*

The six panels in Table 2 show the means and standard deviations for the factor returns for each of the three regions, All-Emerging markets, the U.S., and the Global Developed markets. The *t*-statistics shown in the table are for determining if the average factor return is zero based on the Newey and West (1987) procedure allowing for six lags.

Let's look first at the value effect based on the returns for small and big stocks or equivalently the statistically significance of HML. For all three regions and for All-Emerging markets, HML is positive and statistically at the 5% level, as well as being economically significant. The monthly effects are 1.03%, 0.66%, and 1.88% in Asia, Latin America, and Eastern Europe, respectively. For All-Emerging markets, the value effect is 1.15%. When considering small and big stocks together, not only is the value effect for the U.S. and Global Developed markets smaller in magnitude – 0.30% and 0.40% per month, respectively – but they also have lower *t*-statistics.

Turning to the value effect calculated for small stocks ($HML_S$) and big stocks ($HML_B$) separately, the value premia for both are almost always statistically significant with values that appear similar for all emerging markets. In fact, the *t*-tests imply that the mean premia across small and big stocks in any of the three emerging regions as well as the All-Emerging markets are indistinguishable (i.e., the *t*-statistics in Table 2 for $HML_{S-B}$ are statistically insignificant). These results contrast with what we find for the U.S. and the Global Developed markets where the value premia are much larger for small stocks and statistically significant. For big stocks, in the U.S. and the Global Developed markets, the value premia are small and statistically insignificant. In further support of this result for the value premia point estimates for the U.S. and the Global Developed markets, the *t*-test comparing small and big stock's value premia shows that the small stock value premia are significantly larger than the big stock value premia, with $HML_{S-B}$ *t*-statistics of 2.79, and 2.59, respectively.

Considering small and big stocks together, we find a momentum effect (as measured by WML) for Asia, Latin America, and the All-Emerging markets (i.e., WML means are positive and statistically significant). We do not find a momentum effect for Eastern Europe (i.e., WML mean is insignificant). The mean monthly value of WML is 0.93%, 0.96% for both Asia and Latin America, and −0.41% for Eastern Europe.[4] The momentum effect is strongly present for the All-Emerging markets (the monthly mean WML is a statistically significant 0.86%). For the U.S. and Global Developed markets, we find that the monthly means are 0.55% and 0.63%, respectively, with corresponding *t*-statistics of 1.57 and 2.16.

We can compare the momentum effects separately for small and big stocks. For Asia, Latin America, and All-Emerging markets, the small stock momentum premia point estimates are larger than for big stocks. Moreover, although the small stock premia are significant, the large stock premia are not. The same pattern is found for the U.S. and Global Developed markets. In the U.S., the small stock and big momentum premia are 0.70% (*t*-statistic 1.81), and 0.40% (*t*-statistic 1.17). For the Global Developed, the small and big stock

[4] In recent work, Chui et al. (2010) argue that individualism is positively correlated with the magnitude of momentum profits. They find that Turkey (a large part of our Eastern Europe region) is one of the few countries with a negative momentum effect, a finding partly explained by the low value of the individualism index reported for that country.

**Table 2**
Means, standard deviations, and *t*-statistics for asset pricing factors. The table reports the percent means and standard deviations (Std. Dev.) of the asset pricing factors calculated for the emerging regions, as well as the U.S. and the Global Developed region. Emerging regions are Asia, Latin America, and Eastern Europe. All-Emerging region includes the three emerging regions together. Emerging region factor returns are calculated using stock level data from Datastream; factors for U.S. and Global Developed region are obtained from Kenneth French's website. Countries in each region are given in Section 3 of the paper. All returns are converted into U.S. dollars before forming the portfolios. Market − $R_f$ is the return on the value weighted market minus the U.S. one month T-bill rate. SMB is the small minus big factor, HML is the high minus low factor, and WML is the momentum factor. *S* and *B* stand for small stocks and big stocks respectively: for example $HML_S$ is the high minus low factor for small stocks. $HML_{S-B}$ refers to the $HML_S - HML_B$. The same definition applies to $WML_{S-B}$. The factor calculations are detailed in Section 3.1 of the paper. The table also reports the *t*-statistics (*t*-stat.) calculated for the means using the Newey and West (1987) procedure allowing up to six lags. Data period for the returns is from January 1991 to December 2011.

| | Market − $R_f$ | SMB | HML | $HML_S$ | $HML_B$ | $HML_{S-B}$ | WML | $WML_S$ | $WML_B$ | $WML_{S-B}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| *Asia* | | | | | | | | | | |
| Mean | 0.40 | 0.42 | 1.03 | 1.04 | 1.03 | 0.01 | 0.93 | 1.01 | 0.85 | 0.15 |
| Std. Dev. | 6.50 | 3.31 | 5.74 | 6.85 | 5.78 | 5.36 | 6.52 | 7.55 | 6.61 | 5.62 |
| *t*-stat. | 0.75 | 1.98 | 2.55 | 2.12 | 2.63 | 0.03 | 2.00 | 1.98 | 1.76 | 0.44 |
| *Latin America* | | | | | | | | | | |
| Mean | 1.02 | 0.43 | 0.66 | 0.48 | 0.83 | −0.34 | 0.96 | 1.17 | 0.75 | 0.42 |
| Std. Dev. | 7.72 | 4.40 | 4.36 | 4.52 | 6.59 | 7.18 | 6.12 | 6.19 | 8.27 | 7.99 |
| *t*-stat. | 1.66 | 1.84 | 2.16 | 1.63 | 1.79 | −0.70 | 2.07 | 2.27 | 1.40 | 0.84 |
| *Eastern Europe* | | | | | | | | | | |
| Mean | 1.27 | 0.24 | 1.88 | 1.76 | 2.01 | −0.25 | −0.25 | −0.41 | −0.10 | −0.32 |
| Std. Dev. | 12.47 | 6.47 | 8.25 | 10.61 | 10.42 | 13.04 | 9.78 | 11.16 | 12.17 | 12.77 |
| *t*-stat. | 1.48 | 0.63 | 3.60 | 2.83 | 3.03 | −0.34 | −0.38 | −0.55 | −0.12 | −0.39 |
| *All-Emerging* | | | | | | | | | | |
| Mean | 0.49 | 0.28 | 1.15 | 1.06 | 1.23 | −0.16 | 0.86 | 0.98 | 0.74 | 0.24 |
| Std. Dev. | 6.28 | 3.06 | 4.87 | 5.71 | 5.35 | 5.25 | 5.55 | 6.54 | 5.98 | 5.81 |
| *t*-stat. | 0.97 | 1.33 | 3.13 | 2.54 | 3.17 | −0.47 | 2.02 | 2.06 | 1.63 | 0.65 |
| *U.S.* | | | | | | | | | | |
| Mean | 0.57 | 0.28 | 0.30 | 0.57 | 0.03 | 0.55 | 0.55 | 0.70 | 0.40 | 0.30 |
| Std. Dev. | 4.51 | 3.46 | 3.32 | 3.84 | 3.41 | 2.93 | 5.23 | 5.40 | 5.51 | 3.12 |
| *t*-stat. | 1.81 | 1.48 | 1.22 | 2.05 | 0.11 | 2.79 | 1.57 | 1.81 | 1.17 | 1.36 |
| *Global Developed* | | | | | | | | | | |
| Mean | 0.39 | 0.09 | 0.40 | 0.62 | 0.18 | 0.44 | 0.63 | 0.85 | 0.42 | 0.43 |
| Std. Dev. | 4.43 | 2.15 | 2.43 | 2.72 | 2.69 | 2.38 | 4.15 | 4.03 | 4.62 | 2.51 |
| *t*-stat. | 1.23 | 0.68 | 1.81 | 2.51 | 0.79 | 2.59 | 2.16 | 2.80 | 1.36 | 2.58 |

premia are 0.85% and 0.42% with corresponding *t*-statistics of 2.80 and 1.36. For Eastern Europe, momentum average returns are negative, and more so for small stocks. However, neither premium is indistinguishable from zero. In short, with the exception of Eastern Europe, for all regions and markets studied, the small stock momentum premia tend to drive the results for the broader market (i.e., the market that includes both small and big stocks). However, despite larger momentum premia point estimates for small stocks, the *t*-tests do not allow us to distinguish between the small and large stock momentum premia: $WML_{S-B}$ *t*-statistics are insignificant with the exception of the Global Developed market.[5]

