The volatility effect in emerging markets

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This paper examines the empirical relation between risk and return in emerging equity markets and finds that this relation is flat, or even negative. This is inconsistent with theoretical models such as the CAPM, which predict a positive relation, but consistent with the results of studies which have previously examined the empirical relation between risk and return in the US and other developed equity markets. The findings are robust to considering a universe of large-cap stocks only, to considering longer holding periods and to controlling for exposures to the size, value and momentum effects. The empirical deviation from the theoretical risk-return relation appears to be growing stronger over time, which might be related to the increasing participation of benchmark-driven investors, in line with the 'limits to arbitrage' hypothesis. Finally, it finds low correlations between the volatility effects in emerging and developed equity markets, which argues against a common-factor explanation.

1. INTRODUCTION

This paper examines the empirical relation between risk and return in emerging equity markets. The Nobel-prize winning Sharpe-Lintner Capital Asset Pricing Model (CAPM) postulates that the expected return on a stock is linearly proportional to its market beta. However, the initial empirical tests of the CAPM for the U.S. equity market already indicated that low-beta stocks have higher returns than predicted by the CAPM; see, e.g., Black, Jensen and Scholes (1972), Fama and MacBeth (1973) and Haugen and Heins (1975). Whereas some anomalies tend to weaken or even disappear following their public dissemination, the beta effect only seems to have been growing stronger over time. For instance, the seminal Fama and French (1992) paper documents that the relation between beta and U.S. stock returns is essentially flat over the 1963-1990 period, especially after correcting for size effects. More evidence for a flat, or even negative, relation between risk and return is given by Black (1993), Haugen and Baker (1991, 1996) and Falkenstein (1994), who look at similar or longer sample periods.

More recently, Blitz and van Vliet (2007) provide international evidence, showing that the relation between risk and return is not only negative in the U.S., but also in the European and Japanese equity markets over the 1986 to 2006 period. In addition, they find that the effect is even stronger when risk is measured using simply volatility instead of beta. For the U.S. stock market, Baker, Bradley and Wurgler (2011) confirm that the volatility effect presents an even bigger anomaly than the related beta effect over the 1968 to 2008 period.

In addition, Clarke, de Silva and Thorley (2010) report that the relation between volatility and expected stock returns is flat over the extended 1931 to 2008 period. Ang, Hodrick, Xing and Zhang (2006, 2009) show that also very short-term (past one month daily) idiosyncratic volatility is negatively related to subsequent stock returns in the U.S. and other G7 stock markets, providing further evidence of the robustness of the anomalous empirical relation between risk and return.

The paper extends the existing literature by analyzing the empirical relation between risk and return in emerging equity markets. Emerging markets have become increasingly important to investors due to their fast growing economies. This is clearly reflected in the composition of the MSCI All Countries index, in which the weight of emerging markets has grown from roughly 1 percent in 1988 to around 15 percent nowadays. This increase has mostly come from issuance of new shares, and to a smaller extent from higher realized returns. However, emerging markets have also been characterized by a high volatility and multiple crises, such as Mexico 1994, Asia 1997 and Russia 1998. Several studies have examined the cross-section of stock returns in emerging markets, and conclude that the classic size, value and momentum effects are also present in these markets; see, e.g., Fama and French (1998), Patel (1998), Rouwenhorst (1999) and van der Hart, Slagter and van Dijk (2003). However, the empirical relation between risk, in terms of either volatility or beta, and return in emerging markets has not received much attention. One of the few exceptions is Rouwenhorst (1999), who observes that beta is not related to return in emerging markets over the 1982 to 1997 period.

The analysis presented here of the empirical relation between risk and return in emerging markets is relevant for at least three reasons. First, by considering a fresh dataset with data through 2010, it is possible to test whether conclusions on the empirical relation between risk and return in developed equity markets carry over to emerging equity markets. If the results of our out-of-sample test on emerging markets are similar to previous findings for the U.S. and other developed equity markets, this reduces the probability of a spurious result that might be attributable to data mining. Moreover, by relating the volatility effect in emerging markets to the volatility effect in developed markets, it is possible to assess if the effects in different markets are driven by a common component. High correlations between the alphas in different markets suggest that the volatility effect may represent a global risk factor, while low correlations are indicative of mispricing occurring independently in different markets.

Second, the new sample enables the main criticisms existing studies have received to be addressed. For example, Bali and Cakici (2008) argue that the negative empirical relation between risk and return is driven by small-caps, especially the strong negative returns of high (idiosyncratic) volatility stocks. This paper addresses this concern by including only constituents of the S&P/IFC Investable Emerging Markets Index in the sample, and additionally by conducting a robustness test on the 50% largest stocks within this already liquid universe. Others, such as Scherer (2010), have argued that some of the effect may be due to exposure to the classic value premium. Here, the authors therefore also adjust for such implicit factor loadings, using both parametric and non-parametric techniques. Yet another critique, by Amenc, Martellini, Goltz and Sahoo (2011), is that the relation between risk and return turns positive over longer holding periods. The author's therefore also analyze the performance characteristics of portfolios sorted on past risk over holding periods up to five years.

