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Size, Value, and Momentum in Emerging Market Stock Returns: Integrated or Segmented Pricing?*

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Abstract

In this paper, we examine size, value, and momentum patterns in the stock returns of four emerging market regions—Latin America, EMEA, Asia, and BRIC. We document a strong and highly significant value effect, and a strong but less significant momentum effect. Substantial value and momentum premiums are also present for big stocks and the overall premiums are not mainly driven by small stocks. Furthermore, the value patterns in emerging markets are more pronounced than in developed markets. In order to examine integrated global pricing across these regions, we test whether empirical asset pricing models with global factors explain the variation in average stock returns and, in particular, we assess their ability to capture the value and momentum patterns. Since the global models perform poorly for emerging markets, we examine the performance of local factor models, and find evidence in favor of the local four-factor model with local market, size, value, and momentum factors. On the basis of our results, pricing in emerging markets does not seem to be globally integrated.

Keywords Emerging markets; Integrated pricing; Momentum premium; Size premium; Value premium

JEL Classification: G12, G14, G15

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1. Introduction

Fama and French (2012) test whether empirical asset pricing models capture the value and momentum patterns in four developed regions (North America, Europe, Japan, and Asia Pacific), and whether asset pricing is integrated across these regions. They conclude that there is little evidence supporting integrated asset pricing across the four developed market regions and local models provide better results than the global models. While developed markets have been studied extensively in the past 35 years,[1] few have investigated value and momentum effects in emerging markets, although the importance of emerging market economies and stock markets is constantly rising.[2]

The purpose of examining emerging market stock returns in this paper is threefold. First, we determine the magnitude of standard risk factors on the basis of a broad sample of stocks from 21 emerging countries in a methodologically consistent way.[3] Second, we explore the size patterns in emerging market value and momentum returns. Third, we discuss market integration with a clear focus on emerging markets as a whole and four emerging market regions including the BRIC[4] region.

Our analysis leads to three primary results. First, we find a strong and highly significant value effect, and a strong but less significant momentum effect in emerging markets. The size factor is less pronounced and is only significant in the emerging Asian markets and BRIC. Second, we provide evidence of value and momentum spreads for different size groups. We cannot document that value spreads in emerging markets are smaller for big stocks than for small stocks as reported by Fama and French (2012) for developed markets. Furthermore, we get mixed results for momentum spreads. Third, we find little support for global integrated asset pricing in emerging markets as our global models perform poorly. In contrast to the previous observation, local models with local risk factors fit well, and local four-factor models, in particular, are appropriate asset pricing models to explain emerging market stock returns.

The papers closest to ours are Griffin (2002), Fama and French (2012), and Cakici *et al.* (2013). Griffin (2002) compares world, international, and local three-factor models in order to explain excess returns in the United States, Canada, the United

[1]See, e.g., Basu (1977), Banz (1981), Rosenberg *et al.* (1985), Chan *et al.* (1991), Fama and French (1992, 1993), and Griffin (2002).

[2]The Organization for Economic Co-operation and Development (OECD) estimates a dramatic change in the relative size of economies within the next 50 years, a shift toward emerging countries (Johansson *et al.*, 2012).

[3]First studies of Fama and French (1998), Rouwenhorst (1999), Griffin *et al.* (2003), and van der Hart *et al.* (2003) show that value and momentum effects are also present in emerging markets. Besides these early studies, there mainly exist single emerging country studies, e.g., Drew *et al.* (2003) analyze the Shanghai stock exchange and Waszczuk (2013) examines the Polish market.

[4]The four emerging countries Brazil, Russia, India, and China (BRIC) are said to be the main drivers of rising economic importance (Wilson and Purushothaman, 2003).

Kingdom, and Japan. His main finding is that the choice of the model is relevant and that the local models are more useful in explaining time-varying stock returns.

Fama and French (2012) analyze size, value, and momentum patterns in average stock returns for four regions comprising developed countries in a methodologically consistent way. Therefore, our findings complement their results by analyzing the relevant effects of emerging markets. They report value premiums in all regions that, except for Japan, decrease from smaller to bigger stocks. Significant momentum returns exist in all regions, except Japan. Again, these premiums decrease with firm size. For the size factor, they document non-significant size premiums with different signs for the four regions. Moreover, they conduct performance tests of global and local versions of the CAPM, Fama-French three-factor, and Carhart four-factor asset pricing models. Based on their results, Fama and French (2012) conclude that there is little support for integrated asset pricing across the four developed market regions.

Cakici *et al.* (2013) conduct a similar emerging market study and report that local factors perform much better. Hence, they conclude that emerging markets are segmented. In contrast to Cakici *et al.* (2013), we remain more conservative regarding the observation period, number of portfolios, data selection, and the regional composition. This leads to three major differences. First, we find a positive momentum premium in emerging markets Eastern Europe. Second, and more importantly, we do not reject most of the local four-factor models as they do. Furthermore, as in Fama and French (2012) for developed markets, our models for emerging markets have more problems with size-momentum portfolios than with size-value portfolios, and not vice versa as seen in Cakici *et al.* (2013).

The article proceeds as follows. Section 2 describes the data preparation, selection of the regions, as well as portfolio and risk factor construction. Section 3 provides details about our applied models and performance tests. Section 4 presents the descriptive statistics for our LHS assets and RHS factors. Sections 5 and 6 include asset pricing tests of global and local models for size-value and size-momentum portfolios, respectively. Section 7 presents asset pricing tests with a global emerging market model for regional portfolios. Section 8 concludes.

2. Data, Regions and Risk Factor Construction

2.1. Data

Our sample comprises data from 21 emerging and 24 developed countries over the July 1996 to June 2012 period. When choosing the observation period, we consider whether a longer observation period or a higher minimum amount of stocks per year is more appropriate.

To derive our sample of international stocks, we use Thomson Reuters Datastream. We create a semi-automated and multilevel 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

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

et al. (2010), and Schmidt *et al.* (2010), we apply static screens, the details of which are presented in Appendix 1. These screens ensure that our sample comprises exclusively common stocks.

This screening process results in a sample comprising 63 775 unique securities for developed countries and 21 612 unique securities for emerging countries. We obtain return data from Datastream and accounting data from Worldscope. All items are measured in US$. As Ince and Porter (2006) describe, raw return data from Datastream may not be error-free. To ensure data quality, we follow Ince and Porter (2006) and Schmidt *et al.* (2010) and apply dynamic screens to the monthly return data, as described in Appendix 2.

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 30 June of year y and 31 December of year $y - 1$, a positive book value at the fiscal year end of year $y - 1$ and valid stock returns for the last 12 months. We define book value as common equity plus deferred taxes, if available.

2.2. Regions

The country selection follows the composition of the Morgan Stanley Capital International (MSCI) Emerging Markets Index as of 30 June 2012 and we classify the following countries as emerging market countries: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Russia, South Africa, South Korea, Taiwan, Thailand, and Turkey.[6]

Tables 1–3 show the number and the aggregated market value (MV) in US$ billion for stocks that meet our sample-selection criteria as of end of June of each year. Because the sample size of many emerging countries is too low to meet the demand of diversified portfolios on a country basis,[7] we construct, similar to Fama and French (2012), regional portfolios. This results in a greater diversification and more robust results.

We combine the 21 emerging countries into three emerging market regions: EM Latin America,[8] including Brazil, Chile, Colombia, Mexico, and Peru; EM EMEA,[9] including Czech Republic, Hungary, Russia, Poland, Turkey, Egypt, Morocco, and South Africa; and EM Asia, including China, India, Indonesia, South Korea, Malaysia, Philippines, Taiwan, and Thailand. Because the average number of stocks in

[6]In accordance with the MSCI classification, the following countries are labeled as developed market countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

[7]For Russia, e.g., our sample contains 0 stocks in 1996, 1 stock in 1997, and 2 stocks in 1998.

[8]We prefix "EM" for the emerging market regions to clearly indicate that they are not developed market regions.

[9]EMEA denotes Europe, the Middle East, and Africa.

Table 1 Number and aggregated market value of stocks for EM Latin America

The table shows the number and the aggregated market value (MV) in US$ billion for stocks that meet our sample-selection criteria as of end of June of each year in EM Latin America (LatAm). 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 30 June of year y and 31 December of year $y - 1$, a positive book value at the fiscal year end of year $y - 1$ and valid stock returns for the last 12 months.

	Brazil		Colombia		Chile		Mexico		Peru		LatAm	
	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV
1988												
1989							8	3			8	3
1990							13	7			13	7
1991					18	10	15	13			33	23
1992					26	20	18	17			44	37
1993			9	3	43	20	32	29	6	1	90	52
1994			16	9	55	51	36	41	17	2	124	103
1995			18	11	64	68	50	29	15	5	147	113
1996	26	16	20	9	73	49	52	40	16	7	187	121
1997	29	25	20	12	79	56	53	52	23	12	204	157
1998	31	22	22	7	90	42	64	52	22	8	229	132
1999	34	13	24	6	120	50	73	56	24	7	275	131
2000	52	17	24	3	167	55	85	62	26	6	354	144
2001	58	15	25	4	165	53	81	73	30	4	359	149
2002	55	11	26	5	161	43	78	53	31	5	351	116
2003	52	16	32	7	167	55	75	52	29	7	355	137
2004	48	23	34	12	165	79	75	67	32	10	354	190
2005	52	43	34	24	169	112	79	83	39	12	373	275
2006	58	97	33	30	172	123	79	104	61	19	403	373
2007	69	201	31	50	168	199	86	195	65	38	419	683
2008	105	272	32	44	170	185	83	214	76	43	466	757
2009	127	226	34	96	166	185	85	136	76	38	488	681
2010	128	349	37	134	166	230	80	188	78	52	489	952
2011	137	478	39	198	162	315	79	237	71	56	488	1284

our emerging market regions is smaller when compared with those in developed markets, we split stocks of one region into 16 portfolios, and not 25 portfolios as in Fama and French (2012). Since each portfolio should be well diversified, we target an average of more than ten stocks per portfolio and year, and hence, a minimum of at least 160 stocks per year in each region. Year 1996 is the first year that fulfills the condition of more than 160 stocks per region with 187 stocks in EM Latin America, 224 stocks in EM EMEA, and 1536 stocks in EM Asia. Moreover, the aggregated market value of the regions is considerably smaller before 1996. Hence, it is appropriate to begin the analysis in 1996. Also using data from Thomson Reuters Datastream, Cakici *et al.* (2013) construct 25 portfolios per year, beginning in January 1991. They use the same regional portfolios, except for EM EMEA, as

Table 2 Number and aggregated market value of stocks for EM EMEA

The table shows the number and the aggregated market value (MV) in US$ billion for stocks that meet our sample-selection criteria as of end of June of each year in EM EMEA (EMEA). 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 30 June of year y and 31 December of year $y - 1$, a positive book value at the fiscal year end of year $y - 1$ and valid stock returns for the last 12 months.

