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Overlapping portfolio holdings and unique sources of emerging market risk

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ABSTRACT

Momentum, size, and low volatility in emerging markets regularly exhibit increased correlations across factors and markets in periods of negative returns. I provide a framework to distinguish a unique source of risk from a set of factors in the stage of portfolio formation. The framework is based on discarding duplicate positions that exceed half the portfolios in periods of factor comovement. Unique factors eliminate rising correlation and factor crashes. The results are robust for the most recent financial shocks. For practitioners, the approach helps in distinguishing original investment strategies and provides opportunities for active management in emerging markets.

1. Introduction

There is an enormous volume of research on dissecting stock characteristics or factors. Only published papers in leading academic journals with more than five hundred factors can explain stock returns (Harvey & Liu, 2020). One reason for this financial economic trend is that it directly influences investment practitioners. Factors with persistent explanatory power can be converted into smart beta investment products based on the same characteristics. Assets under management for smart beta funds exceed 1.6 trillion dollars in the U.S. Recent research shows that funds apply academic research not only for marketing purposes, but several funds are loaded with high-ranked stocks of factors from the financial literature. Lettau et al. (2021) provided evidence for active mutual funds, whereas Agarwal et al. (2013) did so for hedge funds.

Not all discoveries are true. Some results are explained by luck or by duplicating existing factors. In the AFA presidential address, John Cochrane asked: "How many of these new factors are really important?" (Cochrane, 2011). One answer is that empirical asset pricing needs persistent factors not resulting from luck or data mining (Harvey et al., 2016). The methodology included out-of-sample tests on different markets (Beck et al., 2016; Fama & French, 2012), asset classes (Asness et al., 2013; Babu et al., 2020), and samples (Baltussen et al., 2021). In out-of-sample and multifactor testing (Harvey et al., 2016; Hou et al., 2020), momentum, value, size, low volatility, and quality are the most sustainable factors.

The modern approach to factor identification compares suggested factors with the existing set. New factors are considered useful if they add new explanatory power to already discovered models. This approach is mainly based on portfolio returns with complicated econometric techniques. For example, Feng et al. (2020) applied the double selection LASSO method of Belloni et al. (2014) with two-pass regressions to distinguish value-added factors from overall discoveries. He et al. (2023) shrunk the factor dimension with the reduced rank approach. Daniel et al. (2020) worked closely with stock characteristics to provide characteristic-efficient portfolios that capture factor premiums with the minimum return variance. These methods help determine the value added in a long sample, not detect a rare and rapidly increasing factor correlation. However, using them in real time is difficult due to the high data and calculation requirements.

Even sustainable factors with solid records struggle with catastrophic losses or crashes (Daniel & Moskowitz, 2016) and decades of underperformance (Arnott et al., 2021). For practitioners, running a multifactor portfolio on the basis of different economic ideas can be reasonable due to low or negative correlation between groups (Arnott et al., 2019). For instance, value and momentum are mostly negatively correlated in countries and even in asset classes (Asness et al., 2013); nevertheless, in some periods, market-neutral factors simultaneously provided negative returns and became strongly correlated (Arnott et al., 2019). An example of factor investing crash is the quant meltdown in August 2007, when quantitative hedge funds lost between 5% and 30%

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Table of abbreviations

SMB	Small Minus Big. The size factor
UMD	Up Minus Down. The momentum factor
VOL	The Low Volatility Factor
WML	Winners Minus Losers. Zero-cost long-short portfolios
GFC	Global Financial Crisis from December 2007 to June 2009

of capital from market-neutral equity strategies, whereas there was no sufficient change on the general market (Khandani & Lo, 2007).

There is a research gap in the asset-pricing literature on the unexplained simultaneous underperformance that cannot be avoided for persistent and value-added factors. This unexplained or hidden risk of multifactor investing is challenging for practitioners and academics. Investors in emerging markets have no opportunities to achieve positive returns due to picking factors in periods of rising correlation. Moreover, none of the sustainable factors can explain stock returns. Frameworks from the asset-pricing literature based on portfolio returns help explain the long-run linkage between new factors and the existing ones. In practice, the 2007 quant crash event took three days. This paper is motivated by distinguishing unique sources of risk and returns from a set of factors in a stage of portfolio formation without analyzing past performance.