We are also interested in the correlations between the factors in a given region because these correlations are important for an investor who is interested in pursuing market, value, and momentum strategies with a geographical focus. The correlations are reported in Table 3. The excess market returns (Market − $R_f$), and WML are negatively correlated in all of the markets investigated in this study. Value and momentum are also consistently negatively correlated for the markets investigated, with correlations ranging from −10.10%

5 Recent work by Bandarchuk and Hilscher (2012) shows that sorting U.S. stocks based on size and momentum entails essentially sorting based on momentum alone, since size correlates significantly with past momentum. Therefore the larger momentum profits reported for small stocks cannot be safely attributed to size per se. The implication for our paper is as follows. The finding that $WML_{S-B}$ has an insignificant *t*-statistic in the emerging markets shows either that size per se does not matter for momentum, or emerging market small stocks simply have similar past momentum than big stocks.

(Eastern Europe) to −26.16% (All-Emerging markets). This finding is consistent with those of Asness et al. (2009) who report negative correlations between the value and momentum returns in developed equity markets and show that a simple equal-weighted portfolio of value and momentum returns has lower volatility and a higher Sharpe ratio relative to value or momentum returns alone. Our study suggests that the same is true in the case of emerging markets. Fig. 1 shows a plot of the cumulative returns from January 1991 to December 2011 for Market − $R_f$, HML and WML, as well as a combination strategy equal-weighted in HML and WML for All-Emerging markets (Panel A), U.S. (Panel B), and the Global Developed market (Panel C). In all cases, this strategy seems to offer steadier and higher returns.

Correlations of the factor returns between any two regions are an interesting statistic to look at, especially for portfolios with exposure to multiple regions that is managed using a fixed style following market, value, or momentum strategies. Focusing on Market − $R_f$, the average of the three correlations between Asia, Latin America, and Eastern Europe is 49% (see Panel A of Table 4). The average of the HML correlations for the three emerging regions is 8% and the average of the WML correlations is 17%. The low value and momentum factor correlations across the emerging regions offer the potential for multi-region diversification.[6]

It is also interesting, especially for an investor with holdings of the U.S. stocks, to consider emerging market factor correlations with the same factor calculated for the U.S. For the Market − $R_f$, the average correlation of Asia, Latin America, and Eastern Europe is 55%, for HML a mere 1%, and for WML, 27%. The low value and momentum factor correlations with the U.S. provide a reason for internationally diversifying value and momentum strategies.

Finally, we test whether the momentum and value strategy returns are distinguishable across the regions. This exercise is of interest to a style investor seeking to identify the most attractive region to implement a value or a momentum strategy. Panel B of Table 4 focuses on Market − $R_f$, SMB, HML, and WML, and reports the *t*-statistics for distinguishing between the factor means in pairs of regions. Looking at HML, at the 5% significance level, we see that the value effect for Eastern Europe is statistically larger than that for Latin America, the U.S., and the Global Developed markets. The All-Emerging markets value effect is marginally significantly larger than the U.S. and Global Developed markets, with *t*-statistics of 1.95 and 1.83, respectively. As for the momentum effect, it is not possible to distinguish between the means in any pair of regions (i.e., all the *t*-statistics are insignificant). The importance of this result for investors seeking to pursue a momentum strategy is that, in fact, Eastern Europe might have just as much momentum premia as any of the other markets. Sampling variation is simply too large to tell.[7]

### *4.2. Portfolios formed on size and B/M and size and momentum*

Table 5 reports the means and standard deviations of 25 portfolios formed based on size and the B/M ratio for all markets studied. The average returns for the 25 portfolios provide a more detailed picture of the results reported for the HML in Section 4.1 and Table 2. For all of the emerging markets, the value effect is present for the five size groups considered: extreme value stocks have higher mean returns than extreme growth stocks.[8] This result explains the positive and statistically significant HML means for all regions.

A second finding is that the magnitudes of the value premia appear fairly similar across the region's size groups. For example, the value premia in Asia are 2.12% (1.80% + 0.32%) for the smallest size group and 1.39% (1.23%+0.16%) for the biggest. For All-Emerging markets, the value are 1.56% (1.87%–0.31%) and 1.58% (1.45%+0.13%) for the smallest and the biggest size groups. A similar finding for the value premia for small and big stocks explains the insignificant *t*-statistics for $HML_{S-B}$ reported in Table 2 and, indeed, contrasts with the findings reported for the U.S. and Global Developed markets reported in the same table (i.e., $HML_{S-B}$ for both are positive and statistically significant).[9] Finally, all of the

[6] Non-synchroneity of stock returns can potentially bias our correlation results. To address this bias, we calculated the correlations in Tables 3 and 4 using quarterly data instead of monthly. The results, available from the authors upon request, indicated that the qualitative conclusions are unaffected. We are grateful to the anonymous referee for raising this issue.

[7] Return variances are high in emerging markets, making the same result true for Market − $R_f$ and SMB (small minus big) factors. In particular, Panel B of Table 4 shows that it is not possible to statistically distinguish between average market return in excess of the U.S. Treasury bill return across any pair of regions. Moreover, SMB is also indistinguishable across any pair of regions.

[8] The only one exception is for Latin America's fourth largest size group.

[9] Fama and French (1993, 2012), Kothari et al. (1995), and Loughran (1997) find larger value premia for small stocks at least for the U.S.

**Table 3**
Correlations between Market − Rf, SMB, HML, and WML factors in the same region: Emerging, U.S. or the Global Developed. The table reports the correlations between the Market − $R_f$, SMB, HML, and WML asset pricing factors in the same emerging region, U.S. or the Global Developed region. Emerging regions are Asia, Latin America, and Eastern Europe. All-Emerging region includes the three emerging regions together. Emerging region factor returns are calculated using stock level data from Datastream; factors for U.S. and Global Developed region are obtained from Kenneth French's website. Countries in each region are given in Section 3 of the paper. All returns are converted into U.S. dollars before forming the portfolios. Market − $R_f$ is the return on the value weighted market minus the U.S. one month T-bill rate. SMB is the small minus big factor, HML is the high minus low factor, and WML is the momentum factor. The factor calculations are detailed in Section 3.1 of the paper. Data period for the returns is from January 1991 to December 2011.

| | SMB | HML | WML | SMB | HML | WML |
|---|---|---|---|---|---|---|
| | Asia | | | Latin | | |
| Market − $R_f$ | 0.02 | 0.15 | −0.11 | −0.42 | 0.01 | −0.19 |
| SMB | | −0.19 | −0.35 | | −0.12 | 0.18 |
| HML | | | −0.24 | | | −0.20 |
| | Eastern Europe | | | All-Emerging | | |
| Market − $R_f$ | −0.35 | −0.07 | −0.18 | −0.20 | 0.20 | −0.15 |
| SMB | | −0.07 | −0.05 | | −0.15 | −0.21 |
| HML | | | −0.10 | | | −0.26 |
| | U.S. | | | Global Developed | | |
| Market − $R_f$ | 0.24 | −0.24 | −0.25 | −0.01 | −0.15 | −0.22 |
| SMB | | −0.34 | 0.08 | | −0.19 | 0.18 |
| HML | | | −0.15 | | | −0.25 |

emerging market returns have higher volatilities than the U.S. and the Global Developed markets. Particularly striking is that while the volatilities of the Eastern European portfolios formed on size and B/M ratio tend to be around 15%, the volatilities are around 5% to 10% for the U.S. and 5% to 6% for Global Developed markets.