Third, emerging markets can shed new light on the different hypotheses which have been proposed in the literature to rationalize the apparently anomalous empirical relation between risk and return. Some, such as Baker, Bradley and Wurgler (2011) and Frazzini and Pedersen (2010) relate the effect to benchmarkdriven institutional investors, while others, such as Black (1993) and de Giorgi and Post (2011) relate the effect to constraints on leverage or constraints on short-selling. Emerging markets are an interesting test case, as due to their rapid growth and progressive liberalization over the past decades, they have grown from a niche into a mainstream asset class for global institutional investors. For developed markets, Blitz and van Vliet (2007) and Baker, Bradley and Wurgler (2011) have suggested that the volatility effect has strengthened over time, something that can now be tested out-of-sample for dozens of new emerging countries.

The main finding of this paper is that, similar to the results documented previously for the U.S. and other developed equity markets, the empirical relation between risk and return is negative in emerging equity markets, and more strongly so when volatility instead of beta is used to measure risk. Specifically, a monthly rebalanced top-minus-bottom quintile hedge portfolio based on past three-year volatility exhibits a negative raw return spread of -4.4% per annum over the 1989 to 2010 sample period. Adjusted for differences in market beta, this amounts to a statistically significant negative alpha spread of -8.8%. The alpha spread remains large and significant after additionally controlling for size, value and momentum effects. In line with other studies on the volatility effect, the authors observe that the negative alpha of the most volatile stocks is larger than the positive alpha of the least volatile stocks. Robustness tests show that the alpha spread remains significant if the 50% smallest stocks in our sample are excluded from the analysis or if the holding period is extended up to five years. The authors also find that the volatility effect has strengthened over time, again in line with results for developed markets. Specifically, the alpha spread amounts to 3.1% in the first half of our sample period (1989-1999), versus -14.4% during the second half of our sample period (2000-2010). Finally, the authors find low correlations between the volatility effects in emerging and developed equity markets, which argues against a common-factor explanation, i.e. the possibility that the volatility effect might reflect a global systematic risk factor. The author's conclude that there exists a significant, robust and distinct volatility effect within emerging markets, which appears to be growing stronger over time. These findings indicate that the relation between risk and return in emerging markets is very similar to developed markets and are consistent with the hypothesis that benchmark-driven institutional investing contributes to the volatility effect.

The remainder of this paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the empirical results and Section 4, the conclusions.

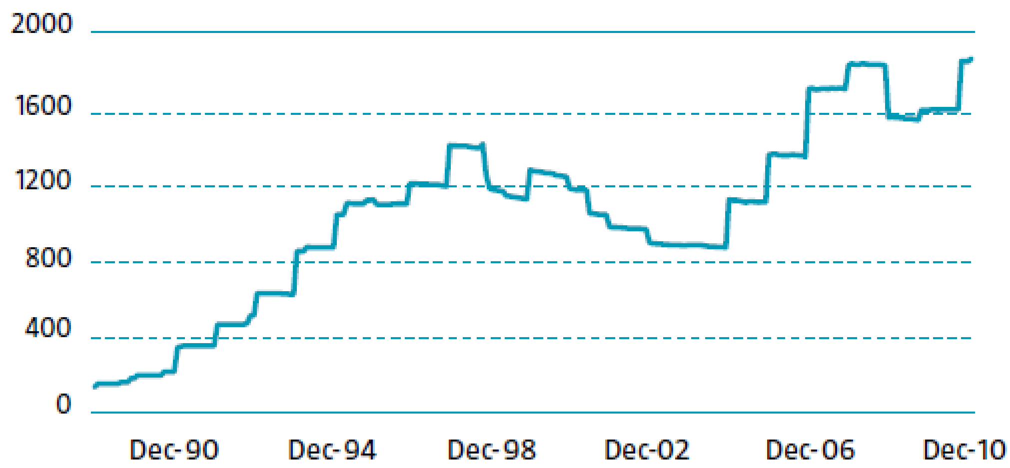
2. DATA AND METHODOLOGY

2.1 Data

The sample was constructed by taking, at the end of every month, all stocks included in the S&P/ IFC Investable Emerging Markets Index at that specific point in time. The sample covers the period from the inception of this index, at the end of December 1988, until December 2010. The S&P/IFC Investable Emerging Markets Index is a subset of the much broader S&P/ IFC Global Emerging Markets Index, containing only stocks considered to be accessible and sufficiently liquid for international investors. The sample covers stocks from 30 different emerging markets. Figure 1 shows that the total number of stocks in the sample starts off low, but grows progressively over time. During the first two years, the sample contains less than 200 stocks, but by the end of 2010 the number of stocks has risen to over 1,800. The average number of stocks is around 1,000.

Note that jumps in the number of index constituents are typically the result of countries entering or leaving the universe. For example, China is included in the index from October 1995 onwards, while Portugal was removed from the index in March 1999.

Figure 1: Number of Stocks over Time



This figure plots the number of constituents in the S&P/IFC Investable Emerging Markets Index over the sample period from December 1988 to December 2010.

Monthly total stocks returns are gathered in local currency as well as in U.S. dollars, taking into account dividends, stock splits and other capital adjustments. The first data source for returns is Interactive Data Exshare. If not available, return data from MSCI are used instead. If also not available, then total returns are calculated using data from S&P/IFC. Monthly returns above 500% are truncated at this level. In addition to returns, free-float adjusted market capitalization data is gathered from S&P/IFC and accounting data (bookto- price ratios) from, in order of preference, MSCI, Thomson Financial Worldscope and S&P/IFC. Finally, the one-month U.S. Treasury bill rate is obtained from the data library of Kenneth French.