For emerging markets, the problems of rising correlation and nonunique sources of risk are even more real for several reasons.

1. Emerging markets contain fewer liquid stocks than the U.S., UK, and Japanese markets, making it much easier to provide high intersection (and nonunique risk) between portfolio holdings for a market with 100 liquid stocks than that with 2000 liquid stocks.
2. A minority of factors have shown persistence in explaining market returns (Zaremba & Czapkiewicz, 2017). Accordingly, there are fewer opportunities for emerging market investors to construct diversified factor portfolios.
3. Persistent factors in emerging markets are highly correlated (up to 92%, according to Cakici et al., 2013). Cross-country diversification is challenging as well.

The reason for factor crashes is straightforward—momentum, size, and low volatility, sometimes long and short, mostly the same stocks (Fig. 1). Portfolio holdings for this factor model overlapped from 15.4% to 35.5%, on average. Simultaneously, the returns correlation is negative or close to zero. Overlapping coefficients between portfolios in some periods increase to 66.3% across emerging markets and 82.7% for a different market (Table 1).

I provide a framework that dropped overlapping positions in all portfolios during portfolio formation. Unique factors include long and short positions not simultaneously held in other factor portfolios. For example, a unique momentum portfolio contains holdings that do not have size or low-volatility portfolios for the same period. I apply this to the portfolio's long and short sides separately.

This study demonstrates that the correlation between factors rises simultaneously for each of the 10 emerging markets. Returns of three well-studied factors simultaneously became negative in each emerging market from different regions. After creating unique factor portfolios without overlapping positions, the return comovement vanished for 10 emerging markets (Fig. 2). The average correlation dropped from −0.13 to −0.3, and the maximum correlation dropped from 0.57 to 0.04. Unique factors provide a different source of risk and nearly eliminate the correlation between rising factors. In addition to reducing correlation, it nearly eliminated factor crashes. The periods when negative returns on all three factors fell from 8.1% to 4.4%. The number of series when

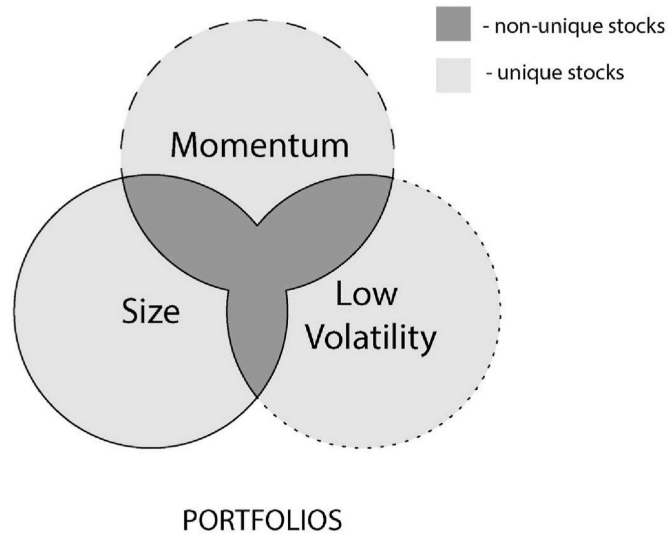

Fig. 1. Overlapping positions in factor portfolios. The shadow area on the chart reflects long or short positions present in two or more portfolios in the same period. Such holdings involve nonunique risks associated with several explanatory factors for the same market. The light area reflects nonrepeating positions in the same period.

returns were negative for two or more consecutive periods decreased from 2.5 to 0.7, and the length of such series decreased from 2.3 to 1.5.

Market returns and risk factors are much more volatile in emerging than in developed markets (Bekaert & Harvey, 2017; Cakici et al., 2013). By decomposing periods of high volatility into currency and inflation shocks, the unique factors remain immune to movement. Even during global crises, e.g., the Asian markets in 1998, the global financial crisis (GFC) in 2008, and COVID-19, the factors remain negatively correlated.

A simple method to eliminate similar risks between factors discards about half the instruments in each portfolio. On average, for all markets, the momentum factor contains 45% of positions that match size and low volatility, which is 43% and 47% for size and low volatility, respectively. Despite this reduction in the stock universe, all factors remain investable for institutional investors. On average, the sample of 10 emerging markets contains 3267 liquid stocks. The ratio of overlapping positions is nearly identical for long and short positions in portfolios. Accordingly, the decrease in factor correlation is not achieved by highly concentrated portfolios or a bias toward long or short positions.