Table 6 reports the means and standard deviations of 25 portfolios constructed based on size and momentum. The results for the average return clearly show the presence of momentum in Asia, Latin America, and the All-Emerging markets. That is, with the exception of the third and fourth size groups for Latin America, extreme high momentum portfolios have higher means than extreme low momentum portfolios across all size groups. This result explains the positive and statistically significant WML means reported in Section 4.1. For Eastern Europe, often *low* momentum portfolios have higher means, which explains why in Table 2 the WML mean for that region is statistically insignificant and negative. It appears that higher momentum premia are typical for small stocks. For example, in Asia, the momentum premium is 0.86% (1.74%–0.88%) and 0.52% (0.62%–0.10%) for the smallest and biggest size groups, respectively. In Latin America, the momentum premium is 1.41% and 0.04% for the smallest and biggest size groups, respectively. The corresponding values for All-Emerging markets are 0.50% and 0.40%. The larger momentum premia finding for the small stocks in emerging markets corroborates the momentum premium results for the developed markets reported by Fama and French (2012).

### 4.3. Asset pricing tests

Here we describe two asset pricing tests based on (1) size and B/M ratio and (2) size and momentum.

#### 4.3.1. Size and B/M ratio cross-sections

Table 7 reports the results of asset pricing regressions given in Eqs. (1), (2), and (3) where we try to explain the returns for the 25 portfolios formed on the basis of size and B/M ratio. We use four sets of 25 portfolios comprising the stocks in Asia, Latin America, Eastern Europe, and All-Emerging markets. As our explanatory factors, we use local, U.S., and Global Developed factors. We calculate the local factors as

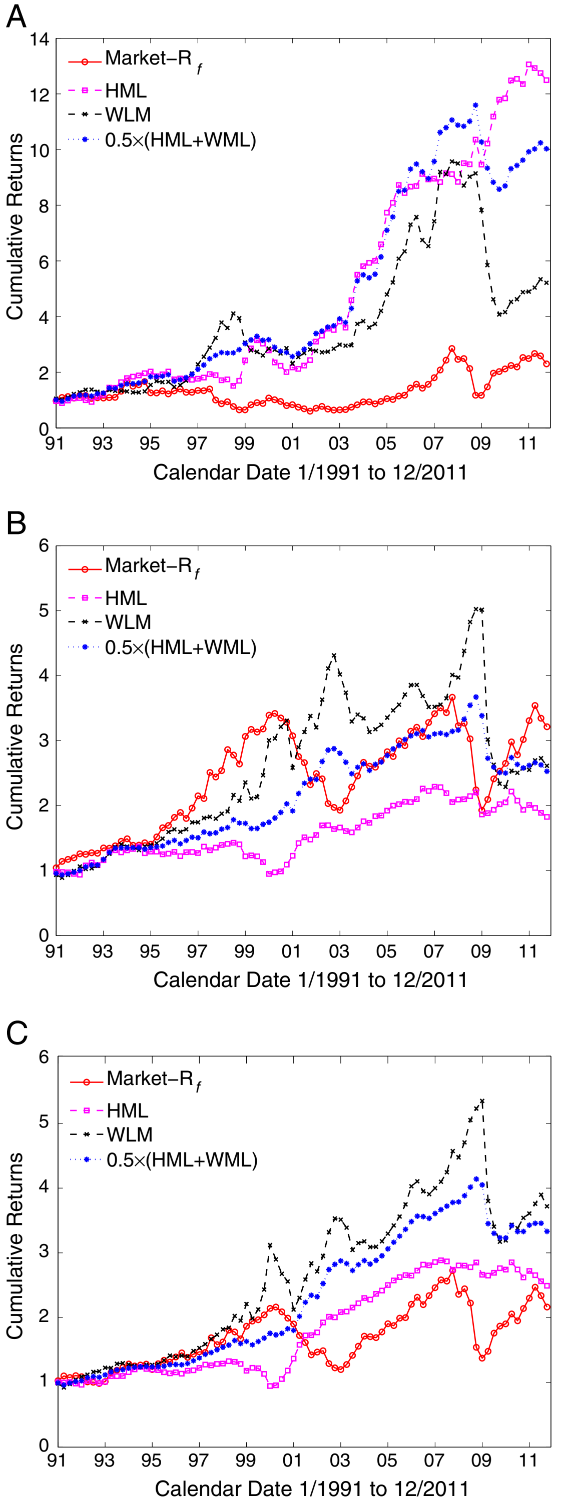
A
Market−R f
HML
WLM
0.5×(HML+WML)
Cumulative Returns
Calendar Date 1/1991 to 12/2011
B
Market−R f
HML
WLM
0.5×(HML+WML)
Cumulative Returns
Calendar Date 1/1991 to 12/2011
C
Market−R f
HML
WLM
0.5×(HML+WML)
Cumulative Returns
Calendar Date 1/1991 to 12/2011

**Table 4**

Correlations between the same factor but in Different Regions and *t*-statistics for testing if the same factor has different means in different regions. Panel A reports the correlations of the same factor but in different regions: Emerging, U.S. and the Developed Global region. Panel B reports the *t*-statistics for testing if the same factor has different means in any two regions. In Panel B, the *t*-statistics are for the mean of the region indicated in the row heading minus the mean of the region indicated in the column heading. Factors are the Market − $R_f$, SMB, HML, and WML. Emerging regions are Asia, Latin America, and Eastern Europe. All-Emerging region includes the three emerging regions together. Emerging region factor returns are calculated using stock level data from Datastream; factors for U.S. and Global Developed region are obtained from Kenneth French's website. Countries in each region are given in Section 3 of the paper. All returns are converted into U.S. dollars before forming the portfolios. Market − $R_f$ is the return on the value weighted market minus the U.S. one month T-bill rate. SMB is the small minus big factor, HML is the high minus low factor, and WML is the momentum factor. The factor calculations are detailed in Section 3.1 of the paper. Data period for the returns is from January 1991 to December 2011.