2.2 Methodology

The methodology consists of creating, at the end of every month, equally-weighted quintile portfolios based on ranking stocks on a past risk measure. The top quintile contains the stocks with the highest risk and the bottom quintile the stocks with the lowest risk. Similar to, for example, Rouwenhorst (1999) and van der Hart, Slagter and van Dijk (2003) the portfolios are constructed in a country neutral manner, meaning that the stocks for a given country are distributed uniformly across the various quintile portfolios. Next for each portfolio, total return is calculated in U.S. dollars in excess of the one-month Treasury bill rate over the subsequent month.

The main risk measures used for ranking stocks are past volatility and past beta. Similar to Blitz and van Vliet (2007), the past volatility of a stock is calculated by taking the standard deviation of its monthly total returns in local currency over the preceding three years. The only difference is that return data with a monthly instead of a weekly frequency is considered, due to data limitations for emerging markets. The past beta of a stock is calculated by regressing its monthly total returns in U.S. dollars over the past three years on the total returns in U.S. dollars of the S&P/IFC Investable index for the country to which the stock belongs.

For each quintile portfolio, the annualized average return, volatility and Sharpe ratio is reported. For the annualized return, both the arithmetic and the geometric average is reported, but the focus is on the latter in order to account for compounding effects, which are particularly relevant when comparing portfolios with different volatilities; see, e.g. van Vliet, Blitz and van der Grient (2011). In addition, 1-factor, 3-factor and 4-factor alphas and their associated t-statistics are reported for each portfolio. These alphas are obtained by first regressing the monthly portfolio returns on a number of risk factors and next using the estimated betas to adjust the geometric average portfolio returns for these implicit factor exposures. The 1-factor alpha is obtained by regressing the portfolio excess returns on the excess returns of the equally weighted universe. In order to calculate the 3-factor alpha, SMB (size) and HML (value) proxies are added to the regression, and in order to calculate the 4-factor alpha a UMD (momentum) proxy is additionally added. The SMB, HML and UMD proxies for emerging markets are calculated by ranking stocks, again in a country neutral manner, on their log market capitalization, book-to-market ratio and past 12-1 month total return respectively, and taking the difference in return between the equally-weighted top and bottom quintiles.

3. RESULTS

This section presents the empirical findings. It first describes the main overall results, followed by results for the separate countries. It then investigates if the results are robust to restricting the universe to a sample which only contains large-cap stocks, to controlling for possible loadings on the value effect and to extending the holding period to up to five years. It next examines the evolvement of the volatility effect over time by considering subsample results. Finally, it examines if the volatility effects in emerging and developed equity markets are driven by a common component.

3.1 Main results

The main results are presented in Figure 2. Panel A contains the results for quintile portfolios sorted on past three-year volatility. Note that past risk is strongly predictive for future risk, as both the realized volatilities and betas of the quintile portfolios are monotonically increasing: the volatilities from roughly 20% to 30% percent, and the betas from 0.79 to 1.15. Turning to the realized returns of the quintile portfolios, observe that the raw risk-return relation is inverted, as the top (high-volatility) quintile portfolio underperforms the bottom (low-volatility) quintile portfolio by 4.4% per annum geometrically and 2.1% per annum arithmetically. As a result, the Sharpe ratio of the bottom (low-volatility) quintile portfolio is over double that of the top (highvolatility) quintile portfolio, at 0.64 versus 0.29. Adjusted for differences in market beta, there are economically and statistically significant 1-factor alphas of 5.4% and +3.5% per annum for the top and bottom quintile portfolios, resulting in a top-minus-bottom 1-factor alpha spread of -8.8% per annum, with an associated t-statistic of 4.10. As in Blitz and van Vliet (2007), this finding will be referred to here as the ‘volatility effect’.

Figure 2: Emerging Markets Portfolios Sorted on Volatility, Beta and Other Factors

Panel A: Portfolios sorted on volatility

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Univ
Mean (simple)	15,3%	15,6%	16,0%	16,5%	13,2%	-2,1%	15,5%
Mean (compounded)	13,1%	12,9%	12,6%	12,6%	8,7%	-4,4%	12,2%
Standard deviation	20,5%	23,2%	25,6%	27,6%	29,9%	13,5%	25,1%
Sharpe	0,64	0,56	0,49	0,46	0,29	-0,32	0,49
Beta	0,79	0,91	1,00	1,08	1,15	0,37	1,00
1-factor alpha	3,5%	1,7%	0,4%	-0,6%	-5,4%	-8,8%	-
(t-value)	2,79	1,93	0,37	-0,69	-3,26	-4,10	-
3-factor alpha	3,8%	2,1%	0,6%	-0,8%	-4,4%	-8,2%	-
(t-value)	3,10	2,30	0,51	-0,90	-2,76	-3,99	-
4-factor alpha	2,9%	1,7%	0,4%	-0,2%	-2,8%	-5,7%	-
(t-value)	2,19	1,71	0,29	-0,17	-1,63	-2,59	-