The following section contains a brief literature review on the correlation of factors and performance of historical anomalies in emerging markets. Section 3 outlines emerging market data, portfolio formation, and the unique factor framework. Section 4 begins with comparing the performance of momentum, size, and low volatility across emerging markets. Further surveys show the correlation structure of anomaly returns, anomaly crushes (sequence of negative returns), and how it changes after creating unique portfolios with nonoverlapping positions. Section 5 verifies the robustness of the results to implementation issues. Section 6 concludes by discussing the findings' implications.

2. Literature review

Published papers mainly indicate strong portfolio outperformance based on target characteristics. Due to information efficiency or by pure chance, factors explaining power drop dramatically in out-of-sample periods (Mclean & Pontiff, 2016). The most persistent factors also provide alpha declines in emerging markets (Zaremba et al., 2020). Dimson et al. (2017) showed that momentum, value, size, and low volatility have a cycling performance with long periods of underperformance. The financial literature combines robust uncorrelated factors with multi-factor models based on different economic ideas and containing

Table 1
Overlapping portfolio holdings. The table contains values of portfolio holdings overlapping between market-neutral portfolios of two-factor pairs. Market-neutral portfolios consists of two parts: long 30% available stocks with the highest factor rank and short 30% stocks with the lowest factor rank. The holding period is 12 months. Values range from zero (no overlapping in longs and shorts) to one (the same portfolios). The mean shows the average overlapping value for all available periods for each country. The maximum and minimum offer the highest and lowest overlapping monthly values, respectively.

	Momentum-Size			Momentum-Low Volatility			Size-Low Volatility		
Country	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
Brazil	0,219	0,458	0	0,369	0,75	0,134	0,229	0,44	0,036
China	0,229	0,451	0,065	0,244	0,441	0	0,323	0,514	0,205
Hong Kong	0,207	0,5	0	0,303	0,827	0,05	0,265	0,568	0,028
India	0,223	0,423	0,076	0,312	0,656	0,061	0,265	0,392	0,174
Indonesia	0,207	0,568	0	0,292	0,808	0	0,298	0,636	0,059
Malaysia	0,227	0,484	0,065	0,305	0,712	0,012	0,26	0,444	0,108
Russia	0,261	0,522	0,087	0,312	0,576	0,094	0,248	0,444	0,116
Taiwan	0,228	0,389	0,027	0,248	0,577	0,036	0,302	0,552	0,14
Thailand	0,23	0,489	0,038	0,298	0,649	0,014	0,345	0,54	0,202
Vietnam	0,25	0,396	0,096	0,3	0,636	0,087	0,338	0,522	0,138
Across all countries	0,228	0,468	0,045	0,298	0,663	0,049	0,287	0,505	0,121