	Czech Republic		Hungary		Russia		Poland		Turkey		Egypt		Morocco		South Africa		EMEA	
	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV
1988															47	37	47	37
1989															47	48	47	48
1990									5	3					54	64	59	67
1991									9	3					96	75	105	79
1992									11	4					102	95	113	98
1993									21	11					103	91	124	102
1994			6	1			5	1	42	10					119	117	172	129
1995			5	<1			7	2	46	20					129	122	187	145
1996	15	4	10	1			21	5	48	18					130	129	224	157
1997	52	11	19	6	1	<1	25	4	61	31					133	133	291	185
1998	60	12	22	7	2	<1	35	6	82	43	5	2	8	8	151	108	365	187
1999	58	12	29	12	3	8	51	12	101	39	14	4	8	7	252	129	516	223
2000	52	12	36	14	7	18	65	26	121	76	13	4	11	7	264	124	569	281
2001	49	8	36	9	10	23	77	22	135	38	19	6	16	7	223	123	565	236
2002	43	10	35	11	15	63	79	24	133	27	20	4	19	7	207	96	551	243
2003	38	13	34	13	16	95	88	28	160	37	29	5	21	10	197	112	583	313
2004	34	19	35	20	20	98	118	42	162	57	37	10	23	14	191	170	620	429
2005	35	30	35	31	26	143	135	55	180	99	44	36	22	14	190	218	667	625
2006	23	38	33	31	66	306	188	98	230	114	85	44	41	36	190	297	856	964
2007	22	52	35	49	96	754	209	194	219	200	94	81	50	55	195	403	920	1788
2008	18	78	37	41	130	1123	247	166	222	172	102	101	56	81	208	377	1020	2139
2009	13	40	36	21	159	444	270	84	150	146	105	58	69	67	193	296	995	1156
2010	14	39	38	24	156	632	295	109	212	233	101	59	71	63	192	360	1079	1518
2011	13	50	39	32	227	947	297	196	249	274	97	53	71	66	198	500	1191	2119

Table 3 Number and aggregated market value of stocks for EM Asia

The table shows the number and the aggregated market value (MV) in US$ billion for stocks that meet our sample-selection criteria as of end of June of each year in EM Asia (Asia) and Emerging Markets (EM). 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 30 June of year y and 31 December of year $y-1$, a positive book value at the fiscal year end of year $y-1$ and valid stock returns for the last 12 months.

	China		India		Indonesia		South Korea		Malaysia		Philipines		Taiwan		Thailand		Asia		EM	
	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV
1988							19	13	37	11					2	<1	58	24	105	61
1989							50	35	46	15	2	1			7	2	105	52	160	103
1990							65	35	63	25	2	1	4	15	10	3	144	79	216	153
1991			4	2	4	1	73	42	70	30	3	1	3	12	15	5	172	93	310	194
1992	1	<1	21	6	54	9	87	38	118	48	14	8	10	17	61	17	366	144	523	279
1993	4	1	97	15	75	13	109	60	164	79	19	10	23	20	116	33	607	231	821	385
1994	16	3	160	51	80	20	171	107	200	135	25	20	45	66	180	68	877	470	1173	703
1995	31	9	175	46	92	30	218	133	218	162	48	28	107	98	218	108	1107	615	1441	872
1996	73	27	253	77	132	56	243	121	306	214	80	53	202	166	247	117	1536	831	1947	1109
1997	82	41	280	112	154	91	275	106	358	228	91	58	219	250	267	52	1726	938	2221	1279
1998	93	43	288	75	149	11	288	35	236	51	67	23	223	183	216	19	1560	439	2154	758
1999	100	56	298	95	126	34	363	165	181	77	57	35	228	236	236	53	1589	752	2380	1106
2000	203	150	312	138	167	30	553	196	380	117	75	30	352	311	229	34	2271	1005	3194	1429
2001	220	186	350	90	194	21	637	157	394	83	81	19	449	216	305	30	2630	803	3554	1188
2002	239	175	385	103	216	32	692	242	439	107	78	17	771	298	311	43	3131	1017	4033	1377
2003	1124	460	408	133	262	40	780	242	382	106	79	17	899	299	317	56	4251	1353	5189	1804
2004	1185	438	464	199	280	45	850	301	441	137	86	21	996	400	345	89	4647	1631	5621	2251
2005	1264	359	538	346	278	76	890	436	392	147	93	27	1103	489	360	100	4918	1979	5958	2879
2006	1282	528	628	527	295	93	1314	670	315	157	106	39	1181	537	399	118	5520	2669	6779	4006
2007	1269	1445	1681	911	300	159	1401	984	330	260	116	84	1223	735	428	155	6748	4733	8087	7204
2008	1372	1863	1874	939	315	182	1483	839	345	221	137	60	1261	674	428	162	7215	4940	8701	7837
2009	1498	2803	2030	946	340	149	1567	599	204	189	124	60	1333	535	375	127	7471	5407	9854	7244
2010	1504	2463	2073	1304	345	258	1599	762	271	268	138	89	1386	648	397	181	7713	5973	9281	8443
2011	1781	3533	2090	1411	348	380	1629	1108	310	375	152	143	1460	866	416	261	8186	8078	9865	11 481

they exclude Egypt, Morocco, and South Africa from this region and name it Eastern Europe.[10] However, if we followed their observation period and portfolio approach for our sample, then Eastern Europe would only include the following number of stocks per year in 1991 to 1995: 9, 11, 21, 53, and 58. Considering 25 portfolios, the fourth year for this approach would be the first year, when each portfolio includes more than one stock on average (as per our dataset). To meet the demand of diversified portfolios, we choose a more conservative method and combine Eastern European and African countries to EM EMEA and begin our analysis in 1996.

Market integration across the regions should be a reasonable assumption. The countries forming EM Latin America and EM Asia, respectively, are economically closely connected and mostly bordering countries. The economic connection is most questionable in EM EMEA with (East) European and African countries. As described above, we combine the countries of both continents as the number of stocks for each continent would be too small in the early years of our analysis to achieve diversified portfolios. Furthermore, they are grouped by MSCI as an emerging market region. BRIC, comprising Brazil, Russia, India, and China, is a fourth additional emerging market region. It is reasonable to analyze BRIC as a whole, since these four countries are at a comparable stage of economic development (Wilson and Purushothaman, 2003). In addition, due to the demand of investors to collectively invest in these four markets, many investment vehicles such as ETFs have been issued for the BRIC markets as a whole.

Finally, we construct both the global sample and the Emerging Markets sample.[11] The global sample contains stocks from all 21 emerging and 24 developed countries. This portfolio should capture all effects in a global context. The Emerging Markets sample contains stocks from the 21 emerging markets. Tests on the Emerging Markets sample are a good indicator of whether a hypothesis or model is valid across the whole emerging market universe.

2.3. Risk Factor and Portfolio Construction

We construct the risk factors (RHS factors) and test portfolios (LHS assets) for the global (only RHS factors) and emerging market sample as well as for each region following an adapted version of the method in Fama and French (2012).[12] The four RHS factors are the market factor (*RMRF*), the size factor (*SMB*, small minus big),

[10]In EM Latin America, Cakici *et al.* (2013) include Argentina instead of Peru.

[11]We denote the sample comprising all 21 emerging market countries as "Emerging Markets" (in capital letters).

[12]We also conduct robustness tests on the methods applied by Griffin (2002) and Schmidt *et al.* (2010). The main results for these two alternative breakpoint methods are the same. However, some observations exhibit more noise due to the less balanced distribution of the aggregated market capitalization over the individual portfolios.

the value factor (*HML*, high minus low), and the momentum factor (*WML*, winner minus losers).

RMRF is the excess return of the market return (*RM*), a value-weighted return of all stocks in a sample over the risk-free rate (*RF*). We use the one-month T-bill rate as a proxy for the risk-free rate.

At the end of June of each year y, we sort all stocks of a region independently into two size groups, Big (*B*) and Small (*S*), and three book-to-market (B/M) groups, High (*H*), Medium (*M*), and Low (*L*). According to Fama and French (2012), big stocks (*B*) represent the top 90% of the aggregate market capitalization for a region at the end of June of year y, while small stocks (*S*) represent the bottom 10%.[13] B/M is calculated as the book value at the fiscal year end of year $y - 1$ divided by the market capitalization at the end of December of year $y - 1$. The B/M breakpoints for all stocks of a region are the 30th and 70th percentiles of B/M for the big stocks, but also applied to small stocks. For our global and Emerging Market sample we use the same approach as for the regions. In contrast, Fama and French (2012) allocate the stocks of their global portfolio on the basis of four regional breakpoints.

At the intersection of the two size and three B/M groups, we construct six portfolios (*S/H*, *S/M*, *S/L*, *B/H*, *B/M*, and *B/L*). Monthly value-weighted returns are calculated for the next 12 months starting from July of year y until June of year $y + 1$. The portfolios are reformed at the end of June of year $y + 1$.

Based on these portfolios, we construct the monthly time-series of *SMB* and *HML* as follows:

$$SMB_t = \frac{(r_t^{S/L} + r_t^{S/M} + r_t^{S/H}) - (r_t^{B/L} + r_t^{B/M} + r_t^{B/H})}{3}. \tag{1}$$

$$HML_t = \frac{(r_t^{S/H} + r_t^{B/H}) - (r_t^{S/L} + r_t^{B/L})}{2}. \tag{2}$$

To construct the momentum factor *WML*, for each month t, we sort stocks by their cumulative performance from month $t-11$ to month $t-1$. Again, the momentum breakpoints for all stocks of a sample are the 30th and 70th percentiles of lagged performance for the big stocks of a sample. *L* denotes losers (bottom 30% of lagged return), *N* denotes neutral (middle 40%), and *W* denotes winners (top 30%). The intersection of the size and momentum sorts results in six portfolios *S/L*, *S/N*, *S/W*, *B/L*, *B/N*, and *B/W* and the calcula-

[13]Fama and French (1993) calculate the median for all NYSE stocks, but apply this breakpoint to all NYSE, AMEX, and NASDAQ stocks. They want to avoid a high weight of tiny stocks within the size dimension as NYSE stocks have on average a higher market capitalization. Fama and French (2012) mention that the NYSE median corresponds roughly to 90% of the aggregate market capitalization.

tion of the momentum factor, *WML*, is similar to that of the value factor, *HML*:

$$WML_t = \frac{(r_t^{S/W} + r_t^{B/W}) - (r_t^{S/L} + r_t^{B/L})}{2}. \quad (3)$$

The determination of the RHS risk factors is similar to the methods adopted in Fama and French (2012). However, we adjust the methods for the generation of test assets, since we allocate stocks to 4 × 4 portfolios and not to 5 × 5 portfolios. These 4 × 4 portfolios serve as LHS assets for our regressions and offer adequate possibilities for interpretation due to a sufficient split within each dimension and good diversification.

By roughly interpolating the four size breakpoints in Fama and French (2012), we attain three size breakpoints which are the 4th, 10th, and 20th percentiles of a sample's aggregate market capitalization. Fama and French (2012) use quintile value breakpoints for big stocks to allocate all stocks to the five value groups. Since we have only four value groups, we use quartile value breakpoints for book-to-market ratios based on the group with the biggest stocks of a sample. Again, we use the breakpoints to allocate all stocks to value groups. The intersection of the four size groups and four value groups forms the 4 × 4 LHS assets for our asset pricing tests (size-value portfolios). Monthly value-weighted returns are calculated for all portfolios for the next 12 months starting from July of year y until June of year $y + 1$. The portfolios are reformed at the end of June of year $y + 1$. To allocate stocks to the four momentum groups, for each month t, we use quartile momentum breakpoints for the biggest stocks of a sample to allocate all stocks. The intersection of the four size groups and four momentum groups forms our second 4 × 4 LHS assets for asset pricing tests (size-momentum portfolios). Again, monthly value-weighted returns are calculated.