Panel B: Portfolios sorted on beta

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Univ
Mean (simple)	13,0%	16,6%	15,3%	17,3%	15,5%	2,5%	15,5%
Mean (compounded)	10,7%	13,6%	11,5%	13,1%	10,3%	-0,4%	12,2%
Standard deviation	20,5%	23,2%	26,1%	27,3%	30,8%	14,2%	25,1%
Sharpe	0,52	0,58	0,44	0,48	0,33	-0,03	0,49
Beta	0,79	0,90	1,02	1,07	1,20	0,41	1,00
1-factor alpha	1,0%	2,5%	-1,0%	0,0%	-4,4%	-5,4%	-
(t-value)	0,86	2,22	-0,97	-0,01	-3,17	-2,57	-
3-factor alpha	1,3%	2,7%	-0,7%	-0,3%	-4,5%	-5,8%	-
(t-value)	1,12	2,33	-0,65	-0,32	-3,15	-2,68	-
4-factor alpha	0,4%	1,5%	-0,6%	0,2%	-2,7%	-3,1%	-
(t-value)	0,33	1,18	-0,49	0,19	-1,76	-1,33	-

Panel C: Portfolios sorted on size

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Univ
Mean (simple)	19,0%	15,6%	14,3%	14,5%	14,2%	-4,8%	15,5%
Mean (compounded)	15,1%	12,3%	10,9%	11,3%	11,1%	-3,9%	12,2%
Standard deviation	27,6%	25,1%	25,9%	24,9%	24,5%	11,6%	25,1%
Sharpe	0,54	0,49	0,42	0,45	0,45	-0,34	0,49
Beta	1,07	0,99	1,02	0,98	0,95	-0,12	1,00
1-factor alpha	2,0%	0,3%	-1,6%	-0,7%	-0,4%	-2,4%	-
(t-value)	1,39	0,30	-1,78	-0,83	-0,34	-1,00	-

Panel D: Portfolios sorted on book-to-market

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Univ
Mean (simple)	11,6%	12,1%	13,0%	16,9%	23,1%	11,5%	15,5%
Mean (compounded)	8,7%	9,0%	9,7%	13,5%	18,9%	10,2%	12,2%
Standard deviation	24,0%	24,7%	25,7%	25,7%	28,3%	12,2%	25,1%
Sharpe	0,36	0,36	0,38	0,53	0,67	0,83	0,49
Beta	0,91	0,95	1,00	0,99	1,08	0,18	1,00
1-factor alpha	-2,4%	-2,6%	-2,5%	1,4%	5,6%	8,0%	-
(t-value)	-1,43	-1,80	-2,02	1,02	3,27	3,26	-

Panel E: Portfolios sorted on 12-1 month momentum

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Univ
Mean (simple)	11,1%	15,9%	15,3%	15,2%	19,9%	8,8%	15,5%
Mean (compounded)	6,8%	12,5%	12,1%	12,4%	16,6%	9,8%	12,2%
Standard deviation	29,1%	25,7%	25,3%	23,3%	25,0%	14,4%	25,1%
Sharpe	0,23	0,49	0,48	0,53	0,66	0,68	0,49
Beta	1,12	1,01	0,99	0,91	0,95	-0,17	1,00
1-factor alpha	-6,9%	0,1%	0,0%	1,3%	5,0%	11,8%	-
(t-value)	-4,04	0,14	0,03	1,28	3,04	3,98	-

At the end of each month between December 1988 and December 2010, all S&P/IFC Investable Emerging Markets Index constituent stocks at that point in time are sorted into quintile portfolios based on their past 3-year monthly local return volatility (Panel A), past 3-year beta against their S&P/IFC Investable country index using monthly U.S. dollar returns (Panel B), log U.S. dollar free-float market capitalization (Panel C), book-to-market ratio (Panel D) or past 12-1 month total return (Panel E). All portfolios are equally weighted and constructed in a country neutral manner, with Q1 containing stocks with the lowest scores and Q5 stocks with the highest scores. The universe is defined as the equally-weighted portfolio of all stocks in the S&P/IFC Investable Emerging Markets Index. Nex, portfolios returns are calculated in U.S. dollars over the subsequent month and repeat the process. For each portfolio, the annualized arithmetic (simple) and geometric (compounded) mean returns in excess of the U.S. dollar risk-free return, standard deviation, Sharpe ratio, CAPM beta, CAPM alpha and related t-statistics are presented. For the volatility and beta sorted portfolios, the annualized 3- and 4-factor alphas and their t-statistics are additionally reported, using the equally-weighted universe as a proxy for the market factor and the top-minus-bottom size, value and momentum quintile portfolios as proxies for the SMB, HML and WML factors.

For portfolios sorted on past three-year beta, shown in Panel B, we can observe directionally similar, but less strong results. Past risk is again strongly predictive for future risk, as the realized volatilities and betas of the quintile portfolios sorted on beta are very similar to those observed before for quintile portfolios sorted on volatility. The raw relation between risk and return appears to be flat rather than inverted though. The 1-factor alpha spread of -5.4% per annum remains economically and statistically significant (with a t-statistic of -

2.57), but is smaller than the corresponding spread for volatility-sorted portfolios. Also observe that the alpha is more asymmetric, as the negative alpha of high-beta stocks is much larger than the positive alpha of lowbeta stocks. The results are consistent with Rouwenhorst (1999), who observes that beta is not related to return in emerging markets over the 1982 to 1997 period. The results are also in line with Blitz and van Vliet (2007) and Baker, Bradley and Wurgler (2011), who find that, also in developed equity markets, portfolios sorted on volatility exhibit larger alphas than portfolios sorted on beta. For this reason, the following sections focus on volatility-sorted portfolios.