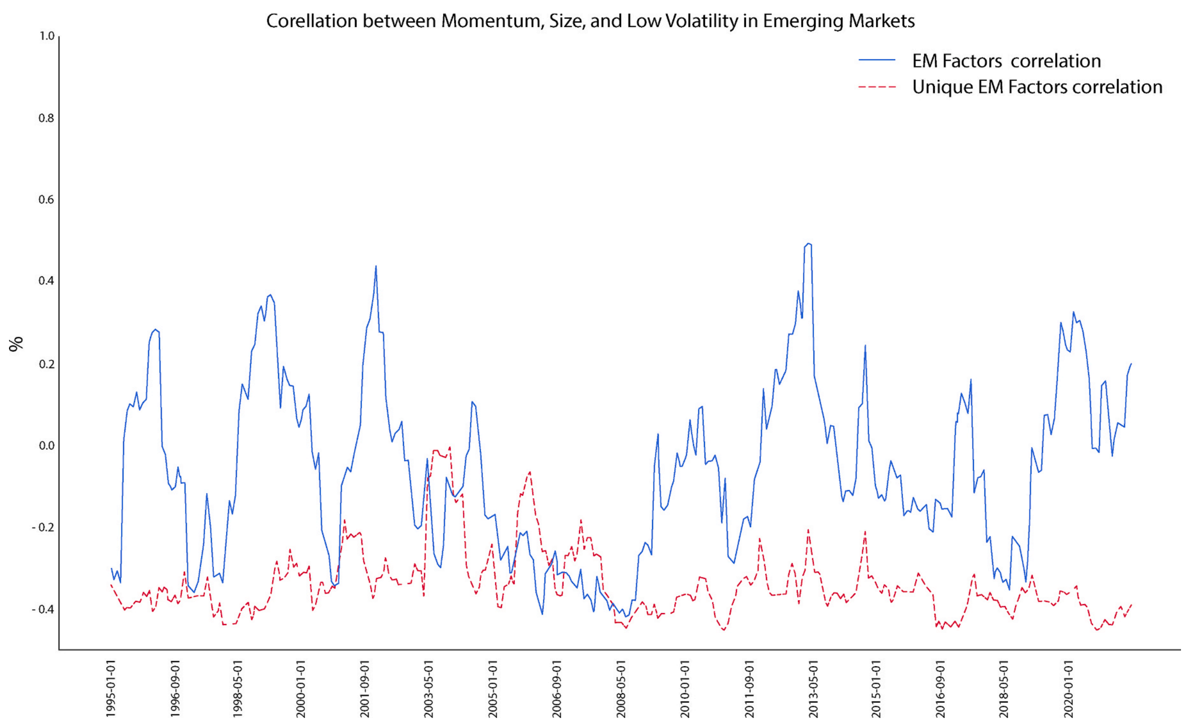

Fig. 2. Factor correlation between emerging markets. The blue line represents the 12-month moving average correlation of the average returns of the three factors between each country pair. The red line represents the same measure for the unique factors after the portfolio cleanup procedure. The return series for each country includes the average value-weighted market returns and the returns of the market-neutral factor—size, momentum, and low volatility of portfolios. Using the methodology of Asness et al. (2013), the resulting time series for each country is scaled by 12-month ex-post volatility. Finally, a moving correlation is found between the average factor returns of each country. The values of such correlation pairs are averaged between all country pairs and plotted. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

uncorrelated portfolio returns. Examples of these models are Fama and French's three- and five-factor models (1992, 2015) for explaining stock returns and the four-factor model (Carhart, 1997) for evaluating mutual fund managers. Practitioners provide alternative methods to taming factor cyclicity based on applying momentum to recent factor performance (Gupta & Kelly, 2019).

Negative factor correlation during market cycles is the core for both multifactor models and factor timing. Kalesnik and Linnainmaa (2018) reflected on the negative correlation between momentum, size, and low volatility and with the broader factor set. Factors from this set are defined as the most persistent in out-of-sample tests (Hou et al., 2020) and multiple testing (Harvey et al., 2016), except size. All three anomalies are based on the simplest price data and are comparable across emerging markets with different accounting standards. At the same time, according to Harvey and Liu (2020), factors are based on another group of economic ideas.

The size effect has a straight economic idea: small companies tend to outperform the market by greater growing opportunities than blue chip companies. Nevertheless, the performance of small minus big (SMB) portfolios in recent years has been relatively poor for emerging markets (Hanauer & Lauterbach, 2019). Asness et al. (2018) showed that a small capitalization portfolio cleared from low fundamental stocks conserves explanatory power. In modern research, capitalization is often used as an exercise for robustness checks rather than individual factors. The relationship between size with momentum and low volatility is ambivalent. Most anomalies, including momentum, perform better across the small-cap stock universe. At the same time, small stocks are more volatile. In the case of emerging markets, SMB represents the lowest capitalization performance in the world.

Low volatility is mainly associated with reverse CAPM evidence. Frazzini and Pedersen (2014) showed that leveraged portfolios with stocks with a beta below zero outperform deleveraged portfolios with high beta stocks. The standard deviation of returns is more suitable for comparison due to the difference in market portfolios for emerging markets. For most emerging markets (Hanauer & Lauterbach, 2019), low risk through standard deviation shows better results than market beta. Low volatility strongly outperforms the market in out-of-sample (Baltussen et al., 2021) and emerging markets (Blitz et al., 2013). Despite these results, low risk is often associated with robustness tests or complemented other anomalies. For example, Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015) distinguished between volatility as a predictor of momentum crash.