3. Methodology

To explain the returns of the LHS assets, we use three factor models—the CAPM, Fama-French three-factor model, and Carhart four-factor model:

CAPM:

$$R_{it} - RF_t = a_i + b_i RMRF_t + e_{it}. \quad (4)$$

Fama-French three-factor model:

$$R_{it} - RF_t = a_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + e_{it}. \quad (5)$$

Carhart four-factor model:

$$R_{it} - RF_t = a_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + w_i WML_t + e_{it}. \quad (6)$$

$R_{it} - RF_t$ is the excess return of portfolio i over the risk-free rate RF for month t. *RMRF*, *SMB*, *HML*, and *WML* denote the risk factors described above and are the respective returns of the factor-mimicking portfolios. They are either constructed from the global or the local samples. The three global models out of global factors are applied on the Emerging Markets sample and all single regions. The local models are separately constructed for each region and the Emerging Markets sample out of local factors. R_{it} can be either the return of a portfolio from sorts on size and value or from sorts on size and momentum.

Applying a global or local model on a sample implies to regress each of the 16 portfolios of a sample on global or local risk factors (set of regressions). If one particular model (local or global) is an appropriate asset pricing model for a sample, then the slopes of the model's risk factors (RHS factors) should explain the average returns of each of the 16 portfolios. Therefore, the regression intercepts should jointly be statistically indistinguishable from zero. To test this hypothesis, we use the F-test of Gibbons *et al.* (1989) (hereafter GRS) and the related p-value. The GRS test statistic indicates whether the applied model is an appropriate estimator for the returns of the 16 portfolios from a statistical perspective.

As Fama and French (2012) highlight, power is often a problem in these tests. While the power of the local models is sometimes too high, that for the global models is at times too low. The higher the explanatory power (R^2) of the regression, the better the regression fits. This can lead to a rejection of a model although the average absolute intercept is rather low, and vice versa. Therefore, we present the average adjusted R^2 and the average absolute intercept for each set of regressions to additionally evaluate a model from an economic perspective. The average absolute intercept for a set of regressions indicates whether the average portfolio returns are explained by the risk factors, while the average adjusted R^2 describes whether the variation in returns for each portfolio is captured by the model.

Furthermore, we provide the average standard error of the intercepts $s(a)$ and the core of the GRS statistic $SR(a)$:

$$SR(a) = (a' S^{-1} a)^{1/2}, \tag{7}$$

where a is the vector of intercepts and S is the covariance matrix of regression residuals. According to Gibbons *et al.* (1989) and Fama and French (2012), $SR(a)$ is the maximum Sharpe ratio that can be constructed from the RHS factors and LHS assets minus the maximum Sharpe ratio that can be constructed from the RHS factors alone.

Similar to Griffin (2002) or Fama and French (2012), we use returns in US$ for the tests of international asset pricing. This would be a problem if purchasing power parity does not hold or the assets we analyze are exposed to exchange rate risk. For example, see Solnik (1983) and Adler and Dumas (1983) for a theoretical background and Zhang (2006) for an empirical implementation of a model that allows exchange rate risk.

4. Descriptive Statistics

This section provides the summary statistics of the RHS explanatory returns—*RMRF*, *SMB*, *HML*, and *WML*—followed by the summary statistics of the 16 size-value and 16 size-momentum portfolios that serve as LHS assets in the analysis presented in Sections 5 and 6.

4.1. Explanatory Returns

Table 4 presents summary statistics for the risk factors *RMRF*, *SMB*, *HML*, and *WML* in the global and Emerging Markets sample and the four emerging market regions. Over the July 1996 to June 2012 period, the average risk-free rate is 0.23% for all regions.

The average market return and average excess market return of the global portfolio are 0.60% and 0.37%, respectively. The global excess market return is slightly lower than the excess return for Emerging Markets of 0.40%. Notably, the excess market returns of these two samples are not significant. Fama and French (2012) determine a market excess return of 0.44% for their global portfolio comprising only developed markets (1991–2010).[14] EM Latin America has the highest excess return of 1.01% and is the only emerging market region with a significant market excess return. The other three emerging market regions including BRIC have insignificant equity premiums between 0.26% and 0.81%.

The size factor is small and insignificant in the global portfolio, which is highly dominated by developed markets. This result is in line with Fama and French (2012). For the Emerging Markets portfolio, the average *SMB* return is 0.25%, however insignificant. The BRIC region has the highest size premium of 0.62% followed by EM Asia with 0.41%, both significant at the 10% level. EM Latin America and EM EMEA have insignificant and smaller size factor mean returns.

In contrast, the value factor is substantial and significant for Emerging Markets (mean of 0.93% and a *t*-statistic of 3.04) and is nearly as twice as high as for the global portfolio with a value of 0.47%. Again, BRIC is the region with the highest *HML* mean of 1.20%. Each of the four emerging market regions exhibits significant value premiums, confirming the strong significance for *HML* in the Emerging Market portfolio. With the exception of EM EMEA, the value premiums are larger for small stocks; however, in emerging markets, the differences are not significant. Furthermore, the magnitude and significance levels of the value premium for big

[14]The residual returns between our global market returns and Emerging Markets returns corresponds to the returns of global developed markets. In unpublished tests, we compare our risk factors for global developed markets with the returns published on Kenneth's French website that are calculated as in Fama and French (2012). We obtain similar levels for the risk factor premiums and pairwise correlations ranging from 1.00 for the market excess returns to 0.91 for the value factors. This should underline our detailed and thorough data process.

Table 4 Descriptive statistic for risk factors

The table reports summary statistics for risk factors of the global sample, Emerging Markets, and the emerging market regions EM Latin America, EM EMEA, and EM Asia. At the end of June of each year *y*, we sort all stocks of a sample independently into two size groups, Big (*B*) and Small (*S*), and three B/M groups, High (*H*), Medium (*M*), and Low (*L*). Big stocks (*B*) represent the top 90% of the aggregate market capitalization of a sample at the end of June of year *y*, while small stocks (*S*) represent the bottom 10%. The B/M breakpoints for all stocks of a sample are the 30th and 70th percentiles of B/M for the big stocks of a sample. At the intersection of the two size and three B/M groups, we construct six value-weighted portfolios (*S/H*, *S/M*, *S/L*, *B/H*, *B/M*, and *B/L*). *SMB* is the difference between the average returns of the three small stock and the three big stock portfolios. We construct value-growth returns for big and small stocks, $HML_B = B/H - B/L$ and $HML_S = S/H - S/L$. *HML* is the average of and HML_{S-B} is the difference between HML_S and HML_B. Furthermore, for each month *t*, we sort stocks by their cumulative performance from month t−11 to month t−1. Again, the momentum breakpoints for all stocks of a sample are the 30th and 70th percentiles of lagged performance for the big stocks of a sample. *L* denotes losers (bottom 30% of lagged return), *N* denotes neutral (middle 40%), and *W* denotes winners (top 30%). The intersection of the size and momentum sorts results in six value-weighted portfolios *S/L*, *S/N*, *S/W*, *B/L*, *B/N*, and *B/W*. We construct winner-looser returns for big and small stocks, $WML_B = B/W - B/L$ and $WML_S = S/W - S/L$. *WML* is the average of and WML_{S-B} is the difference between WML_S and WML_B. *RMRF* is the excess return of the market return (*RM*), a value-weighted return of all stocks in a sample over the risk-free rate (*RF*). We use the one-month T-bill rate as a proxy for the risk-free rate. All returns are in US$. The statistics are computed over the period July 1996 to June 2012.

	RM	*RMRF*	*SMB*	*HML*	HML_S	HML_B	HML_{S-B}	*WML*	WML_S	WML_B	WML_{S-B}
Global											
Mean	0.60	0.37	0.03	0.47	0.74	0.21	0.53	0.88	1.07	0.69	0.38
Std dev	4.81	4.82	2.35	3.11	4.04	2.80	3.11	5.13	4.88	5.91	3.50
t-Mean	1.74	1.07	0.19	2.10	2.52	1.03	2.35	2.38	3.04	1.62	1.50
Emerging Markets											
Mean	0.63	0.40	0.25	0.93	1.05	0.80	0.25	0.97	0.99	0.96	0.03
Std dev	6.71	6.72	2.70	4.23	5.27	3.92	3.84	6.84	8.02	6.73	5.63
t-Mean	1.30	0.82	1.28	3.04	2.76	2.85	0.89	1.97	1.71	1.98	0.07
EM Latin America											
Mean	1.24	1.01	−0.11	0.55	0.61	0.49	0.12	0.41	0.51	0.32	0.19
Std dev	6.65	6.67	3.15	3.33	3.71	4.39	4.66	4.74	5.72	5.62	6.20
t-Mean	2.58	2.09	−0.47	2.30	2.30	1.55	0.37	1.20	1.23	0.78	0.42

Table 4 (*Continued*)

	RM	*RMRF*	*SMB*	*HML*	HML_S	HML_B	HML_{S-B}	*WML*	WML_S	WML_B	WML_{S-B}
EM EMEA											
Mean	1.04	0.81	0.05	1.10	1.04	1.16	−0.12	0.67	0.61	0.73	−0.12
Std dev	8.05	8.06	3.68	4.77	5.73	5.53	5.99	6.72	6.62	8.00	5.90
t-Mean	1.80	1.40	0.19	3.21	2.52	2.92	−0.28	1.38	1.27	1.26	−0.29
EM Asia											
Mean	0.49	0.26	0.41	0.79	0.91	0.66	0.25	0.94	0.93	0.95	−0.02
Std dev	7.06	7.07	3.06	5.15	6.08	5.17	4.61	7.76	9.04	7.72	6.48
t-Mean	0.97	0.51	1.88	2.11	2.08	1.77	0.76	1.68	1.43	1.71	−0.04
BRIC											
Mean	0.89	0.65	0.62	1.20	1.58	0.82	0.77	1.07	1.47	0.67	0.80
Std dev	6.84	6.83	4.54	6.13	7.35	6.76	7.02	8.24	9.54	8.18	6.65
t-Mean	1.80	1.33	1.90	2.71	2.98	1.67	1.51	1.79	2.13	1.13	1.67

stocks in Emerging Markets and emerging market regions are higher than those for the global or developed markets (Fama and French, 2012).

The momentum factor, *WML*, has the highest mean return for BRIC (1.07%), followed by Emerging Markets (0.97%), EM Asia (0.94%), and the global portfolio (0.88%). For the global and Emerging Markets sample, *WML* is significant at the 5% level and has the highest magnitude of the three factors. This is also stated for developed markets by Fama and French (2012). Contrary to the global and Emerging Markets sample, the momentum factor is not statistically significant in EM Latin America and EM EMEA. In EM Asia and BRIC, the *WML* mean is the highest within the region, significant at the 10% level. The momentum premiums for small and big stocks are statistically indistinguishable for Emerging Markets and all emerging market regions, with the exception of BRIC. For the global sample, we report higher momentum returns for small stocks than for big stocks; however, the difference is less significant as in Fama and French (2012).

Analyzing EM Eastern Europe instead of EM EMEA would result in risk premiums of 0.89%, −0.49%, 0.94%, and 0.51% for *RMRF*, *SMB*, *HML*, and *WML*, respectively, with the same significance levels as in EM EMEA. Thus, in contrast to Cakici *et al.* (2013), we document a positive momentum premium for EM Eastern Europe. As mentioned in Section 2, the low number of stocks in the early years of their study (not included in our analysis) could be the reason for this difference.

In sum, the excess market return is only significant for EM Latin America and the size factor is only significant at the 10% level for BRIC and EM Asia. The value factor is significant in the global and Emerging Markets sample as well as in all emerging market regions. The momentum factor is also positive for all samples, however, despite the high magnitude, the momentum factor is not as significant as the value factor. Moreover, in the BRIC region *SMB*, *HML*, and *WML* have the highest means compared to other regions. In contrast to global and developed markets, significant value and momentum premiums are present for big stocks, and the overall premiums are not mainly driven by small stocks.