| | Latin America | Eastern Europe | All-Emerging | U.S. | Global Developed | Latin America | Eastern Europe | All-Emerging | U.S. | Global Developed |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Correlations of factor returns across regions | | | | | | | | | | |
| | Market − $R_f$ | | | | | SMB | | | | |
| Asia | 0.62 | 0.42 | 0.94 | 0.56 | 0.61 | 0.16 | 0.04 | 0.83 | 0.00 | 0.15 |
| Latin America | | 0.43 | 0.83 | 0.66 | 0.65 | | 0.21 | 0.49 | −0.09 | 0.10 |
| Eastern Europe | | | 0.53 | 0.44 | 0.48 | | | 0.22 | −0.02 | 0.03 |
| All-Emerging | | | | 0.67 | 0.70 | | | | −0.04 | 0.13 |
| U.S. | | | | | 0.92 | | | | | 0.76 |
| | HML | | | | | WML | | | | |
| Asia | 0.10 | 0.12 | 0.90 | 0.01 | 0.03 | 0.16 | 0.14 | 0.92 | 0.28 | 0.30 |
| Latin America | | 0.02 | 0.36 | −0.02 | 0.03 | | 0.21 | 0.45 | 0.26 | 0.29 |
| Eastern Europe | | | 0.25 | 0.04 | 0.12 | | | 0.28 | 0.28 | 0.32 |
| All-Emerging | | | | 0.04 | 0.08 | | | | 0.34 | 0.37 |
| U.S. | | | | | 0.87 | | | | | 0.91 |
| Panel B: *t*-statistics testing if factor means are equal in two regions: Row minus column | | | | | | | | | | |
| | Market − $R_f$ | | | | | SMB | | | | |
| Asia | −1.23 | −1.31 | −0.48 | −0.35 | 0.00 | −0.04 | 0.66 | 1.18 | 0.51 | 1.44 |
| Latin America | | −0.37 | 1.70 | 0.93 | 1.28 | | 0.65 | 0.61 | 0.57 | 1.52 |
| Eastern Europe | | | 1.15 | 1.03 | 1.33 | | | −0.42 | −0.36 | 0.12 |
| All-Emerging | | | | −0.17 | 0.25 | | | | −0.02 | 0.85 |
| U.S. | | | | | 1.47 | | | | | 1.28 |
| | HML | | | | | WML | | | | |
| Asia | 0.89 | −1.32 | −0.81 | 1.55 | 1.41 | −0.05 | 1.04 | 0.35 | 0.88 | 0.73 |
| Latin America | | −2.13 | −1.55 | 0.86 | 0.68 | | 1.14 | 0.29 | 0.81 | 0.66 |
| Eastern Europe | | | 1.46 | 2.77 | 2.87 | | | −1.23 | −0.58 | −0.75 |
| All-Emerging | | | | 1.95 | 1.83 | | | | 0.76 | 0.59 |
| U.S. | | | | | −0.75 | | | | | −0.63 |

described in Section 3.1; the U.S. and Global Developed factors are obtained from Kenneth French's website. Comparing the results for the U.S. and Global Developed factors with local factors allows us to comment on the integration of local emerging markets with global capital markets. We report the GRS test statistic and the associated *p*-values (1 minus the cumulative distribution function value) for testing if all the regression intercepts are zero.

**Fig. 1.** Cumulative factor returns. Panels A to C plot the cumulative returns of the asset pricing factors calculated for the All-Emerging region, U.S., and the Global Developed region from January 1991 to December 2011. The All-Emerging region consists of Asia, Latin America, and Eastern Europe emerging regions all together. The factors are Market − $R_f$, HML and WML. Market − $R_f$ is the return on the value weighted market minus the U.S. one-month T-bill rate. HML is the difference between the returns on diversified portfolios of high B/M and low B/M stocks and represents the value factor. WML is the momentum factor measured by the difference between the returns on diversified portfolios of the winners and losers of the past year. A combination strategy equal-weight in HML and WML: 0.5 × (HML + WML) is also calculated. This paper calculates the All-Emerging region factor returns using stock level data from Datastream, whereas factors for the U.S. and the Global Developed markets are available from Kenneth French's website. Countries in each region are given in Section 3 of the paper. All returns are converted into US dollars before forming the portfolios. The factor calculations are detailed in Section 3.1 of the paper.

**Table 5**
Means and standard deviations of 25 portfolios formed on size and B/M. The table reports the means and the standard deviations of 25 portfolios formed on size and the book equity-to-market equity ratios (B/M) for the emerging regions as well as the U.S. and the Global Developed region. Emerging regions are Asia, Latin America, and Eastern Europe; All-Emerging region is the three emerging regions together. Firms are sorted into five size groups, from small to big, based on market capitalization. Firms are also sorted into five B/M groups, from low to high, based on the book equity to market equity ratio. We intersect the two sorts and value weight to obtain 25 portfolios. Section 3.2 of the paper details the portfolio formation procedure. Emerging region factor returns are calculated using stock level data from Datastream; factors for U.S. and Global Developed region are obtained from Kenneth French's website. Countries in each region are given in Section 3 of the paper. All returns are converted into U.S. dollars before forming the portfolios. Data period for the returns is from January 1991 to December 2011.

| | Mean | | | | | Standard Deviation | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| *Asia* | | | | | | | | | | |
| Small | −0.32 | 0.61 | 0.26 | 0.84 | 1.80 | 9.41 | 9.98 | 8.54 | 8.10 | 8.11 |
| 2 | −0.33 | 0.31 | 0.74 | 0.82 | 1.44 | 9.82 | 9.65 | 8.30 | 7.93 | 8.61 |
| 3 | 0.10 | 0.66 | 0.61 | 0.74 | 1.17 | 8.33 | 8.09 | 7.99 | 7.92 | 8.42 |
| 4 | 0.13 | 0.18 | 0.50 | 0.54 | 0.88 | 7.36 | 7.67 | 7.39 | 7.39 | 8.64 |
| Big | −0.16 | 0.05 | 0.30 | 0.56 | 1.23 | 6.82 | 6.99 | 6.97 | 6.93 | 8.89 |
| *Latin America* | | | | | | | | | | |
| Small | 1.30 | 0.67 | 0.77 | 1.10 | 2.28 | 8.24 | 7.02 | 6.97 | 6.72 | 7.89 |
| 2 | 1.37 | 0.88 | 0.56 | 1.37 | 2.80 | 9.78 | 8.42 | 7.62 | 10.47 | 11.11 |
| 3 | 1.13 | 0.68 | 1.19 | 1.09 | 2.04 | 9.40 | 8.32 | 7.41 | 8.00 | 7.93 |
| 4 | 1.64 | 0.90 | 1.07 | 1.14 | 1.19 | 10.04 | 8.17 | 7.52 | 8.57 | 7.81 |
| Big | −0.06 | 0.81 | 0.90 | 1.48 | 1.77 | 13.11 | 8.76 | 8.50 | 9.04 | 9.98 |
| *Eastern Europe* | | | | | | | | | | |
| Small | −0.44 | 1.30 | 2.27 | 2.69 | 3.02 | 14.33 | 15.60 | 15.90 | 15.95 | 12.80 |
| 2 | 1.10 | 0.69 | 1.17 | 2.35 | 1.92 | 13.84 | 16.25 | 13.97 | 16.39 | 12.46 |
| 3 | 0.49 | 0.46 | 0.47 | 1.40 | 1.69 | 12.73 | 13.50 | 12.86 | 14.43 | 13.14 |
| 4 | 0.49 | 1.44 | 0.20 | 0.86 | 2.64 | 14.19 | 14.24 | 12.38 | 13.96 | 14.55 |
| Big | 0.49 | 0.78 | 0.57 | 1.55 | 2.98 | 16.01 | 14.56 | 15.22 | 14.86 | 16.55 |
| *All-Emerging* | | | | | | | | | | |
| Small | 0.31 | 0.41 | 0.77 | 1.05 | 1.87 | 7.49 | 7.27 | 7.80 | 7.31 | 7.31 |
| 2 | 0.47 | 0.68 | 0.76 | 0.80 | 1.54 | 8.07 | 7.22 | 7.33 | 7.19 | 7.68 |
| 3 | 0.45 | 0.40 | 0.52 | 0.67 | 1.21 | 7.15 | 7.03 | 7.04 | 6.98 | 7.68 |
| 4 | 0.30 | 0.21 | 0.66 | 0.62 | 1.23 | 6.66 | 6.93 | 6.82 | 6.90 | 7.88 |
| Big | −0.13 | 0.31 | 0.39 | 0.62 | 1.45 | 6.56 | 6.72 | 6.87 | 7.14 | 8.37 |
| *U.S.* | | | | | | | | | | |
| Small | 0.35 | 1.05 | 1.18 | 1.27 | 1.30 | 9.27 | 7.84 | 6.33 | 5.93 | 6.51 |
| 2 | 0.67 | 0.94 | 1.12 | 1.01 | 1.04 | 7.94 | 6.28 | 5.72 | 5.83 | 6.72 |
| 3 | 0.60 | 0.97 | 1.07 | 0.96 | 1.31 | 7.37 | 5.83 | 5.38 | 5.55 | 5.79 |
| 4 | 0.89 | 0.96 | 0.87 | 1.05 | 0.82 | 6.62 | 5.45 | 5.66 | 5.33 | 5.90 |
| Big | 0.68 | 0.80 | 0.70 | 0.63 | 0.54 | 4.91 | 4.59 | 4.94 | 4.93 | 5.74 |
| *Developed Global* | | | | | | | | | | |
| Small | 0.36 | 0.67 | 0.94 | 1.02 | 1.31 | 5.93 | 5.51 | 5.13 | 4.67 | 4.41 |
| 2 | 0.34 | 0.65 | 0.80 | 0.87 | 0.99 | 5.86 | 5.25 | 4.73 | 4.46 | 4.57 |
| 3 | 0.49 | 0.61 | 0.75 | 0.82 | 0.96 | 5.75 | 5.24 | 4.69 | 4.48 | 4.69 |
| 4 | 0.63 | 0.65 | 0.75 | 0.83 | 0.91 | 5.65 | 4.66 | 4.56 | 4.52 | 4.84 |
| Big | 0.54 | 0.60 | 0.71 | 0.76 | 0.68 | 4.62 | 4.33 | 4.52 | 4.55 | 5.48 |