Panels C, D and E of Figure 2 show the performance characteristics of quintile portfolios sorted on size, value and momentum respectively. Consistent with the results of Fama and French (1998), Patel (1998), Rouwenhorst (1999) and van der Hart, Slagter and van Dijk (2003) there is clear evidence of size, value and momentum premiums in emerging markets. Based on the 1-factor alphas, the authors conclude that the low-volatility premium is much larger than the size premium, and comparable in magnitude to the value premium. Only the raw momentum premium is larger, but it should be noted that, due to its high associated turnover, this is the premium which is likely to be eroded most by transaction costs in practical applications.

In order to examine whether systematic exposures to the size, value and momentum effects may explain some, or perhaps even all, of the performance of portfolios sorted on volatility or beta, 3- and 4-factor alphas are also reported in Panels A and B of Figure 2. As described in the methodology section, the top-minus-bottom size, value and momentum quintile portfolios are used as a proxy for the SMB, HML and WML factors in emerging markets. Observe that the 3-factor alphas are, in fact, very similar to the 1-factor alphas, indicating that systematic size or value exposures do not explain the volatility and beta effects in emerging markets. Only the 4-factor alphas are slightly lower, indicating that some of the alpha may be attributable to implicit loadings on the momentum effect. However, at -5.7%, the spread remains significant for volatility-sorted portfolios, both economically and statistically. Only the 4-factor alpha of -3.1% for beta-sorted portfolios is no longer statistically significant.

3.2 Results by country

Examining the results per country, the analysis only includes country-month observations that are based on at least 25 stocks, and results are only reported for countries for which this leaves at least 60 monthly return observations (19 out of 30 countries). An example of a country which is excluded altogether from this analysis is the Czech Republic, which structurally consists of only a small number of stocks. Note that the period that is effectively considered for each country can be different. Figure 3 reports 1-factor alphas for the top-minus-bottom quintile of volatility-sorted portfolios per country, where the market factor is assumed to be the equally-weighted return of only the stocks in the country under consideration, instead of the entire emerging markets universe. Observe that 15 out of the

19 1-factor alphas are below -5%, two are between -5% and 0%, and only two are (slightly) positive at 1.30% (Mexico) and 3.59% (Russia). Based on this finding, the volatility effect is generally robust across countries.

Figure 3: Volatility Effect for Individual Countries

	Volatility	
	1-factor alpha	t-statistic
Argentina	-17,6%	-1,54
Brazil	-11,9%	-0,93
Chile	-5,3%	-1,25
China	-21,8%	-2,82
Egypt	-19,3%	-2,31
Greece	-16,4%	-1,57
India	-15,7%	-2,69
Indonesia	-5,9%	-0,79
Israel	-15,7%	-2,62
Korea	-14,4%	-2,71
Malaysia	-11,2%	-1,38
Mexico	1,3%	0,31
Philippines	-6,9%	-0,53
Poland	-9,5%	-1,23
Russia	3,6%	0,33
South Africa	-6,9%	-1,18
Taiwan	-1,4%	-0,29
Thailand	-11,1%	-2,01
Turkey	-3,2%	-0,54

This follows the same methodology as used to construct Figure 2, but instead of reporting results for the broad emerging markets universe, results are reported for individual countries. To be included, a country should have at least 60 monthly data points that are each based on at least 25 stocks, which excludes 11 emerging countries from this analysis. The table reports 1-factor alphas and related t-statistics calculated against local market returns, defined as the equally-weighted return of only the stocks in the country under consideration.

3.3 Results for large-caps only

Bali and Cakici (2008) argue that the negative empirical relation between risk and return is concentrated in small, illiquid stocks, especially the strong negative returns of high (idiosyncratic) volatility stocks. The analysis in this paper already attempts to address this concern by including only constituents of the S&P/IFC Investable Emerging Markets Index in the sample, but in this section, this goes one step further by conducting a robustness test on the 50% largest stocks within this already liquid universe. Specifically, every month, the stocks in our universe are first ranked on their free-float adjusted market capitalization, and next the 50% smallest stocks are removed from that month's sample. The results for volatility-sorted portfolios based on this large-cap only universe are reported in Figure 4. The main effect of removing the smaller stocks from the sample appears to be that the average annual returns of all quintile portfolios drop by around 3% to 4%, indicating that large-cap stocks on average exhibited lower returns than small-cap stocks during this particular sample period. The alphas drop accordingly, but the net effect on the top-minusbottom quintile alpha spreads is small. At -9.1% to -7.1% per annum, the 1-, 3- and 4-factor alpha spreads for the large-cap only universe remain both economically and statistically highly significant. Based on this finding, the volatility effect in emerging markets is not concentrated in less liquid small-cap stocks.