Table 5 presents the correlations between market, size, value, and momentum factors in the same region, while Table 6 shows the correlations between the same factors in different regions. In each of the six regions, the size and value factors are negatively correlated. For developed markets, Asness *et al.* (2013) report that value and momentum are negatively correlated. For the regions analyzed in this paper, we can confirm this result for the global portfolio and EM Latin America.[15] Nevertheless, we can confirm the consistent negative correlation of the market and momentum factors, which is also reported by Cakici *et al.* (2013), for all regions except BRIC. A potential explanation for this result might be that momentum

[15]Asness *et al.* (2013) use the market capitalization of the most recent month to compute the B/M ratio. They highlight that the correlation between value and momentum becomes more negative when using this approach than when using the lagged market capitalization as we do.

Table 5 Correlations between market, size, value, and momentum factors in the same sample

The table presents the correlations between market, size, value, and momentum factors in the same sample. The samples are the global (Global) and Emerging Markets (EM) sample, and the emerging market regions EM Latin America (EM LatAm), EM EMEA, EM Asia, and BRIC. Details for the construction of the factors are provided in Table 4. The statistics are computed over the period July 1996 to June 2012.

	RMRF	*SMB*	*HML*	*RMRF*	*SMB*	*HML*
	Global			EM		
RMRF	1.00			1.00		
SMB	−0.03	1.00		−0.09	1.00	
HML	−0.15	−0.27	1.00	0.14	−0.15	1.00
WML	−0.21	0.09	−0.15	−0.16	−0.20	0.08
	EM LatAm			EM EMEA		
RMRF	1.00			1.00		
SMB	−0.57	1.00		−0.34	1.00	
HML	0.05	−0.05	1.00	−0.09	−0.28	1.00
WML	−0.24	0.13	−0.04	−0.14	0.13	0.26
	EM Asia			BRIC		
RMRF	1.00			1.00		
SMB	0.03	1.00		0.03	1.00	
HML	0.12	−0.13	1.00	0.10	−0.15	1.00
WML	−0.22	−0.20	0.05	0.06	−0.06	0.16

returns tend to be negative when the market rebounds after a period of poor performance.[16]

For market, size, value, or momentum strategies across regions, the correlations of the factors between different regions might be interesting. The mean correlation of the four factors—market, size, value, and momentum—in Table 6 are 78%, 26%, 31%, and 47%, respectively. The low factor correlations might offer multiregional diversification potentials for size, value, or momentum strategies, but they also indicate potential market segmentation.

4.2. Excess Returns for the 16 Size-Value and 16 Size-Momentum Portfolios

Between 1963 and 1991, Fama and French (1993) find a negative relationship between size and average returns, and a strong positive relationship between average returns and book-to-market equity in the U.S. Nevertheless, they report low returns for small growth stocks. This finding is confirmed by Fama and French (2012) for North America, Europe, and Asia Pacific, but not for Japan (1991–2010). Besides Japan, Fama and French (2012) report a standard size effect for extreme value stocks and a reverse size effect for extreme growth stocks.

[16]See Asem and Tian (2010) and Hanauer (2014) for further information.

Table 6 Correlations between the same risk factors for different samples

The table reports the correlations between the same risk factors in different samples. The samples are the global (Global) and Emerging Markets (EM) sample, and the emerging market regions EM Latin America (LatAm), EM EMEA, EM Asia, and BRIC. The four RHS factors are *RMRF*, *SMB*, *HML*, and *WML*. Details for the construction of the factors are provided in Table 4. The statistics are computed over the period July 1996 to June 2012.

	Global	EM	LatAm	EM EMEA	EM Asia	Global	EM	LatAm	EM EMEA	EM Asia
	RMRF					*SMB*				
Global	1.00					1.00				
EM	0.83	1.00				0.34	1.00			
LatAm	0.82	0.85	1.00			−0.04	0.23	1.00		
EM EMEA	0.81	0.82	0.81	1.00		0.02	0.19	0.29	1.00	
EM Asia	0.74	0.97	0.75	0.68	1.00	0.31	0.91	0.05	−0.06	1.00
BRIC	0.65	0.82	0.67	0.65	0.81	0.19	0.64	0.17	0.03	0.60
	HML					*WML*				
Global	1.00					1.00				
EM	0.56	1.00				0.66	1.00			
LatAm	0.18	0.13	1.00			0.53	0.41	1.00		
EM EMEA	0.33	0.27	−0.02	1.00		0.52	0.42	0.31	1.00	
EM Asia	0.44	0.94	0.07	0.04	1.00	0.58	0.95	0.32	0.26	1.00
BRIC	0.43	0.56	0.14	0.11	0.52	0.44	0.58	0.26	0.25	0.56

The left half of Table 7 presents the descriptive statistics for the 16 size-value portfolios. We document a size effect—rising portfolio returns from the bottom to the top for a value group—for all value portfolios of Emerging Markets. The same applies for most of the value portfolios of EM Asia and BRIC, and the two growth portfolios of EM EMEA. In contrast to Fama and French (2012), the reverse size effect for growth stocks does not exist in emerging market samples, with the exception of EM Latin America.

Our sample displays the typical value premium—rising portfolio returns from the left to the right of a size group. The value-growth spread—excess return of the value minus excess return of the growth portfolio for a specific size group—is highly positive for all size groups. The value premium is larger for the smallest stocks than for the biggest stocks in EM Latin America and BRIC, smaller in EM EMEA, and about the same in EM Asia and Emerging Markets. An explanation for this deviation from developed markets is that the reverse size effect for growth stocks is not present in our samples except EM Latin America. Furthermore, the value patterns for big stocks are more pronounced in emerging market samples compared with developed markets in Fama and French (2012).

Besides Japan, Fama and French (2012) report a momentum premium in all size groups and a size premium in the two momentum groups with the past year's winners for all regions. The right half of Table 7 shows the results for the average excess market returns of the 16 size-momentum portfolios.

We find a size effect for all momentum groups—decreasing returns from the top to the bottom for the second and third column—for Emerging Markets. This finding confirms the results of Fama and French (2012) regarding their global portfolio. Size patterns in the single regions exist in most of the momentum groups but contain some more outliers compared with Emerging Markets.

The momentum effect is present within all size groups in all samples, although the effect is not very strong for the biggest stocks in EM Latin America. With one exception, the momentum premium is highly consistent for Emerging Markets—the equity premiums in each line continuously increase from left to right. We find smaller momentum spreads for the biggest stocks than for the smallest stocks in EM Latin America and BRIC but also higher spreads in Emerging Markets, EM EMEA, and EM Asia. This underlines the mixed results for *WML* in Table 4.

In sum, we document size, value, and momentum pattern in emerging market size-value and size-momentum sorted portfolios; however, we cannot provide clear evidence that these patterns decrease with size as shown for developed markets by Fama and French (2012).

5. Asset Pricing Tests for Size-Value Portfolios

We primarily analyze market integration of emerging markets, and extend the results of Fama and French (2012) to these emerging markets. In this section, we regress the excess returns of the 16 size-value portfolios on global and local risk

Table 7 Descriptive statistics for size-value and size-momentum portfolios

The table reports summary statistics for the 16 size-value and 16 size-momentum sorted portfolios in Emerging Markets (EM) and the emerging market regions EM Latin America (EM LatAm), EM EMEA, and EM Asia. At the end of June of each year y, we attain three size breakpoints which are the 4th, 10th, and 20th percentiles of a sample's aggregate market capitalization. We use quartile value breakpoints on book-to-market ratios for the group of the biggest stocks of a sample to allocate all stocks. At the intersection of these four size groups and four value groups, we construct the 4 × 4 value-weighted LHS portfolios for the asset pricing tests (size-value portfolios). Furthermore, for each month t, we use quartile momentum breakpoints for the biggest stocks of a sample to allocate all stocks. The intersection of the four size groups and four momentum groups form the second 4 × 4 LHS value-weighted portfolios for asset pricing tests (size-momentum portfolios). All returns are in US$. The statistics are computed over the period July 1996 to June 2012.

	Size-value portfolios								Size-momentum portfolios							
	Mean				Standard deviation				Mean				Standard deviation			
	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
EM																
Small	0.44	0.85	0.59	1.32	7.90	7.45	7.09	7.97	0.74	1.07	1.62	1.26	10.62	7.01	6.71	7.44
2	−0.11	0.33	0.59	1.11	7.47	7.19	7.13	7.74	0.00	0.62	1.13	1.36	9.86	7.12	6.56	7.66
3	−0.09	0.16	0.47	0.85	6.94	6.91	6.87	7.45	−0.23	0.22	0.78	1.09	9.22	6.66	6.14	7.48
Big	−0.05	0.22	0.43	0.85	6.93	6.89	6.97	7.33	−0.07	0.25	0.27	0.70	9.02	6.87	6.67	7.70
EM LatAm																
Small	0.22	1.28	1.05	1.45	6.39	6.42	5.72	6.01	1.11	1.14	1.76	1.69	7.43	5.85	6.12	5.89
2	0.65	1.29	1.00	0.93	7.04	9.68	6.88	6.50	0.76	0.67	1.27	1.22	8.12	7.03	6.28	6.83
3	0.66	0.67	1.11	1.17	8.87	6.50	7.14	6.56	0.74	0.92	1.24	1.36	8.60	6.73	6.52	7.12
Big	0.66	1.08	1.19	1.30	7.56	7.01	7.08	8.19	1.00	0.80	1.27	1.09	9.12	7.30	6.84	7.77
EM EMEA																
Small	0.67	0.82	0.90	1.41	9.09	9.54	9.10	7.04	0.69	1.31	1.39	1.30	9.03	7.96	7.36	8.26
2	0.24	0.55	0.90	1.34	9.88	8.26	8.58	7.65	0.62	0.52	0.62	1.72	9.85	7.38	7.57	9.28
3	0.21	0.72	0.97	0.84	9.32	7.91	8.39	8.11	0.25	0.54	0.67	0.81	9.53	7.72	7.56	8.99
Big	0.10	0.71	0.96	1.54	9.34	8.60	8.63	8.84	0.68	0.58	0.49	1.33	10.53	9.09	8.82	9.16

Table 7 (*Continued*)

	Size-value portfolios								Size-momentum portfolios							
	Mean				Standard deviation				Mean				Standard deviation			
	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
EM Asia																
Small	0.51	0.54	0.35	1.22	8.94	8.28	7.81	9.00	0.65	0.77	1.25	1.08	11.95	8.23	7.63	8.36
2	0.12	0.70	0.45	1.15	8.37	8.21	8.07	8.57	0.09	0.46	1.17	1.45	10.65	8.42	7.59	8.36
3	0.15	0.20	0.28	0.79	7.44	7.83	7.63	8.37	−0.24	0.03	0.60	1.08	10.33	7.88	6.75	8.05
Big	−0.07	0.05	0.18	0.58	7.35	7.42	7.16	8.07	−0.16	−0.21	0.16	0.70	10.44	7.47	6.78	8.10
BRIC																
Small	1.08	0.93	1.25	2.07	9.33	9.40	8.96	9.64	0.89	1.70	2.03	2.43	10.46	9.28	9.31	10.27
2	0.22	0.88	0.87	2.33	8.99	8.88	9.22	9.35	0.67	1.09	1.51	2.42	10.09	8.73	8.60	9.96
3	0.40	−0.04	0.75	1.42	7.77	9.53	8.23	9.25	0.19	0.53	0.81	1.48	9.49	8.12	8.62	9.03
Big	0.56	−0.06	0.33	1.13	7.58	7.07	7.39	8.24	0.34	0.37	0.18	1.00	8.73	7.36	7.16	8.90

factors. Table 8 summarizes the CAPM, Fama-French three-factor model, and Carhart four-factor model regressions for each region. We present the GRS statistic of Gibbons *et al.* (1989), respective p-value p, average absolute intercept $|a|$, average adjusted R^2, average standard error of the intercepts $s(a)$, and the core of the GRS statistics $SR(a)$. The regression intercepts of selected models and regions are shown in Table 9.