To account for possible autocorrelations and heteroscedasticity, we also report the *p*-values associated with our GMM-based test statistic which we construct to test the same hypothesis. In our GMM procedure, we allow error term autocorrelations up to six months. We can think of the *p*-values as the measure of the econometric success of the model. Additionally, we report the average of the absolute values of the regression intercepts, the average of the intercept standard errors (calculated using the Newey and West (1987) procedure with six lags), and the average regression $R^2$s. We refer to $SR(a) \equiv \hat{a}'\hat{\sum}^{-1}\hat{a}$ as the

**Table 6**
Means and Standard Deviations of 25 Portfolios Formed on Size and Momentum. The table reports the means and the standard deviations of 25 portfolios formed on size and lagged momentum for the emerging regions as well the U.S. and the Global Developed region. Emerging regions are Asia, Latin America, and Eastern Europe; All-Emerging region is the three emerging regions together. Firms are sorted into five size groups, from Small to Big, based on market capitalization. Firms are also sorted into five lagged momentum groups, from Low to High, based on the cumulative return from time $t-12$ to $t-2$. We intersect the two sorts and value weight to obtain 25 portfolios. Section 3.2 of the paper details the portfolio formation procedure. Emerging region factor returns are calculated using stock level data from Datastream; factors for U.S. and Global Developed region are obtained from Kenneth French's website. Countries in each region are given in Section 3 of the paper. All returns are converted into U.S. dollars before forming the portfolios. Data period for the returns is from January 1991 to December 2011.

| | Mean | | | | | Standard deviation | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | High | Low | 2 | 3 | 4 | High |
| *Asia* | | | | | | | | | | |
| Small | 0.88 | 1.06 | 1.32 | 1.56 | 1.74 | 9.22 | 6.71 | 6.51 | 7.03 | 8.68 |
| 2 | 0.50 | 0.58 | 1.13 | 1.51 | 1.45 | 9.74 | 7.14 | 6.71 | 7.26 | 8.99 |
| 3 | 0.22 | 0.32 | 0.82 | 1.11 | 1.18 | 9.33 | 7.02 | 6.72 | 7.11 | 8.82 |
| 4 | 0.09 | −0.07 | 0.46 | 0.84 | 1.10 | 9.38 | 6.91 | 6.42 | 6.92 | 8.27 |
| Big | 0.10 | −0.10 | 0.11 | 0.46 | 0.62 | 8.90 | 6.99 | 6.41 | 6.56 | 8.11 |
| *Latin America* | | | | | | | | | | |
| Small | 0.14 | 0.64 | 1.36 | 1.57 | 1.55 | 9.79 | 6.77 | 6.99 | 7.24 | 6.67 |
| 2 | −1.16 | 0.39 | 0.94 | 0.78 | 0.38 | 11.73 | 7.60 | 7.07 | 9.86 | 7.67 |
| 3 | 0.17 | 0.37 | 0.24 | 0.87 | −0.04 | 17.99 | 11.63 | 7.53 | 7.31 | 10.80 |
| 4 | 0.95 | 0.02 | 0.37 | 0.35 | 0.90 | 13.85 | 11.02 | 8.66 | 11.43 | 13.19 |
| Big | −0.23 | −0.63 | 0.01 | −0.14 | −0.19 | 11.04 | 11.82 | 9.35 | 11.73 | 10.52 |
| *Eastern Europe* | | | | | | | | | | |
| Small | 2.10 | 1.89 | 2.01 | 2.96 | 1.76 | 11.92 | 12.00 | 14.09 | 14.82 | 12.00 |
| 2 | 0.93 | 1.51 | 1.45 | 1.89 | 1.22 | 10.66 | 12.26 | 14.33 | 13.97 | 11.71 |
| 3 | 1.02 | 1.35 | 1.54 | 1.87 | 2.03 | 12.34 | 12.21 | 13.55 | 13.38 | 12.33 |
| 4 | 1.00 | 0.52 | 0.70 | 1.13 | 0.61 | 11.93 | 13.91 | 13.69 | 13.40 | 12.81 |
| Big | 1.47 | 0.33 | 0.27 | 0.88 | 0.72 | 13.71 | 16.74 | 14.05 | 14.01 | 12.33 |
| All-Emerging | | | | | | | | | | |
| Small | 1.09 | 0.98 | 1.23 | 1.68 | 1.59 | 8.88 | 6.73 | 6.35 | 6.26 | 7.19 |
| 2 | 0.50 | 0.77 | 1.15 | 1.31 | 1.69 | 8.72 | 6.75 | 6.44 | 6.88 | 7.85 |
| 3 | 0.17 | 0.37 | 0.80 | 1.11 | 1.34 | 8.65 | 6.73 | 6.35 | 6.54 | 7.52 |
| 4 | 0.01 | 0.27 | 0.50 | 0.88 | 1.27 | 8.27 | 6.85 | 6.23 | 6.42 | 7.31 |
| Big | 0.45 | −0.06 | 0.33 | 0.63 | 0.85 | 8.36 | 6.70 | 6.75 | 6.45 | 7.37 |
| *U.S.* | | | | | | | | | | |
| Small | 0.62 | 1.04 | 1.23 | 1.49 | 1.86 | 9.04 | 5.77 | 5.03 | 5.08 | 6.88 |
| 2 | 0.79 | 1.07 | 1.19 | 1.31 | 1.55 | 9.04 | 6.11 | 5.05 | 5.12 | 7.06 |
| 3 | 0.92 | 0.98 | 1.11 | 1.13 | 1.37 | 8.51 | 5.67 | 4.92 | 4.76 | 6.49 |
| 4 | 0.68 | 1.02 | 1.08 | 1.08 | 1.23 | 8.65 | 5.62 | 4.65 | 4.39 | 5.93 |
| Big | 0.50 | 0.82 | 0.74 | 0.95 | 1.04 | 7.78 | 5.26 | 4.22 | 4.10 | 5.19 |
| *Developed Global* | | | | | | | | | | |
| Small | 0.35 | 0.87 | 1.00 | 1.35 | 1.74 | 6.45 | 4.40 | 3.99 | 4.11 | 5.49 |
| 2 | 0.34 | 0.71 | 0.77 | 1.00 | 1.31 | 6.72 | 4.67 | 4.21 | 4.24 | 5.60 |
| 3 | 0.46 | 0.69 | 0.79 | 0.83 | 1.07 | 6.68 | 4.93 | 4.28 | 4.21 | 5.57 |
| 4 | 0.45 | 0.68 | 0.75 | 0.81 | 1.12 | 6.62 | 4.79 | 4.23 | 4.27 | 5.40 |
| Big | 0.33 | 0.55 | 0.63 | 0.76 | 0.83 | 6.29 | 4.60 | 4.13 | 4.24 | 5.42 |

unexplained squared Sharpe ratio and report this value in Table 7. Larger values of $SR(a)$ indicate poorer economic performance for the model.[10]