Figure 4: Volatility Effect among the 50% Largest Stocks

Volatility sorted results

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Univ
Mean (simple)	11,1%	12,1%	12,8%	14,1%	9,2%	-1,9%	11,9%
Mean (compounded)	9,1%	9,6%	9,9%	10,5%	4,8%	-4,3%	9,0%
Standard deviation	20,0%	22,4%	23,7%	26,5%	29,9%	14,0%	24,0%
Sharpe	0,46	0,43	0,42	0,40	0,16	-0,31	0,38
Beta	0,72	0,84	0,89	1,01	1,11	0,39	1,00
1-factor alpha	0,3%	-0,7%	-1,0%	-1,8%	-8,8%	-9,1%	-
(t-value)	0,15	-0,43	-0,60	-1,04	-3,77	-4,20	-
3-factor alpha	0,9%	0,3%	-0,5%	-1,1%	-6,7%	-7,6%	-
(t-value)	0,60	0,24	-0,34	-0,68	-3,03	-3,56	-
4-factor alpha	0,1%	-0,3%	-1,2%	-1,4%	-7,0%	-7,1%	-
(t-value)	0,08	-0,21	-0,70	-0,86	-2,92	-3,06	-

This follow the same methodology as used to construct Figure 2, but instead of considering the entire S&P/IFC Investable Emerging Markets Index, results are shown based on the 50% largest stocks in this index. Specifically, every month stocks in the universe are first ranked by their free-float adjusted market capitalization, and next the 50% smallest stocks are removed from that month's sample.

3.4 Is the volatility effect a value effect?

Scherer (2010) argues that the alpha of low-versus- high volatility portfolios in the U.S. equity market is mainly a value effect. The earlier finding that 3-factor alphas are hardly different from 1-factor alphas already indicated that the value (or size) effect does not explain the performance of volatility-sorted portfolios. Specifically, the author's found a 1-factor alpha of -8.8% with a t-statistic of 4.10 and a 3-factor alpha -8.2% with a t-statistic of -3.99 for the top-minus-bottom quintile hedge portfolio. However, a limitation of this parametric adjustment is that it implicitly assumes that the value exposure of volatility-sorted portfolios is linear and constant over time. This assumption may not be valid though, as value portfolios are known to have a time-varying beta, with risk going up during recessions and down during expansions; see, e.g., Petkova and Zhang (2005). In order to address this concern, double-sorted portfolios are considered. This nonparametric technique allows adjustment for possible loadings on other effects ex ante, as opposed to merely adjusting estimated alphas ex post.

The double-sort approach consists of first sorting stocks, within each country, into five portfolios on their value characteristics, next sorting the stocks within each of these five portfolios into five sub-portfolios based on their past 3-year volatility, and finally merging the five lowest volatility subportfolios, the five next lowest volatility portfolios, etc., thereby obtaining five new volatility-sorted portfolios which are designed to be not only country neutral, but also ex ante value neutral.

The results, reported in Figure 5 (below), do not differ much from our base-case results. In fact, the 1-, 3- and 4-factor alpha spreads of the portfolios sorted first on value and then on volatility are even slightly larger than the alpha spreads of portfolios sorted only on volatility (-9.0% to -6.8% versus -8.8% to -5.7%). Also, the alphas of the top quintile portfolio of high-volatility stocks remain consistently negative, the alphas of the bottom quintile portfolio of low-volatility stocks remain consistently positive, and the magnitude of both effects remains statistically and economically significant. The volatility effect in emerging markets is a distinct effect, which cannot be explained by either explicit or implicit loadings on the wellknown value effect.

Figure 5: Double Sort on Value and Volatility

Volatility sorted results

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Univ
Mean (simple)	16,8%	16,7%	15,8%	17,3%	13,5%	-3,4%	15,5%
Mean (compounded)	14,0%	13,7%	12,6%	13,5%	8,8%	-5,2%	12,2%
Standard deviation	22,9%	23,9%	25,1%	27,2%	30,4%	13,0%	25,1%
Sharpe	0,61	0,57	0,50	0,49	0,29	-0,40	0,49
Beta	0,85	0,92	0,97	1,07	1,16	0,31	1,00
1-factor alpha	3,7%	2,5%	0,7%	0,4%	-5,3%	-9,0%	-
(t-value)	1,97	1,85	0,55	0,38	-2,72	-4,01	-
3-factor alpha	4,3%	2,4%	0,4%	0,2%	-4,9%	-9,2%	-
(t-value)	2,27	1,78	0,33	0,18	-2,53	-4,07	-
4-factor alpha	3,3%	2,1%	0,9%	1,3%	-3,5%	-6,8%	-
(t-value)	1,61	1,45	0,68	1,16	-1,68	-2,81	-

This follow the same methodology as used to construct Figure 2, but instead of considering single-sorted portfolios, the analysis considers portfolios that are double sorted on value and volatility. Our double-sort approach consists of first sorting stocks, within each country, into five portfolios on their book-to-market ratio, next sorting the stocks within each of these five portfolios into five subportfolios based on their past 3-year volatility, and finally merging the five lowest volatility subportfolios, the five next lowest volatility portfolios, etc., thereby obtaining five new volatility-sorted portfolios which are designed to be not only country neutral, but also ex ante value neutral. All portfolios are equally weighted and constructed in a country neutral manner, with Q1 containing stocks with the lowest scores and Q5 stocks with the highest scores.