The ideal asset pricing model for a region should have a small GRS statistic with a high corresponding p-value. The p-value represents the confidence level for the rejection of the hypothesis that the intercepts of a regression set are jointly zero. The average absolute intercept $|a|$, the average standard error of the intercepts $s(a)$, and the Sharpe Ratio for the intercepts $SR(a)$ should be small. However, it is also important for an appropriate asset pricing model that the model explains the variation in returns as much as possible. An indicator of a good explanatory power is a high adjusted R^2.

We present the regression results for Emerging Markets in Subsection 5.1, while Subsection 5.2 shows the results for the emerging market regions.

5.1. Global and Local Models for Emerging Market Size-Value Portfolio Returns

The global CAPM and the local CAPM have GRS statistics at approximately 1.30; thus, these models cannot be rejected. However, we observe a high average absolute intercept $|a|$ of more than 0.30 for both models and a low R^2 (51%) for the global model. The explanatory power for the local model is higher with 80% but fails to explain the patterns in the average returns of the 16 size-B/M portfolios. Table 9 documents the remaining value and size patterns in the intercepts of the local CAPM.

For the three-factor model, the GRS statistic of the local model is 0.85 compared with 1.02 for the global model; again, we cannot reject both models. However, for the global model, the missing (explanatory) power and the high average absolute intercept are the problem. The explanatory power of the global model is only 66% compared with 92% for the local model; the average absolute intercept sharply drops to 0.09 for the local model compared to 0.20 for the global model. Among all the regressions of portfolios from different regions on local and global factors, the average absolute intercept $|a|$ of the local model for Emerging Markets has the smallest value, and the GRS statistic is one of the best values. Consequently, the local three-factor model does a reasonable job in explaining excess returns of Emerging Markets portfolios. In contrast, the global model fails in economic terms due to missing (explanatory) power and a higher average absolute intercept, although it is not rejected by the GRS test. Table 9 shows no remaining value or size patterns in the intercepts of the local three-factor model.

There is only a marginal improvement in Emerging Markets by adding the momentum factor. For the global model, the GRS statistic decreases by 0.05 to 0.97 and the R^2 increases by 1pp to 67%. For both, global and local models, the average absolute intercepts increase by 0.03 and $s(a)$ and $SR(a)$ remain unchanged,

Table 8 Summary statistics for regressions to explain returns on portfolios from sorts on size and value, with (4 × 4) and without (3 × 4) microcaps

The table presents the summary statistics for the following regions: Emerging Markets (EM), EM Latin America (EM LatAm), EM EMEA, EM Asia, and BRIC. The regressions use local or global versions of the CAPM (4), three-factor model (5), and four-factor model (6) with global or local factors. The GRS statistic tests whether all intercepts for a set of 16 (4 × 4) or 12 (3 × 4) regressions are jointly zero; p denotes the respective p-statistic for the GRS statistic; $|a|$ is the average absolute intercept for a set of regressions; R^2 is the average adjusted R^2; $s(a)$ is the average standard error of the intercepts; and $SR(a)$ is the Sharpe Ratio for the intercepts. All returns are in US$. The statistics are computed over the period July 1996 to June 2012.

	Global model									Local model								
	4 × 4						3 × 4			4 × 4						3 × 4		
	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2
EM																		
CAPM	1.27	0.22	0.32	0.51	0.37	0.34	1.09	0.29	0.52	1.30	0.20	0.33	0.80	0.23	0.34	1.23	0.30	0.82
Three-Factor	1.02	0.43	0.20	0.66	0.31	0.31	0.66	0.19	0.67	0.85	0.62	0.09	0.92	0.15	0.29	0.52	0.07	0.92
Four-Factor	0.97	0.49	0.23	0.67	0.31	0.31	0.69	0.17	0.67	0.83	0.66	0.12	0.92	0.15	0.29	0.52	0.10	0.93
EM LatAm																		
CAPM	1.70	0.05	0.63	0.45	0.38	0.39	1.13	0.58	0.47	1.46	0.12	0.31	0.67	0.29	0.37	0.77	0.23	0.70
Three-Factor	1.60	0.07	0.53	0.49	0.37	0.39	1.02	0.48	0.51	1.31	0.19	0.24	0.75	0.25	0.35	0.73	0.19	0.78
Four-Factor	1.37	0.16	0.54	0.49	0.38	0.37	0.79	0.50	0.51	1.22	0.26	0.21	0.76	0.25	0.34	0.59	0.16	0.78
EM EMEA																		
CAPM	1.72	0.05	0.46	0.49	0.45	0.40	1.46	0.44	0.50	2.15	0.01	0.33	0.72	0.33	0.44	1.71	0.35	0.74
Three-Factor	1.38	0.16	0.32	0.53	0.44	0.36	1.09	0.28	0.54	1.20	0.27	0.19	0.85	0.25	0.34	1.22	0.16	0.85
Four-Factor	1.13	0.33	0.27	0.53	0.45	0.33	0.88	0.22	0.54	1.19	0.28	0.19	0.85	0.25	0.34	1.22	0.17	0.85
EM Asia																		
CAPM	1.22	0.26	0.27	0.39	0.45	0.33	1.41	0.26	0.39	1.25	0.24	0.30	0.76	0.28	0.34	1.45	0.27	0.78
Three-Factor	1.24	0.24	0.22	0.55	0.39	0.34	1.20	0.23	0.56	0.71	0.78	0.11	0.89	0.19	0.26	0.74	0.10	0.90
Four-Factor	1.19	0.28	0.24	0.56	0.40	0.34	1.19	0.20	0.56	0.68	0.81	0.12	0.89	0.19	0.26	0.72	0.12	0.90
BRIC																		
CAPM	1.69	0.05	0.67	0.20	0.56	0.39	2.20	0.55	0.21	1.73	0.04	0.52	0.61	0.39	0.40	2.20	0.47	0.64
Three-Factor	1.62	0.07	0.62	0.36	0.51	0.39	2.12	0.52	0.37	1.12	0.34	0.26	0.81	0.28	0.33	1.39	0.29	0.81
Four-Factor	1.50	0.10	0.58	0.36	0.52	0.38	1.85	0.47	0.37	1.07	0.39	0.23	0.82	0.27	0.32	1.34	0.26	0.82

Table 9 Intercepts from CAPM, three-factor, and four-factor regressions to explain returns on portfolios from sorts on size and value

For selected regions and models, the table reports intercepts, a, and t-statistics, $t(a)$, for the intercepts. All returns are in US\$. The statistics are computed over the July 1996 to June 2012 period.

	a				$t(a)$			
	Low	2	3	High	Low	2	3	High
Emerging Markets: Local CAPM								
Small	0.06	0.46	0.21	0.91	0.17	1.74	0.94	3.17
2	−0.47	−0.04	0.21	0.70	−1.49	−0.13	0.93	2.78
3	−0.42	−0.20	0.09	0.44	−1.40	−0.93	0.47	2.06
Big	−0.44	−0.18	0.03	0.44	−2.85	−1.44	0.22	2.61
Emerging Markets: Local three-factor model								
Small	0.06	0.26	−0.16	0.10	0.28	1.48	−1.02	0.60
2	−0.21	0.02	−0.02	−0.06	−1.31	0.11	−0.13	−0.57
3	−0.11	−0.04	−0.02	−0.12	−0.54	−0.24	−0.12	−0.81
Big	−0.07	0.05	0.00	0.06	−0.67	0.52	−0.03	0.54
Emerging Markets: Local four-factor model								
Small	0.09	0.26	−0.12	0.21	0.40	1.46	−0.75	1.36
2	−0.16	−0.06	−0.12	−0.09	−0.97	−0.37	−0.81	−0.86
3	−0.16	−0.13	−0.15	−0.14	−0.78	−0.75	−0.88	−0.97
Big	−0.06	0.09	−0.02	0.08	−0.51	0.85	−0.18	0.71
EM Latin America: Local four-factor model								
Small	−0.36	0.57	0.28	0.28	−1.29	1.56	1.40	1.81
2	−0.07	0.19	−0.11	−0.26	−0.23	0.39	−0.44	−1.63
3	−0.29	−0.06	0.18	0.11	−0.79	−0.22	0.71	0.46
Big	−0.11	0.17	0.17	−0.19	−0.86	0.93	0.91	−1.20
EM EMEA: Local four-factor model								
Small	0.22	0.37	0.14	0.24	0.74	1.32	0.50	1.58
2	0.13	−0.19	−0.30	0.03	0.57	−0.75	−1.14	0.12
3	0.05	−0.16	−0.24	−0.46	0.16	−0.57	−0.83	−1.73
Big	0.15	−0.03	0.04	0.28	0.72	−0.12	0.19	1.44
EM Asia: Local four-factor model								
Small	−0.02	−0.07	−0.28	0.22	−0.06	−0.32	−1.44	1.12
2	−0.18	0.21	−0.25	0.02	−0.79	1.12	−1.33	0.17
3	0.08	−0.09	−0.23	−0.12	0.30	−0.39	−1.01	−0.64
Big	0.03	0.10	−0.04	−0.07	0.20	0.84	−0.25	−0.45
BRIC: Local four-factor model								
Small	0.39	−0.04	−0.01	0.17	1.17	−0.16	−0.05	0.54
2	−0.23	−0.09	−0.14	0.35	−1.02	−0.30	−0.48	1.64
3	0.08	−0.79	−0.14	−0.32	0.30	−1.63	−0.42	−1.11
Big	0.47	−0.35	−0.09	0.05	2.39	−1.58	−0.43	0.26

respectively. The GRS statistic for the local four-factor model falls to 0.83, while the explanatory power remains at 92%. There are negligible changes in the intercepts by adding *WML* to the regressions. Using the four-factor model instead of the three-factor model only adds little value for size-value portfolios. As global models fail due to the low power, we do not find support for global market integration of Emerging Markets.

Fama and French (2012) demonstrate that excluding microstocks helps the models to survive the GRS statistics as they have problems explaining the wider value spreads for the smallest stocks. When regressing portfolios from 3 × 4 sorts on global risk factors, the GRS statistics on the right-hand side of Table 8 improve for all three global models, but the explanatory powers remain nearly unchanged. Furthermore, the average intercepts are still high compared to the local model. The tests of the local model on 3 × 4 portfolios result in better GRS statistics, and nearly unchanged explanatory powers. As the multifactor models in Emerging Markets do not leave patterns in the intercepts of the small stocks as in developed markets, the asset pricing tests in Emerging Markets do not improve much when microcaps are excluded. A potential reason is that the value-growth spreads of the portfolios show little variation among the four size groups of the Emerging Market portfolios (Table 7).

In sum, the global models fail to explain the returns of Emerging Market size-value portfolios. Although they pass the GRS test, missing (explanatory) power and higher average absolute intercepts are the problems. Instead, the local three-factor model is a good asset pricing model for Emerging Market size-value portfolios. Adding *WML* is not necessary but does not harm the results. In contrast to developed markets, microcaps do not seem to be a problem for Emerging Market size-value portfolios.