[10] Gibbons et al. (1989) show that $SR(a)$ is the difference between the squared Sharpe ratios of the maximum Sharpe ratio portfolio constructed using the returns of the portfolios to be explained in conjunction with the returns of the explanatory factors, and the maximum Sharpe ratio portfolio constructed using the returns of the explanatory factors only. Lewellen et al. (2010) suggest using confidence intervals for $SR(a)$ as a more intuitive measure of model performance.

**Table 7**

Asset pricing test summary statistics of 25 portfolios formed on size and B/M. The table reports the regression results for the CAPM, three-factor, and the four-factor models. We try to explain the returns of the 25 portfolios formed on size and B/M in emerging regions, U.S. and the Global Developed region. We use asset pricing factors calculated using local, U.S. or Developed Global stock markets data to explain them. Emerging regions are Asia, Latin America, and Eastern Europe; All-Emerging region is the three emerging regions together. GRS and GMM test statistics are described in Section 3. cdf refers to the cumulative distribution function. |a| and $R^2$ refer to the average absolute value of regression intercepts and $R^2$s. Finally, $s(a)$ and $SR(a)$ refer to the average regression intercept standard deviations and the unexplained squared Sharpe ratio. These variables are detailed in Section 4.3.1. Data period for the returns is from January 1991 to December 2011.

| | GRS | GRS-cdf | GMM-cdf | \|a\| | $R^2$ | $s(a)$ | $SR(a)$ | GRS | GRS-cdf | GMM-cdf | \|a\| | $R^2$ | $s(a)$ | $SR(a)$ | GRS | GRS-cdf | GMM-cdf | \|a\| | $R^2$ | $s(a)$ | $SR(a)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Local factors | | | | | | | U.S. factors | | | | | | | Global Developed factors | | | | | | |
| | Asia | | | | | | | Asia | | | | | | | Asia | | | | | | |
| CAPM | 3.05 | 1.00 | 1.00 | 0.41 | 0.68 | 0.29 | 0.58 | 3.00 | 1.00 | 1.00 | 0.38 | 0.20 | 0.47 | 0.58 | 2.98 | 1.00 | 1.00 | 0.41 | 0.23 | 0.45 | 0.57 |
| Three-factor | 2.85 | 1.00 | 1.00 | 0.31 | 0.83 | 0.25 | 0.56 | 2.79 | 1.00 | 1.00 | 0.34 | 0.20 | 0.46 | 0.56 | 2.71 | 1.00 | 1.00 | 0.36 | 0.27 | 0.43 | 0.55 |
| Four-factor | 2.83 | 1.00 | 1.00 | 0.33 | 0.83 | 0.25 | 0.56 | 2.77 | 1.00 | 1.00 | 0.43 | 0.22 | 0.46 | 0.56 | 2.75 | 1.00 | 1.00 | 0.51 | 0.29 | 0.44 | 0.55 |
| | Latin America | | | | | | | Latin America | | | | | | | Latin America | | | | | | |
| CAPM | 2.07 | 1.00 | 1.00 | 0.49 | 0.55 | 0.38 | 0.48 | 2.11 | 1.00 | 1.00 | 0.72 | 0.25 | 0.49 | 0.48 | 2.18 | 1.00 | 1.00 | 0.86 | 0.26 | 0.48 | 0.49 |
| Three-factor | 1.67 | 0.97 | 0.98 | 0.32 | 0.66 | 0.31 | 0.43 | 2.01 | 1.00 | 0.97 | 0.60 | 0.26 | 0.49 | 0.47 | 2.12 | 1.00 | 0.96 | 0.74 | 0.27 | 0.49 | 0.48 |
| Four-factor | 1.88 | 0.99 | 1.00 | 0.34 | 0.66 | 0.32 | 0.46 | 2.13 | 1.00 | 0.99 | 0.64 | 0.26 | 0.50 | 0.49 | 2.29 | 1.00 | 0.97 | 0.76 | 0.27 | 0.50 | 0.50 |
| | Eastern Europe | | | | | | | Eastern Europe | | | | | | | Eastern Europe | | | | | | |
| CAPM | 2.29 | 1.00 | 1.00 | 0.80 | 0.49 | 0.66 | 0.50 | 2.27 | 1.00 | 1.00 | 0.83 | 0.14 | 0.85 | 0.50 | 2.31 | 1.00 | 1.00 | 0.91 | 0.15 | 0.84 | 0.51 |
| Three-factor | 1.73 | 0.98 | 1.00 | 0.53 | 0.59 | 0.59 | 0.44 | 2.21 | 1.00 | 1.00 | 0.82 | 0.13 | 0.87 | 0.50 | 2.26 | 1.00 | 0.99 | 0.95 | 0.16 | 0.86 | 0.50 |
| Four-factor | 1.80 | 0.99 | 0.99 | 0.55 | 0.60 | 0.58 | 0.45 | 2.23 | 1.00 | 1.00 | 0.90 | 0.14 | 0.88 | 0.50 | 2.38 | 1.00 | 0.99 | 1.11 | 0.16 | 0.88 | 0.51 |
| | All-Emerging | | | | | | | All-Emerging | | | | | | | All-Emerging | | | | | | |
| CAPM | 2.22 | 1.00 | 0.98 | 0.34 | 0.69 | 0.25 | 0.49 | 2.22 | 1.00 | 0.98 | 0.34 | 0.29 | 0.39 | 0.50 | 2.21 | 1.00 | 0.99 | 0.39 | 0.32 | 0.38 | 0.49 |
| Three-factor | 1.63 | 0.97 | 0.98 | 0.18 | 0.84 | 0.18 | 0.42 | 2.08 | 1.00 | 0.95 | 0.31 | 0.29 | 0.39 | 0.48 | 1.99 | 1.00 | 0.96 | 0.34 | 0.36 | 0.36 | 0.47 |
| Four-factor | 1.79 | 0.99 | 0.99 | 0.17 | 0.84 | 0.18 | 0.44 | 2.22 | 1.00 | 0.99 | 0.41 | 0.31 | 0.39 | 0.50 | 2.32 | 1.00 | 1.00 | 0.49 | 0.38 | 0.37 | 0.51 |

As can be seen in Table 7, according to the GRS statistic, all models – CAPM, three-factor model, and four-factor model – are rejected when we try to explain the returns of 25 portfolios sorted based on size and B/M ratio. The three models are rejected regardless of the region or whether the local, U.S. and Global Developed factors are used. The GRS *p*-values are always less than 3%, highlighting that the B/M ratio sorted portfolios are a challenge for asset pricing in emerging markets. The rejections are slightly weaker (as implied by larger *p*-values but still less than 5%) when using the local factors relative to the U.S. and the Global Developed factors. Therefore, from an econometric point of view, the models with local factors perform slightly better than U.S. and Global Developed factors.