3.5 Results for longer holding periods

Amenc, Martellini, Goltz and Sahoo (2011) argue that the negative relation between risk and return is only present in the short run, and that over longer holding periods the relation does turn positive as predicted by theory. In order to address this concern, the performance characteristics of volatility-sorted portfolios is analysed over holding periods up to five years. Specifically, if the holding period is assumed to be N months, the return in month t is calculated by taking the unweighted average return of the portfolios formed in the N most recent months, as in Jegadeesh and Titman (1993, 2001). The results are summarised in Figure 6.

Observe that the 1-factor alphas for the top and bottom quintile portfolio decrease as the holding period increases, but only very gradually. The annualised alpha spread, which starts at -8.8% with a 1-month holding period, drops to 7.3% with a 1-year holding period and 6.3% with a 3-year holding period. Even when the holding period is extended to five years, the alpha spread remains economically and statistically significant at 4.4 percent per annum. The volatility effect is highly persistent and not only present at short investment horizons.

Figure 6: Longer Holding Periods

Holding period	Q1	Q2	Q3	Q4	Q5	Q5-Q1
1 month	3,5%	1,7%	0,4%	-0,6%	-5,4%	-8,8%
(t-value)	2,79	1,93	0,37	-0,69	-3,26	-4,10
6 months	2,5%	1,4%	-1,5%	-1,5%	-6,0%	-8,5%
(t-value)	1,85	1,14	-0,89	-1,04	-2,98	-4,08
12 months	2,5%	2,1%	-2,0%	-1,0%	-4,7%	-7,3%
(t-value)	1,70	1,48	-1,05	-0,64	-2,26	-3,50
24 months	2,5%	1,7%	-1,3%	-1,6%	-3,8%	-6,4%
(t-value)	1,59	0,95	-0,65	-0,94	-1,76	-3,10
36 months	2,9%	1,7%	-0,7%	-0,8%	-3,4%	-6,3%
(t-value)	1,69	0,91	-0,35	-0,43	-1,54	-3,12
48 months	2,4%	1,7%	-0,2%	-0,1%	-2,7%	-5,1%
(t-value)	1,37	0,92	-0,08	-0,03	-1,24	-2,69
60 months	2,2%	1,3%	-0,3%	0,3%	-2,2%	-4,4%
(t-value)	1,23	0,69	-0,14	0,14	-0,98	-2,38

This follows the same methodology as used to construct Figure 2, but instead of showing results based on a 1-month holding period, it show results over N-month holding periods for N = 1, 6, 12, 24, 36, 48 and 60 by calculating every month the unweighted average return of the portfolios formed in the N most recent months, as in Jegadeesh and Titman (1993, 2001). The table reports 1-factor alphas and related t-statistics, using the equally-weighted universe as a proxy for the market factor.

3.6 Subsample results

Emerging markets can shed new light on the different hypotheses which have been proposed in the literature to rationalise the apparently anomalous empirical relation between risk and return. Some, such as Baker, Bradley and Wurgler (2011) and Frazzini and Pedersen (2010) relate the effect to benchmarkdriven institutional investors, while others, such as Black (1993) and de Giorgi and Post (2011) relate the effect to constraints on leverage or short-selling. Emerging markets are an interesting test case, as due to their rapid growth and progressive liberalization over the past decades, they have grown from a niche into a mainstream asset class for international institutional investors. For developed markets, Blitz and van Vliet (2007) and Baker, Bradley and Wurgler (2011) have suggested that the volatility effect has strengthened over time, something which is possible to now test out-of-sample on previously unexplored markets.

Figure 7 breaks down the results for volatility-sorted portfolios over the first and second half of our sample. Observe that the raw relation between risk and return appears to be flat over the first half of our sample (1989-1999), while turning strongly negative over the second half of our sample (2000-2010). This is also reflected in the alpha spreads, which are less than half their full-sample average over the first period, and almost double their full-sample average over the second period. For example, the 1-factor alpha spreads amount to -3.1% and -14.4%, respectively. A formal difference-in-means test indicates that this difference is statistically significant (p-value 0.0047). These findings indicate that, similar to developed markets, the volatility effect in emerging markets appears to be growing stronger over time, consistent with the hypothesis that benchmarkdriven institutional investing contributes to the volatility effect.

Figure 7: Sub-sample results

Panel A: 1989-1999

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Univ
Mean (simple)	14,3%	13,8%	14,6%	17,2%	15,2%	0,8%	15,3%
Mean (compounded)	11,9%	11,0%	11,3%	13,6%	11,4%	-0,5%	12,2%
Standard deviation	21,6%	23,2%	25,2%	26,3%	27,1%	12,0%	24,3%
Sharpe	0,55	0,47	0,45	0,52	0,42	-0,04	0,50
Beta	0,84	0,93	0,99	1,06	1,05	0,21	1,00
1-factor alpha	1,7%	-0,4%	-0,7%	0,7%	-1,4%	-3,1%	-
(t-value)	0,76	-0,22	-0,31	0,41	-0,51	-0,93	-
3-factor alpha	2,5%	0,2%	-0,4%	0,3%	-0,8%	-3,2%	-
(t-value)	1,13	0,09	-0,17	0,19	-0,28	-1,01	-
4-factor alpha	2,8%	0,6%	-0,3%	0,7%	-0,6%	-3,4%	-
(t-value)	1,20	0,37	-0,11	0,41	-0,22	-1,00	-