5.2. Global and Local Models for Regional Emerging Market Size-Value Portfolio Returns

To analyze the four emerging markets regions in detail, we examine the statistics listed in Table 8. The global CAPM for EM Latin America, EM EMEA, and BRIC, and the three-factor model for EM Latin America and BRIC are the global models that are rejected at the 90% level. We cannot reject the other global CAPM, three-factor, or four-factor pricing models due to their GRS statistics. For the three global models in EM Asia, we determine marginally differing GRS statistics around 1.20. The average absolute intercepts for EM Asia range between 0.22 and 0.27, but the global models have low explanatory power with a maximum of 56% for the four-factor model, which is the highest average value among all regressions of regional excess returns on global factors. The global models in Latin America and BRIC exhibit high average absolute intercepts (0.54 and 0.58 for the global four-factor model), which are approximately twice as high as the $|a|$ of the global models in Emerging Markets. The explanatory power is low with a maximum of 49% and 36% for the four-factor models. The average absolute intercepts and explanatory powers for the global models in EM EMEA are in-between the corresponding values for EM Asia and EM Latin America. Adding the momentum factor improves the GRS statistic for all models but does not improve the models from an economic perspective. Thus, the global models do poorly for emerging market regions due to power and intercepts, although the four-factor models, in particular, pass the GRS statistic.

In contrast, the local models are better suited for emerging market regions. The GRS statistics for the three models in EM Latin America are 1.46, 1.31, and 1.22. With those values, none of the models are rejected. This is an improvement, as the global CAPM and the global three-factor model for EM Latin America are rejected at the 10% significance level. Moreover, the absolute alphas are not even half the values of the respective global model, and especially the average absolute intercepts for the three-factor and four-factor models are within an acceptable range at 0.24 and 0.21, respectively. The explanatory power R^2 is 67% for the CAPM, 75% for the three-factor model, and 76% for the four-factor model. The intercepts for the local four-factor model in EM Latin America are listed in Table 9. The four-factor model has some problems with the smallest stocks which may be partly explained by the reverse size effect of growth stocks in this region (see Table 7).

In EM EMEA, the local CAPM must be rejected at the 99% level and a GRS statistics of 2.15. This rejection level is higher than the rejection level for the global CAPM, although the average alpha is lower. The main reason for the higher GRS statistic is the higher power for the local model with a R^2 of 72% that is 13% higher than the one of the global model. Another reason for the weak GRS statistics of the local CAPM is the very pronounced value pattern in all four size groups in EM EMEA (see Table 7), which are not captured by the CAPM. The three-factor model is doing a good job explaining the returns and reaches a GRS statistic of 1.20; therefore, the three-factor model cannot be rejected. Moreover, there is no value pattern in the intercepts of the three-factor model (not reported) as it is able to capture that effect by the value factor. The R^2 jumps to 85% and the average absolute intercept $|a|$ is 0.19 with an average standard error of 0.25. Adding *WML* results in nearly identical summary statistics. Also, the intercepts from four-factor pricing (Table 9) are nearly unchanged compared with those of the three-factor pricing. Therefore, EM EMEA local multifactor models are doing better than the global multifactor models, as each single statistic is superior, especially the higher R^2 and lower alphas for the three-factor and four-factor models.[17]

For EM Asia, we can observe low GRS statistics for both global and local models and none of them are rejected. However, the local three-factor and four-factor models have better GRS statistics compared to the global models for EM Asia returns. The R^2 of 76% of the local CAPM is substantially higher than the corresponding R^2 of the

[17]The GRS statistic of the global four-factor model is marginally lower; however, both global and local four-factor models cannot be rejected. Moreover, this discrepancy is outbalanced by the higher R^2 and the lower average absolute intercept of the local model.

global CAPM, while the average absolute intercept of the local CAPM is 0.30. This value drops by nearly two-thirds to 0.11 when adding *SMB* and *HML* to the local CAPM. The average standard error of the intercepts also drops to 0.19 and the R^2 jumps to 89%, which is the best value for all the regressions in the three emerging market regions. The GRS statistic is 0.71 which results in a p-value of 0.78, and is only surpassed by the GRS statistic of 0.68 for the local four-factor model in EM Asia, with a p-value of 0.81. Aside from a minimal increase of $|a|$ to 0.12, this is the only change when adding *WML*. The explanatory power R^2 for the four-factor pricing is also 89%, and the intercepts in Table 9 show no common pattern.

As observed for the other regions, the local three-factor and four-factor models dominate the global models for BRIC in explaining returns. In contrast to the local CAPM, the local three-factor and four-factor models are not rejected, their average absolute intercepts are less than the half of the ones of the global models, and their explanatory power of 81% and 82% is acceptable. The intercepts in Table 9 do not exhibit size or value patterns; however, six out of eight intercepts of the extreme growth and extreme value portfolios are positive and the remaining intercepts of the portfolios with moderate book-to-market ratios (portfolios of value groups 2 and 3) are negative.

Our main results for regional size-value portfolios do not change when microcaps are excluded from our analysis. Although the GRS statistic improves for some global models, they still fail from an economic perspective. We can notice a considerable improvement for the local model in EM Latin America—the region that shows an inverse size effect for growth stocks and a more pronounced value pattern for the smallest stocks (Table 7). Besides EM Latin America, microcaps do not seem to cause problems for asset pricing models in emerging market samples as they do in developed markets. Thus, we conclude that local three-factor and four-factor models are reasonable asset pricing models for size-value portfolios in emerging market regions.

6. Asset Pricing Tests for Size-Momentum Portfolios

This section presents our results for sorts on size and momentum. Similar to the table structure for sorts on size and value, Table 10 presents the summary statistics of regressions to explain excess returns on size-momentum portfolios while Table 11 documents regression intercepts for the most relevant model-sample combinations.

6.1. Global and Local Models for Emerging Market Size-Momentum Portfolio Returns

The global CAPM, global three-factor model, and global four-factor model are rejected by the GRS statistic at the 99% level for Emerging Markets. The results when applying the models on the size-value portfolios are different, and none of the models are rejected. This shows that the models are doing a better job in capturing the value effect than the momentum effect. We also find relatively high average absolute intercepts ranging from 0.54 for the CAPM to 0.36 for the four-factor model. The (unreported) intercept matrices show strong momentum patterns in the intercepts for each size group for the global CAPM and three-factor model, and a mild reverse momentum pattern for the megacaps of the global four-factor model. With values of 48%, 61%, and 65%, the R^2 of the three models are up to 5% smaller than the R^2 for the size-value portfolios. For the 3 × 4 Emerging Market portfolios, the global three-factor model is rejected at the 90% level, while the global four-factor model is rejected at the 95% level. Also, the explanatory powers do not increase significantly. As for the size-value portfolios, the global models explain Emerging Markets size-momentum excess returns poorly, and we find no support for global market integration of Emerging Markets.

As previously stated, the local models perform well in the explanation of Emerging Markets size-value portfolio returns. For the tests on size-momentum portfolio returns, the three local models have GRS statistics of 2.90, 2.59, and 2.29, implying that we have to reject them at the 99% level. The average R^2 is 75% for the local CAPM, 81% for the local three-factor model, and 90% for the local four-factor model. Therefore, the explanatory power of the local models for the size-momentum portfolios is smaller than those for the size-value portfolios. For the four-factor model, however, the difference is only 2%. The average absolute intercepts are also higher compared to the tests on size-value portfolios.

Table 11 shows strong momentum patterns in the intercepts for the CAPM and the three-factor model. The small portfolio with the second highest past year performance has the highest intercept because the models are unable to explain the abnormally high return of this portfolio. When adding *WML*, these patterns vanish; however, high positive intercepts for three of the four microcaps portfolios remain. We expect that dropping microcaps results in an improvement of the model fit. Excluding microcaps (see Table 10) and considering the twelve portfolios from 3 × 4 sorts on size and momentum primarily improves the GRS statistic for local models. For the regressions of the Emerging Market excess returns on the local risk factors, the GRS statistic for the three-factor and four-factor models drop to 1.41 and 1.01 and these models do not have to be rejected. This result confirms our expectation of a noticeable improvement for the 3 × 4 portfolio formation. The local four-factor model outperforms the local three-factor model in economic terms due to the lower average intercepts and higher average R^2. Therefore, we conclude that the local four-factor model is doing well in pricing Emerging Market size-momentum portfolio returns, if microcaps are excluded. However, based on the statistics of the global models for the 3 × 4 sort portfolios, we gain no support for global integrated pricing for Emerging Markets.

6.2. Global and Local Models for Regional Emerging Market Size-Momentum Portfolio Returns

This subsection evaluates the effectiveness of global and local models for regional portfolios. In contrast to EM EMEA and EM Asia, we reject all global models for

Table 10 Summary statistics for regressions to explain returns on portfolios from sorts on size and momentum, with (4 × 4) and without (3 × 4) microcaps

The table presents the summary statistics for the following regions: Emerging Markets (EM), EM Latin America (EM LatAm), EM EMEA, EM Asia, and BRIC. The regressions use local or global versions of the CAPM (4), three-factor model (5), and four-factor model (6) with global or local factors. The GRS statistic tests whether all intercepts for a set of 16 (4 × 4) or 12 (3 × 4) regressions are jointly zero; p denotes the respective p-statistic for the GRS statistic; $|a|$ is the average absolute intercept for a set of regressions; R^2 is the average adjusted R^2; $s(a)$ is the average standard error of the intercepts; and $SR(a)$ is the Sharpe Ratio for the intercepts. All returns are in US$. The statistics are computed over the period July 1996 to June 2012.

	Global model									Local model								
	4 × 4						3 × 4			4 × 4						3 × 4		
	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2
EM																		
CAPM	2.78	0.00	0.54	0.48	0.40	0.50	1.99	0.47	0.48	2.90	0.00	0.54	0.75	0.28	0.51	1.97	0.46	0.77
Three-Factor	2.46	0.00	0.47	0.61	0.36	0.48	1.75	0.45	0.61	2.59	0.00	0.44	0.81	0.25	0.50	1.41	0.41	0.82
Four-Factor	2.22	0.01	0.36	0.65	0.34	0.47	1.83	0.24	0.66	2.29	0.00	0.20	0.90	0.18	0.48	1.01	0.15	0.91
EM LatAm																		
CAPM	2.06	0.01	0.76	0.43	0.38	0.43	1.50	0.64	0.46	1.97	0.02	0.40	0.66	0.29	0.43	1.25	0.30	0.69
Three-Factor	1.94	0.02	0.63	0.47	0.38	0.43	1.37	0.51	0.49	2.02	0.01	0.36	0.72	0.27	0.44	1.07	0.31	0.73
Four-Factor	1.53	0.09	0.68	0.48	0.38	0.39	1.02	0.56	0.51	1.87	0.03	0.26	0.77	0.24	0.43	0.81	0.19	0.79
EM EMEA																		
CAPM	1.10	0.36	0.42	0.49	0.44	0.32	1.06	0.31	0.50	1.08	0.38	0.35	0.70	0.34	0.31	1.00	0.29	0.72
Three-Factor	1.29	0.21	0.36	0.53	0.43	0.35	1.18	0.28	0.54	1.44	0.13	0.33	0.77	0.31	0.38	1.31	0.33	0.77
Four-Factor	1.14	0.32	0.34	0.55	0.44	0.34	0.97	0.26	0.56	1.44	0.13	0.31	0.84	0.25	0.38	1.30	0.31	0.84
EM Asia																		
CAPM	1.41	0.14	0.51	0.37	0.49	0.36	1.66	0.51	0.36	1.54	0.09	0.54	0.72	0.33	0.37	1.79	0.50	0.74
Three-Factor	1.28	0.21	0.46	0.50	0.45	0.35	1.55	0.51	0.50	1.06	0.40	0.47	0.78	0.30	0.32	1.20	0.51	0.79
Four-Factor	1.01	0.45	0.32	0.55	0.44	0.32	1.21	0.28	0.55	0.85	0.63	0.18	0.87	0.23	0.29	0.94	0.17	0.88
BRIC																		
CAPM	1.46	0.12	0.83	0.20	0.58	0.36	1.62	0.63	0.21	1.42	0.14	0.64	0.58	0.42	0.36	1.52	0.49	0.61
Three-Factor	1.63	0.07	0.77	0.32	0.55	0.39	1.92	0.60	0.34	0.97	0.50	0.40	0.68	0.38	0.31	0.80	0.37	0.69
Four-Factor	1.53	0.09	0.72	0.34	0.55	0.39	1.78	0.53	0.36	0.85	0.63	0.24	0.80	0.29	0.29	0.66	0.18	0.81