From an economic perspective, however, using the local factors leads to drastically better performance, although still rejected statistically. This finding leads us to conclude that emerging stock markets are segmented from the U.S. or Global Developed economies.[11] To understand why the U.S. or the Global Developed factors have poorer economic performance, we can compare the average absolute value of the regression intercepts $|a|$, regression $R^2$s, intercept standard deviations, denoted by $s(a)$, and the model unexplained squared Sharpe ratios across the models. Using local factors, the average model intercepts, intercept standard deviations, and unexplained squared Sharpe ratios are a lot lower than when the U.S. or the Global Developed factors are used. Moreover, regressions using local factors have much higher $R^2$s relative to regressions using the U.S. or Global Developed factors. The intuition for this economic result is the same as given for the slightly weaker econometric result in the previous paragraph: emerging equity markets lack a degree of integration with the U.S. or Global Developed capital markets.[12]

We also find two other intuitive results. First, the three-factor model has much better performance than the CAPM as evidenced by lower intercepts, higher $R^2$s, lower intercept standard errors, and lower unexplained squared Sharpe ratios. Second, for the size and B/M cross-section, the four-factor model does not seem to improve much over and above the three-factor model: the economic performances across the two models are very close. These two results strongly suggest that the three-factor model is the best suited model for explaining the size and B/M cross-section. In general, for a given region and a set of explanatory factors (local, U.S. or Global Developed), the GRS statistics for the three-factor model are the lowest, supporting the model's better economic performance.

There is a sizeable literature exploring stock return statistics in emerging markets which document autocorrelation, heteroscedasticity, and predictability characteristics (see, for example, Harvey, 1995 and Bekaert and Harvey, 1997).[13] In the light of all of these results, it is useful to consider the results of a GMM-based test which is robust to potential serial autocorrelations, heteroscedasticity, and non-normality in

[11] Since both local and U.S. (or Developed Global) factor models are rejected, we cannot base our segmentation argument solely on econometric tests. Note, however, that consistent with segmentation we find that model rejections are weaker when we use local factors rather than U.S. or Developed Global factors.

[12] Other studies characterize the lack of complete integration. Bekaert and Harvey (1995), for example, propose a measure of capital market integration using a conditional regime-switching model. This measure is calculated for a total of 12 emerging markets as well as developed markets covering (for most countries) 1970 to 1992. They find a reasonable amount of segmentation, particularly for emerging markets. Focusing on emerging markets for the period 1995 to 2004, Chambeta and Gibson (2008) explore financial integration though a multivariate GARCH(1,1)-M return generating model. They conclude that emerging markets still remain to a large extent segmented. Exploring a somewhat similar specification to assess the evolution of market integration in emerging markets from 1977 to 2000, Carrieri et al. (2007) conclude that while local risks are still prevalent, none of the emerging markets appear completely segmented. Moreover, they find that emerging markets become more integrated through time, despite some episodic reversals. Bekaert and Harvey (2002, 2003) provide an extensive survey of the emerging markets finance literature, including the literature on integration. Bekaert et al. (2002) explore structural breaks in a number of financial and macroeconomic variables in emerging markets, showing that breaks are often dated after the official announcements of financial market reforms. Kearney (2012) provides an extensive literature review of the emerging markets research with many additional references related to the integration of emerging markets.

[13] Harvey (1995) reports that emerging market returns have positive and large monthly autocorrelations, whereas the autocorrelations are much closer to zero in developed markets. Bekaert and Harvey (1997) study the time variation of volatility in emerging markets. They present the results of GARCH models exploring whether the cross-sectional dispersion in volatility is related to a number of macroeconomic and microstructure variables as well as measures related to financial integration. Both papers report GMM results which almost always reject the normality assumption for emerging equity returns. In related work, Bekaert et al. (1998a) study the evolution of emerging stock market volatilities and find substantial time variation during the1980s and 1990s. Bekaert (1995) provides evidence for emerging market return predictability using variables such as lagged local dividend yield and excess market return using data from 1985 to 1992. Bekaert et al. (1998b) explore the implications of non-normal emerging market returns for asset allocation in a portfolio choice model.

the data. The GMM statistic, which we described in Section 2, is geared towards testing if all regression intercepts are jointly zero in regression Eqs. (1), (2), and (3).

Focusing on the GMM-based statistic allowing for serial correlations up to six months, we continue to reject at the 5% significance level all models, regardless of the region or whether the local, U.S. or Global Developed factors are used. This finding shows that the rejections using the GRS test statistic are robust with respect to the relaxation of the restrictive assumptions. However, with GMM it is no longer true that the local factor models always lead to weaker rejections (as implied by larger *p*-values, but still less than 5%) than the U.S. or Global Developed factors. For example, for All-Emerging markets, the *p*-value is 5% using the U.S. factors, and 2% using local factors. However, when moving to the U.S. factors from local factors, the improvements are minor, and certainly do not compensate for the great loss of economic performance. The GMM results discussed here highlight that while conclusions based on the econometric analysis about relative factor performance can be sensitive to the assumptions, the economic results strongly favor local factors.

#### 4.3.2. Size and momentum cross-sections

Table 8 reports the results of the same tests reported in Table 7 to explain the returns of 25 portfolios formed on the basis of size and momentum. The rejections for the size and momentum sorts are significantly weaker than the rejections for the size and B/M ratio sorts (as implied by larger *p*-values, but still smaller than 5%) reported in Section 4.3.1. To see this, recall that for the size and B/M cross-sections all cases are unanimously rejected using the GRS test. In contrast, for the size and momentum sorts, the four-factor model survives when using local factors for Asia and All-Emerging markets at the 5% significance level. The reason is that, almost always, the value effect point estimates are larger than the momentum effect for all of emerging regions: HML means are larger than the WML, except for Latin America, as reported in Table 2.

The four-factor model seems to perform the best from both an econometric and economic perspective. First, the GRS test statistics are significantly lower for the four-factor model relative to the three-factor model or the CAPM, especially when local factors are used. Second, the economic measures of performance are almost always better for the four-factor model compared to the CAPM or the three-factor model: Average intercepts are lower, $R^2$'s are higher, intercept standard errors are lower, and unexplained squared Sharpe ratios are lower.

Local factors appear to outperform, in an economic sense, using the U.S. and Global Developed factors. This finding is similar to those reported for the size and B/M ratio portfolios. All economic measures are almost always appreciably better using local factors. This finding reinforces the lack of integration between emerging markets, on the one hand, and U.S. and the developed markets on the other hand. The GMM results reported in Table 8, which allow for more realistic features of the return data, indicate that the tests have a lot less power (as implied by large *p*-values), and as a consequence many cases pass. In fact, the four-factor model using local factors is not rejected for any of the emerging regions. And, often cases with the U.S. or Global Developed factors fail to be rejected. The lack of power means that our statistical tests fail to provide additional evidence for emerging markets segmentation on top of evidence based on the economic performance of our models.

## 5. Conclusions

Emerging stock markets are clearly a significant part of the world portfolio today and therefore more empirical work on the behavior of these markets is needed. Numerous studies have identified important facts about size, value, and momentum effects in the U.S. equity market, as well as in other developed equity markets. Size, value, and momentum effects are a lot less explored for emerging markets. This paper presents results to fill this lacuna by considering stock returns for 18 emerging countries divided into three emerging regions (Asia, Latin America, and Eastern Europe).

The paper makes two main contributions. First, we explore the size patterns in value and momentum returns. Second, we form 25 portfolios based on both size and B/M ratio and size and lagged momentum for emerging markets, and try to explain the returns of these portfolios in asset pricing regressions — the CAPM, the Fama–French three-factor model, and Carhart four-factor model. We allow the factors to be calculated using the local, U.S. and Global Developed stock market data.