Panel B: 2000-2010

	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Univ
Mean (simple)	16,2%	17,5%	17,4%	15,8%	11,2%	-5,0%	15,6%
Mean (compounded)	14,3%	14,7%	14,0%	11,7%	6,1%	-8,2%	12,3%
Standard deviation	19,5%	23,2%	26,2%	28,8%	32,4%	14,9%	25,9%
Sharpe	0,73	0,64	0,53	0,41	0,19	-0,55	0,47
Beta	0,74	0,89	1,01	1,11	1,24	0,50	1,00
1-factor alpha	5,2%	3,8%	1,6%	-1,9%	-9,2%	-14,4%	-
(t-value)	4,92	4,68	2,46	-2,59	-6,74	-6,45	-
3-factor alpha	4,7%	3,3%	1,1%	-2,0%	-8,2%	-12,9%	-
(t-value)	4,51	4,07	1,60	-2,62	-6,16	-5,99	-
4-factor alpha	2,7%	2,1%	0,3%	-1,3%	-5,8%	-8,5%	-
(t-value)	2,52	2,39	0,38	-1,54	-4,19	-3,87	-

This follows the same methodology as used to construct Figure 2, but instead of showing full sample results, it shows results for two subperiods, 1989-1999 and 2000-2010.

3.7 Is there a global volatility effect?

Rouwenhorst (1998) finds that the returns on international and U.S. momentum strategies are correlated, and interprets this as evidence that exposure to a common factor may drive the profitability of such strategies. This section examines the correlation between the volatility effect in emerging equity markets, as documented in this paper, and the previously documented volatility effect in developed equity markets. For this analysis, the authors constructed volatility-sorted hedge portfolios for the U.S., European and Japanese markets based on a survivorship bias-free sample of FTSE World Developed Index constituent stocks, as in Blitz and van Vliet (2007). The only difference is that instead of calculating past 3-year volatilities using weekly data, monthly data is used, similar to the analysis of the volatility effect for emerging markets.

Figure 8 exhibits the estimated correlations between the 1-factor alphas of volatility hedge portfolios in the various regions over the full sample period 1989-2010 and the two subperiods used before, 1989 to 1999 and 2000 to 2010. The correlation between the volatility effects in emerging and developed equity markets is moderately positive, at 0.26 with the U.S., 0.19 with Europe and 0.24 with Japan. Correlations are somewhat higher in the more recent subperiod but never exceed 0.36. Only the correlation between the volatility effects within the U.S. and European equity markets has gone up sharply in the more recent subperiod, from 0.27 to 0.73, but the volatility effects in Japan and Emerging markets remain weakly correlated with the other regions. These findings suggest that the volatility effect in emerging markets is largely independent from the volatility effect in developed markets. This argues against a common-factor explanation, i.e. the possibility that the volatility effect might reflect a global systematic risk factor. For the value and momentum effects in emerging markets, van der Hart, de Zwart and van Dijk (2005) have previously argued against risk-based explanations as well. For investors, the practical implication of the low observed correlation levels is that significant diversification benefits may be achieved by exploiting the volatility effect in multiple markets simultaneously.

Figure 8: Correlation of 1 -factor alphas across regions

Panel A: 1989-2010

	US	Europe	Japan	Emerging
US	1,00			
Europe	0,61	1,00		
Japan	0,17	0,18	1,00	
Emerging	0,26	0,19	0,24	1,00

Panel B: 1989-1999

	US	Europe	Japan	Emerging
US	1,00			
Europe	0,27	1,00		
Japan	0,12	0,20	1,00	
Emerging	0,18	0,01	0,25	1,00

Panel C: 2000-2010

	US	Europe	Japan	Emerging
US	1,00			
Europe	0,73	1,00		
Japan	0,21	0,18	1,00	
Emerging	0,36	0,33	0,20	1,00

Sources: This table reports the correlation coefficients of 1-factor alphas of top-minus-bottom quintile
volatility hedge portfolios in the U.S., European, Japanese and Emerging equity markets. The 1-factors alphas for emerging markets are calculated in the same way as described in Table 1. The 1-factor alphas for the U.S., Europe and Japan are calculated in the same fashion as for emerging markets, but based on FTSE World Developed Index constituent stocks instead. Panel A shows full sample correlations (1989-2010) and Panels B and C show correlationsover the 1989-1999 and 2000-2010 subperiods.

4. SUMMARY

This paper has documented the clear presence of a volatility effect in emerging markets. Contrary to the predictions of theoretical models such as the CAPM, which postulate that the relation between risk and return should be positive, the authors find that the empirical relation between risk and return in emerging equity markets is flat, or even negative, in particular for portfolios of stocks sorted on past volatility. The findings are consistent with studies which have previously established the existence of a volatility effect in the U.S. and other developed equity markets. The volatility effect in emerging markets is found to be robust to considering a universe of large-cap stocks only, to considering longer holding periods and to controlling for exposures to the size, value and momentum effects. The volatility effect also appears to have strengthened over time, which might be related to the increasing participation of benchmark-driven investors, in line with the 'limits to arbitrage' hypothesis. Finally, the analysis finds low correlations between the volatility effects in emerging and developed equity markets, which argues against a common factor explanation.

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