Table 11 Intercepts from CAPM, three-factor, and four-factor regressions to explain returns on portfolios from sorts on size and momentum

For selected regions and models, the table reports intercepts, *a*, and *t*-statistics, *t*(*a*), for the intercepts. All returns are in US$. The statistics are computed over the period July 1996 to June 2012.

	a				$t(a)$			
	Low	2	3	High	Low	2	3	High
Emerging Markets: Local CAPM								
Small	0.27	0.72	1.27	0.88	0.53	2.80	5.37	3.15
2	−0.47	0.25	0.79	0.99	−1.07	0.99	3.53	3.17
3	−0.68	−0.14	0.45	0.71	−1.80	−0.72	2.43	2.46
Big	−0.53	−0.14	−0.10	0.29	−1.67	−0.85	−0.70	1.18
Emerging Markets: Local three-factor model								
Small	−0.50	0.28	0.79	0.45	−1.14	1.41	4.59	1.73
2	−0.84	0.03	0.53	0.64	−2.16	0.17	3.11	2.22
3	−0.85	−0.19	0.42	0.55	−2.42	−1.15	2.34	1.89
Big	−0.49	−0.07	0.01	0.31	−1.50	−0.42	0.10	1.27
Emerging Markets: Local four-factor model								
Small	0.22	0.42	0.69	0.07	0.75	2.25	4.10	0.36
2	−0.12	0.16	0.36	0.11	−0.60	0.83	2.33	0.73
3	−0.23	−0.10	0.27	0.06	−1.12	−0.59	1.60	0.34
Big	0.09	0.14	−0.05	−0.08	0.49	1.05	−0.34	−0.50
EM Latin America: Local four-factor model								
Small	0.24	0.38	0.78	0.57	1.00	1.68	2.86	2.42
2	−0.10	−0.27	0.33	−0.13	−0.42	−0.89	1.19	−0.51
3	−0.16	0.17	0.34	0.28	−0.59	0.69	1.19	0.93
Big	−0.01	−0.02	0.25	−0.18	−0.06	−0.09	1.49	−0.93
EM EMEA: Local four-factor model								
Small	0.09	0.34	0.52	0.25	0.37	1.34	2.27	0.97
2	−0.07	−0.17	−0.43	0.45	−0.29	−0.66	−1.49	1.82
3	−0.24	−0.31	−0.25	−0.52	−0.97	−1.13	−0.85	−1.70
Big	0.52	−0.07	−0.38	0.29	2.49	−0.35	−1.58	1.29
EM Asia: Local four-factor model								
Small	0.24	0.12	0.37	−0.03	0.64	0.47	1.57	−0.11
2	−0.07	−0.13	0.37	0.20	−0.31	−0.47	1.96	1.08
3	−0.28	−0.22	0.09	0.20	−1.13	−0.88	0.41	0.94
Big	0.21	−0.15	0.02	0.15	0.86	−0.90	0.11	0.81
BRIC: Local four-factor model								
Small	0.19	0.52	0.43	0.44	0.59	1.78	1.15	1.15
2	0.16	0.00	0.16	0.49	0.61	0.00	0.47	1.98
3	−0.20	−0.15	−0.34	0.01	−0.67	−0.47	−0.93	0.02
Big	0.26	0.11	−0.30	0.02	1.22	0.47	−1.29	0.10

EM Latin America and global multifactor models for BRIC (see Table 10) due to their GRS statistics. The models for EM Latin America and BRIC produce high average absolute alphas up to 0.83 and low average explanatory powers between 20% and 48%. The GRS statistics of the three global models for EM EMEA and EM Asia are significantly lower. Nevertheless, even the four-factor models have low explanatory powers (55%) and leave high average absolute intercepts of 0.34 and 0.32 for EM EMEA and EM Asia, respectively. In sum, the global four-factor models of EM EMEA and EM Asia produce similar statistics, especially GRS statistics, but suffer from low explanatory powers. In economic terms, the global four factors explain regional emerging market returns insufficiently. The models for EM Latin America fail due to the GRS statistics and the low R^2. As already suggested by the size-value portfolios and the Emerging Market size-momentum portfolios, integrated global pricing does not seem to be a valid assumption for the emerging market regions.

For EM Latin America, all local models are rejected at the 95% level, although the R^2 increases to values ranging between 66% and 77%, and the average absolute intercepts simultaneously fall compared to the global models. Compared to the results for the size-value portfolios, the GRS statistics, in particular, are worse and the average absolute intercepts are higher for the size-momentum portfolios.

The explanatory power for the three local models in EM EMEA is acceptable and ranges between 70% and 84%. Although the GRS statistics for the local three-factor and four-factor model are higher than for the global multifactor models, they are not rejected. In EM Asia and BRIC, both the GRS statistics and R^2 are better for the local three-factor and four-factor models; thus, we cannot reject both local models. Among all tests on size-momentum portfolios, the GRS statistic of 0.85 for local four-factor pricing in EM Asia and BRIC are the lowest values. The average absolute intercepts for four-factor pricing in EM Latin America, EM EMEA, EM Asia, and BRIC are 0.26, 0.31, 0.18, and 0.24, respectively, which are the lowest values within each region.

Table 11 presents the intercepts for the regressions of the regional emerging market size-momentum portfolio returns on the local four-factor models. In the intercepts of the four-factor model in EM Latin America, we find a momentum pattern for microcaps and a milder reverse momentum pattern for megacaps. The winner-loser spread in mean returns of Table 7 for microcaps is 0.58 (1.69–1.11), and therefore approximately six times as large as the winner-loser spread for megacaps of 0.09 (1.09–1.00). However, the spreads in the four-factor *WML*-slopes (unreported) are 0.87 and 1.09 for small and large stocks, and therefore the four-factor model does poorly in explaining the returns. The intercept matrices of EM EMEA and EM Asia do not show such patterns.

Thus, we expect the largest improvement in the statistics for EM Latin America using 3×4 sorts instead of 4×4 sorts for emerging market regions. Table 10 confirms our expectation, and neither any global nor local model is rejected for EM Latin America. The local four-factor model in EM Latin America has the lowest

GRS statistic (0.81) among all tests of global and local models on 3 × 4 portfolio sorts. Compared to the tests on 4 × 4 portfolios, the explanatory power of the local and global models in EM EMEA and EM Asia either marginally improves or remains constant. The GRS statistics for the models in EM EMEA marginally decrease, while those in EM Asia marginally increase. For BRIC the tests on 3 × 4 portfolio sorts result in worse GRS statistics for the global models and marginally higher explanatory powers compared to the tests on 4 × 4 portfolios. Deleting microcaps in BRIC improves the GRS statistic of the local four-factor model on size-momentum portfolios to 0.66, and the R^2 slightly increases to 81%. Consequently, the local four-factor models are reasonable asset pricing models for all regional size-momentum portfolios when microcaps are excluded.

In sum, the local four-factor models are good pricing models in emerging market regions, expect for EM Latin America. For EM Latin America the global and local models fail due to the high GRS statistics when microcaps are included. The problems of the local four-factor model are, however, largely concentrated in microcaps. When microcaps are dropped, the performance of the local four-factor model significantly improves.

7. Asset Pricing Tests with an Emerging Market Model

Our results in the previous two sections provide little evidence of integrated global pricing for both Emerging Markets and emerging market regions. But perhaps emerging markets integrated pricing is present within emerging market regions instead of integrated global pricing. Given the good performance of the local four-factor model in Emerging Markets (keeping microcaps for size-momentum sorts aside), we propose an Emerging Market (EM) model consisting of the risk factors from Emerging Markets as an alternative global model. This is analogous to the approach of Fama and French (2012), who construct their global model from regional stock returns. As these regional stocks are solely from developed markets, their global model is basically a developed market model. The tests of the EM model on the emerging market regions are presented in Table 12, Panels A (size-value sorted portfolios) and B (size-momentum sorted portfolios).

The explanatory power of the three EM models for EM Latin American, EM EMEA, and BRIC size-value portfolio returns is low and between 36% and 52%. The average absolute intercepts for the tests are high and range from 0.42 to 0.69. The magnitude of both these statistics is similar to those for the regressions of the standard global models for EM Latin American and EM EMEA. For BRIC, we can see similar absolute intercepts but a higher explanatory power for the EM model. For both global and EM model regressions, the CAPM, three-factor models, and four-factor models are rejected for EM Latin America; however, at a higher rejection level for the EM model. In contrast to their global counterparts, the EM multi-factor models are rejected for EM EMEA excess returns, and vice versa for BRIC excess returns. For EM Asia, we find comparable GRS statistics for the tests of the

Table 12 Robustness—Summary statistics for regressions to explain returns from sorts on size and value, and size and momentum with an Emerging Market model

The table presents the summary statistics for sorts on size and value (Panel A), and size and momentum (Panel B) for the following regions: EM Latin America (EM LatAm), EM EMEA, EM Asia, and BRIC. The regressions use versions of the CAPM (4), three-factor model (5), and four-factor model (6) with RHS factors from Emerging Markets. The GRS statistic tests whether all intercepts for a set of 16 (4 × 4) regressions are jointly zero; p denotes the respective p-statistic for the GRS statistic; $|a|$ is the average absolute intercept for a set of regressions; R^2 is the average adjusted R^2; $s(a)$ is the average standard error of the intercepts; and $SR(a)$ is the Sharpe Ratio for the intercepts. All returns are in US$. The statistics are computed over the period July 1996 to June 2012.

	EM model					
	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$
Panel A: Size-value portfolios						
EM LatAm						
CAPM	1.78	0.04	0.69	0.49	0.36	0.40
Three-Factor	2.07	0.01	0.65	0.50	0.37	0.45
Four-Factor	1.96	0.02	0.61	0.50	0.38	0.44
EM EMEA						
CAPM	1.90	0.02	0.51	0.51	0.44	0.42
Three-Factor	1.68	0.05	0.50	0.52	0.45	0.40
Four-Factor	1.58	0.08	0.42	0.52	0.45	0.40
EM Asia						
CAPM	1.27	0.22	0.28	0.71	0.31	0.34
Three-Factor	1.31	0.19	0.21	0.85	0.23	0.36
Four-Factor	1.09	0.37	0.18	0.85	0.23	0.33
BRIC						
CAPM	1.72	0.05	0.67	0.36	0.50	0.40
Three-Factor	1.24	0.24	0.64	0.50	0.46	0.35
Four-Factor	1.05	0.40	0.51	0.51	0.46	0.32
Panel B: Size-momentum portfolios						
EM LatAm						
CAPM	2.30	0.00	0.84	0.48	0.37	0.46
Three-Factor	2.80	0.00	0.75	0.50	0.37	0.52
Four-Factor	2.48	0.00	0.73	0.50	0.37	0.50
EM EMEA						
CAPM	1.11	0.34	0.50	0.51	0.43	0.32
Three-Factor	1.18	0.28	0.53	0.52	0.44	0.34
Four-Factor	1.02	0.44	0.44	0.53	0.44	0.32
EM Asia						
CAPM	1.49	0.11	0.51	0.66	0.36	0.37
Three-Factor	0.97	0.49	0.45	0.75	0.32	0.31
Four-Factor	0.70	0.79	0.14	0.83	0.26	0.26
BRIC						
CAPM	1.49	0.11	0.83	0.35	0.53	0.37
Three-Factor	1.25	0.23	0.78	0.43	0.51	0.35
Four-Factor	1.08	0.38	0.67	0.48	0.49	0.33

global and EM models, but the R^2 is significantly higher for the EM models and reach an acceptable level of 85% for the three-factor and four-factor models. Also, the average absolute intercepts are significantly lower, for example, 0.18 for the test of the EM four-factor model versus 0.24 for the global four-factor model. A potential explanation for the good statistics of the EM models for EM Asian returns is the high influence of stocks from EM Asia on EM risk factors. Around eight out of ten stocks in the Emerging Markets portfolio are from EM Asia. In sum, our results indicate that Emerging Markets pricing is not applicable to size-value portfolios of EM Latin America, EM EMEA, and BRIC. For EM Asia, we find support for integrated pricing based on the EM model. This might be due to the fact that the EM sample is highly influenced by EM Asia.