For all the emerging markets studied (i.e., three regions and All-Emerging markets), we find a value effect when we study small and big stocks together. Moreover, the big stock value premia point estimates are slightly larger than small stock value premia and both premia are individually statistically significant.

**Table 8**

Asset pricing test summary statistics of 25 LHS portfolios formed on size and momentum. The table reports the regression results for the CAPM, three-factor, and the four-factor models. We try to explain the returns of the 25 portfolios formed on size and lagged momentum in emerging regions, U.S. and the Global Developed region. We use asset pricing factors calculated using local, U.S. or Developed Global stock markets data to explain them. Emerging regions are Asia, Latin America, and Eastern Europe; All-Emerging region is the three emerging regions together. GRS and GMM test statistics are described in Section 3. cdf refers to the cumulative distribution function. |a| and $R^2$ refer to the average absolute value of regression intercepts and $R^2$s. Finally, $s(a)$ and $SR(a)$ refer to the average regression intercept standard deviations and the unexplained squared Sharpe ratio. These variables are detailed in Section 4.3.1. Data period for the returns is from January 1991 to December 2011.

| | GRS | GRS-cdf | GMM-cdf | $\lvert a \rvert$ | $R^2$ | $s(a)$ | $SR(a)$ | GRS | GRS-cdf | GMM-cdf | $\lvert a \rvert$ | $R^2$ | $s(a)$ | $SR(a)$ | GRS | GRS-cdf | GMM-cdf | $\lvert a \rvert$ | $R^2$ | $s(a)$ | $SR(a)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Local factors | | | | | | | U.S. factors | | | | | | | Global Developed factors | | | | | | |
| | Asia | | | | | | | Asia | | | | | | | Asia | | | | | | |
| CAPM | 1.61 | 0.96 | 0.92 | 0.56 | 0.63 | 0.30 | 0.42 | 1.43 | 0.91 | 0.81 | 0.54 | 0.18 | 0.43 | 0.40 | 1.44 | 0.91 | 0.81 | 0.58 | 0.22 | 0.42 | 0.40 |
| Three-factor | 1.44 | 0.91 | 0.83 | 0.61 | 0.70 | 0.28 | 0.40 | 1.26 | 0.81 | 0.81 | 0.52 | 0.19 | 0.44 | 0.38 | 1.30 | 0.84 | 0.77 | 0.57 | 0.28 | 0.42 | 0.38 |
| Four-factor | 1.04 | 0.58 | 0.77 | 0.17 | 0.78 | 0.25 | 0.34 | 1.30 | 0.84 | 0.83 | 0.55 | 0.21 | 0.43 | 0.38 | 1.37 | 0.88 | 0.78 | 0.60 | 0.30 | 0.42 | 0.39 |
| | Latin America | | | | | | | Latin America | | | | | | | Latin America | | | | | | |
| CAPM | 1.96 | 0.99 | 0.91 | 0.62 | 0.34 | 0.48 | 0.47 | 1.87 | 0.99 | 0.90 | 0.55 | 0.17 | 0.50 | 0.46 | 1.87 | 0.99 | 0.84 | 0.51 | 0.19 | 0.46 | 0.45 |
| Three-factor | 1.91 | 0.99 | 1.00 | 0.68 | 0.37 | 0.50 | 0.46 | 1.77 | 0.98 | 0.95 | 0.53 | 0.17 | 0.52 | 0.44 | 1.80 | 0.99 | 0.92 | 0.49 | 0.20 | 0.48 | 0.45 |
| Four-factor | 1.70 | 0.98 | 0.93 | 0.59 | 0.39 | 0.50 | 0.44 | 1.72 | 0.98 | 0.97 | 0.51 | 0.18 | 0.51 | 0.44 | 1.86 | 0.99 | 0.98 | 0.50 | 0.20 | 0.49 | 0.45 |
| | Eastern Europe | | | | | | | Eastern Europe | | | | | | | Eastern Europe | | | | | | |
| CAPM | 1.58 | 0.96 | 0.95 | 0.60 | 0.58 | 0.56 | 0.42 | 1.36 | 0.88 | 0.40 | 0.79 | 0.13 | 0.77 | 0.39 | 1.41 | 0.90 | 0.42 | 0.91 | 0.15 | 0.76 | 0.40 |
| Three-factor | 1.62 | 0.96 | 0.95 | 0.48 | 0.66 | 0.52 | 0.42 | 1.29 | 0.83 | 0.31 | 0.70 | 0.13 | 0.79 | 0.38 | 1.30 | 0.84 | 0.34 | 0.85 | 0.15 | 0.78 | 0.38 |
| Four-factor | 1.60 | 0.96 | 0.93 | 0.48 | 0.66 | 0.52 | 0.42 | 1.42 | 0.90 | 0.57 | 0.81 | 0.14 | 0.79 | 0.40 | 1.54 | 0.95 | 0.60 | 1.02 | 0.15 | 0.80 | 0.41 |
| | All-Emerging | | | | | | | All-Emerging | | | | | | | All-Emerging | | | | | | |
| CAPM | 2.18 | 1.00 | 1.00 | 0.53 | 0.69 | 0.25 | 0.49 | 2.01 | 1.00 | 1.00 | 0.53 | 0.27 | 0.38 | 0.47 | 2.05 | 1.00 | 1.00 | 0.57 | 0.32 | 0.36 | 0.48 |
| Three-factor | 1.99 | 1.00 | 0.99 | 0.54 | 0.78 | 0.23 | 0.47 | 1.89 | 0.99 | 1.00 | 0.50 | 0.28 | 0.38 | 0.46 | 1.96 | 0.99 | 1.00 | 0.53 | 0.36 | 0.36 | 0.47 |
| Four-factor | 1.30 | 0.84 | 0.64 | 0.15 | 0.84 | 0.20 | 0.38 | 1.88 | 0.99 | 1.00 | 0.51 | 0.30 | 0.38 | 0.46 | 1.95 | 0.99 | 1.00 | 0.56 | 0.37 | 0.37 | 0.46 |

We cannot statistically distinguish between the small and big value premia. This size pattern in emerging market value premia contrasts with results for the U.S. or Global Developed markets where we find that the small stock value premia are statistically and economically larger than the big stock value premia.

With the exception of Eastern Europe, we find a momentum effect when we study small and big stocks together. With respect to the size patterns in momentum, small stock momentum premia point estimates exceed that of big stock premia. Moreover, small stock momentum premia are individually statistically significant, whereas the big stock premia are not. These results suggest that emerging market momentum effects are largely driven by small stocks. Momentum effects that decrease with size are a finding consistent with momentum results that have been found to characterize developed equity markets.

The finding in the literature that in developed equity markets momentum and value returns are negatively correlated has implications for investors with long investment horizons. We confirm the same finding for emerging equity markets. This is an important market feature because emerging market volatilities are higher and therefore combining negatively correlated value and momentum returns helps reduce this volatility.

For our three asset pricing tests, we found disappointing results when trying to explain local returns using the U.S. or Global Developed factors. A degree of capital market segmentation remains, making the economic performance of local factor models so much better relative to either the U.S. or Global Developed factors. We find this result despite a positive trend for global capital market integration over the last few decades that has been documented in the capital markets' literature. Although the cross-sections based on size and B/M ratio are easily rejected even when using local factors, for the size and momentum sorts, the local four-factor models are often successful.

For future research, it would be interesting to see whether liquidity characteristics can shed some light on value and momentum returns in emerging equity markets. There is some pioneering work by Lesmond (2005) and Bekaert et al. (2007a,b), but no analysis of the relationship between value and momentum returns with liquidity has been provided.

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