Panel B of Table 12 presents the summary statistics for EM models on size-momentum portfolios. All three EM models for EM Latin America are rejected at the 99% level; however, the models are not rejected for EM EMEA, EM Asia, and BRIC. All average absolute intercepts of the EM models on regional emerging market portfolios are high (>0.44), except for the regression of the EM four-factor model on EM Asian portfolios. Similar to the regression of size-momentum portfolios on the global factors, we find low explanatory power for all models in EM Latin America, EM EMEA, and BRIC, ranging between 35% and 53%. The average R^2 for the models in EM Asia is higher than for the three other regions; however, we only find an explanatory power of more than 80% for the EM four-factor model. Furthermore, we document a low average intercept and a high explanatory power for the four-factor model. Again, the high influence of stocks from EM Asia on EM risk factors seems to be the reason for the good performance. In sum, our results provide little evidence supporting integrated Emerging Markets pricing for regional size-value or size-momentum portfolios.

8. Summary

Although the importance of emerging market economies and stock markets are constantly rising, only a few studies have investigated value and momentum effects in emerging markets compared to developed markets. The purpose of examining emerging market stock returns in this paper is threefold. First, we determine the magnitude of standard risk factors on the basis of a broad sample of stocks from 21 emerging market countries in a methodologically consistent way. Second, we explore the size patterns in value and momentum returns of emerging market stock returns. Third, we discuss global market integration for Emerging Markets (comprising all 21 emerging market countries) and four emerging market regions—EM Latin America, EM EMEA, EM Asia, and BRIC.

We report only weak statistical evidence for the market and size premiums. The market risk premium is only significant for EM Latin America, while the size premium is only significant for EM Asia and BRIC. In contrast, the value premium is highly significant for the Emerging Markets sample as well as in all emerging market regions. The momentum premium is also positive for all regions; however, despite the high magnitude, the factor is not as significant as the value factor. Moreover, the three cross-sectional factor premiums have the highest means in the BRIC region. In contrast to the global and developed markets, significant value and momentum premiums are present for big stocks, and overall premiums are not mainly driven by small stocks.

Value premiums exist for all size groups of the size-value portfolios. In contrast to Fama and French (2012), the reverse size effect for growth stocks does not exist in emerging markets samples, with the exception of EM Latin America. The value-growth spreads for emerging markets samples are substantially higher than for developed markets. Besides EM Latin America, the value premium for microcaps is not the highest premium within the different size groups. Furthermore, we document a momentum effect for all size groups of the size-momentum portfolios within all samples—although it is not very strong for the biggest stocks in EM Latin America. We find smaller momentum spreads for the biggest stocks than for the smallest stocks in EM Latin America and BRIC, but also higher spreads in Emerging Markets, EM EMEA, and EM Asia. Thus, we document value and momentum patterns in emerging market size-value and size-momentum portfolios. However, we cannot provide clear evidence that these patterns decrease with size as for developed markets.

The global models perform poorly for Emerging Markets and the emerging market regions. They primarily fail in explaining returns of size-value and size-momentum portfolios due to high average absolute intercepts and low explanatory powers. Consequently, the global models fail in economic terms although not all are formally rejected. Therefore, we get little support for integrated global pricing, at least with our asset pricing models. Nevertheless, if we substitute global risk factors by local risk factors, the results generally support the validity of local four-factor pricing. Also, an alternative global emerging markets model is less successful in explaining the returns of the sub-regions than the local models.

In general, the models applied in this paper face more problems in explaining size-momentum than size-value portfolio returns. For size-value portfolios, there is only a marginal difference between the results of the three-factor and the four-factor model. Consequently, for portfolios without momentum tilts, the three-factor model is sufficient for accurate pricing. In this case, adding *WML* is not necessary but does not harm the results. However, the four-factor model is superior when applied to size-momentum portfolios. Microcaps in Emerging Markets and emerging market regions are not as challenging for the models as in developed markets. Only for the size-momentum portfolios in Emerging Markets and for both portfolio sorts in EM Latin America, the models perform significantly better if microcaps are excluded. When microcaps are dropped, the local four-factor models also have significantly fewer problems with size-momentum portfolios. In sum, the local four-factor models are a reasonable choice to explain the excess returns of diversified emerging market portfolios.

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Appendix 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) and Schmidt *et al.* (2010). To avoid a survivorship bias, we use the intersection of Datastream research lists, Worldscope lists, and dead lists for each of the 45 regarded countries. Table A1 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.

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 A2. 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 A2 and not as common equity. The keywords of Table A3 are country-specific and only the names of the stocks of the corresponding country are matched to these keywords.[18] After a manual review, the identified securities are excluded from the sample.

[18]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 A1 Constituent lists: Emerging markets

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 45 regarded countries. The table presents the identifiers of the constituent lists of the 21 emerging market countries.

Country	Lists	Country	Lists
Brazil	DEADBRA	Morocco	DEADMOR
	WSCOPEBR		WSCOPEMC
	FBRA		FMOR
Chile	DEADCHI	Peru	DEADPE
	WSCOPECL		WSCOPEPE
	FCHILE		FPERU
China	DEADCH	Philippines	DEADPH
	WSCOPECH		WSCOPEPH
	FCHINA		FPHI
Colombia	DEADCO		FPHIQ
	WSCOPECB	Poland	DEADPO
	FCOL		WSCOPEPO
Czech Republic	DEADCZ		FPOL
	WSCOPECZ	Russia	DEADRU
	FCZECH		WSCOPERS
Egypt	DEADEGY		FRUS
	WSCOPEEY	South Africa	DEADSAF
	FEGYPT		WSCOPESA
Hungary	DEADHU		FSAF
	WSCOPEHN	South Korea	DEADKO
	FHUN		WSCOPEKO
India	DEADIND		FKOR
	WSCOPEIN	Taiwan	DEADTW
	FINDIA		WSCOPETA
Indonesia	DEADIDN		FTAI
	WSCOPEID		FTAIQ
	FINO	Thailand	DEADTH
Malaysia	DEADMY		WSCOPETH
	WSCOPEMY		FTHA
	FMAL		FTHAQ
	FMALQ	Turkey	DEADTK
Mexico	DEADME		WSCOPETK
	WSCOPEMX		FTURK
	FMEX		

Table A2 Generic filter rules to exclude non-common equity securities

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.

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" "PREF" "'PF'" "PRF"
Warrants	"WARRANT" "WARRANTS" "WTS" "WTS2" "WARRT"
Debt	" DEB " " DB" "DCB" " DEBT " "DEBENTURES" " DEBENTURE" "BOND" "%"
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"
Ince and Porter (2006)	"500" " BOND " "DEFER" " DEP " "DEPY" "ELKS" " ETF" "FUND" "FD" "IDX" "INDEX" " MIPS" " MITS" "MITS." " MITT " " MITT." "NIKKEI" " NOTE." " NOTE " "PERQS" " PINES " " PINES." "PRTF" "PTNS" "PTSHP" "QUIBS" " QUIDS" " RATE" "RCPTS" "RECEIPTS" "REIT" "RETUR" " SCORE" "SPDR" "STRYPES" "TOPRS" "WTS" "XXXXX" "YIELD" "YLD" " QUIDS"
Expired securities	"EXPIRED" "EXPD" "EXPIRY" "EXPY"

Table A3 Country-specific filter rules to exclude non-common equity securities

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.

Country	Keywords
Developed Markets	
Australia	” RTS” ” DEF” ”DFD” ”PAID” ”PRF”
Austria	” PC” ”.PC” ”GSH” ”Genussscheine”
Belgium	”CONV” ”VVPR” ”STRIP”
Canada	”.RTS” ” RTS” ”SHS” ”VTG” ”SBVTG” ”SUBD” ”SR.” ”SER.” ”RECPT” ”Receipt” ”EXH” ”EXCHANGEABLE” ”SPLIT”
Denmark	”VXX” ”CSE”
Finland	” USE ”
France	”ADP” ” CI ” ”CI.” ” CIP ” ”CIP.” ” ORA ” ” ORA.” ”ORCI” ”OBSA” ”OPCSM” ”SGP” ”SICAV” ”FCP” ”FCPR” ”FCPE” ”FCPI” ”FCPIMT” ”OPCVM”
Germany	”GENUSSCHEINE” ”.GSH” ” GSH” ”%”
Greece	” PR ” ”PB” ”PR.” ”.PR” ”.PR”
Italy	”RNC” ”RIGHTS” ”PV” ” RP ”
Netherlands	”CERT” ”CERTS”
New Zealand	”RTS”
Portugal	” R ” ”’R’”
Singapore	”NCPS” ”NCPS100” ”NRFD” ”FB” ”FBDEAD”
Sweden	”VXX” ” USE ” ”CONVERTED” ” CONV”
Switzerland	” USE ” ”CONVERTED” ”CONV” ”CONVERSION”
United Kingdom	”PAID” ” NV ” ” NV.”
Emerging Markets	
Brazil	” PN” ”PNA” ”PNB” ”PNC” ”PNC” ”PNE” ”PNF” ”PNG” ”RCSA” ”RCTB” ”PNDEAD” ”PNADEAD” ”PNBDEAD” ”PNCDEAD” ”PNDDEAD” ”PNEDEAD” ”PNFDEAD” ”PNGDEAD”
Colombia	”PFCL” ”PRIVILEGIADAS” ”PRVLG”
India	”XNH”
Indonesia	”FB” ”FBDEAD” ” RTS” ”RIGHTS” ”RIGHTS”
Israel	”P1”
Malaysia	” A ” ”’A’” ”FB” ”(XCO)” ”XCODEAD” ” SES” ”(SES)” ”RIGHTS”
Mexico	”ACP” ”BCP” ” ’C’” ” ’L’” ” ’L’” ” O ” ” ’O’” ” C ” ” L ”
Peru	”INVERSION” ”INVN” ” INV”
Philippines	”PDR”
South Africa	”’N’” ”CPF” ”OPTS” ”OPTS”
South Korea	”1P” ”2P” ” 3P” ”1PB” ”1PB” ”3PB” ”4PB” ”5PB” ”6PB” ”1PFD” ”1PF” ”PF2” ”2PF”
Taiwan	”TDR” ”’TDR’”
Thailand	”FB” ”FBDEAD”

Appendix 2 Dynamic Screens

For the securities, remaining from the static screens above, we obtain return and market capitalization data from Datastream and accounting data from Worldscope. We calculate returns from the total return index in US$ and delete all zero returns (in local currency) from the end of the time-series to the first non-zero return. In addition, we remove all observations for which the return is greater than 890%, 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%.