Finally, momentum is the primary challenge to market efficiency (Fama & Litterman, 2012). Compared with size and low-volatility effects, momentum has no clear upsides. Small-capitalization stocks can at least grow to the market average capitalization. Low-volatility stocks can become normally volatile. High momentum rising stops, changing with underperformance relatively fast (Daniel & Moskowitz, 2016). A possible explanation of momentum premiums is compensation for a rare catastrophic loss during a market rebound or an alternative reason is that momentum contains other factors. Guo et al. (2022) decomposed momentum returns to different characteristics. Sixty-nine percent of momentum returns remain unexplained. An additional 31% include fundamental factors and anchoring effects. For emerging markets, Teplova et al. (2022) show the rising sentiment of retail investors in messengers ahead of the momentum. In addition to low volatility, the momentum effect has survived an out-of-sample (Asness et al., 2013; Babu et al., 2020; Baltussen et al., 2021) and emerging markets (Hanauer & Lauterbach, 2019). Nevertheless, momentum's explanatory power is inconsistent in the case of emerging markets in eastern Europe (Cakici et al., 2013; Zaremba & Czapkiewicz, 2017).

Even uncorrelated factors, such as momentum, size, and low volatility, have periods of rising correlation with negative returns. Arnott et al. (2019) and Aghassi, Asness, Fattouche, and Moskowitz (2022) reflected on evidence of the factor crash, and Arnott et al. (2019) also showed that a portfolio from 15 well-studied factors regularly shows a rising correlation with market rebounds. Exhibit 3 in Arnott et al. (2019) shows that factor portfolios generally correlate negatively with rare and strong correlation spikes. This crash effect is a pitfall of factor-investing literature and a challenge for practitioners. A more unconventional way to form factor portfolios due to clustering shows spikes of correlation returns between factors (Geertsema & Lu, 2020). In Table 3, a mean maximum correlation of 0.69 within a cluster was conducted. Twenty-eight clusters contain from one to nine factors based on 80 published anomalies. It shows that stock overlapping in portfolio holdings is a possible reason for the correlation spikes.

Most papers presenting new stock returns explanatory factors contain a robustness check section to show the difference with similar discovered characteristics. Common examples are the double-sorting portfolio procedure and control variables in regression. The first method is based on factor portfolio holding data, showing the efficiency of factor one inside the quantiles of factor two. The test indicates that explanatory power survives under another anomaly adjustment. Double-sorting procedures can be hacked by applying two factors with overlapping holdings. The second framework with controlling variables in OLS can detect similar sources of risk between two factors even when holdings differ. The hidden risk can be omitted if a few nonoverlapping positions provide a return difference. Both frameworks have been applied intensively since the first market anomalies were published to distinguish value, size, low volatility, and momentum performance from market risk (Banz, 1981; Basu, 1977; Haugen & Heins, 1975; Jegadeesh & Titman, 1993). Even recent research applies these tests to illustrate the link between characteristics (Asness et al., 2013).

The modern financial literature has many papers with frameworks to measure factor (fund manager) performance persistence. Examples are a bootstrap simulation to distinguish luck (Fama & French, 2010; Kosowski et al., 2006), multiple hypotheses testing by enhancing the threshold of statistical significance (Harvey et al., 2016), and a variety of out-of-sample tests (Baltussen et al., 2021; Hou et al., 2020). After all, the problem with momentum, size, and low volatility is not one of performance persistence; they passed most of the above tests. The problem is hidden and rising commitment risk.

He et al. (2023) applied a reduced rank approach to distinguish factors with added value to the existing set. Extracted factors from the 202 characteristic portfolios outperform the five-factor model (Fama & French, 2015), corresponding principal component analysis, partial least squares, and least absolute shrinkage frameworks. Nevertheless, the tested factor set does not contain information to explain individual stock returns. Daniel et al. (2020) provided the characteristic portfolios by sorting on characteristics related to average returns. The procedure allows removing unpriced risk using covariance estimation from past returns. Feng et al. (2020) stipulated that the discovered factor set contains sufficient highly correlated factors even with different economic ideas. For example, the seasonality factor of Heston and Sadka (2008) is highly significant to the three-factor model (t-statistic 2.06) and mostly correlated with momentum (0.63). Feng et al. (2020) provided the framework to distinguish factors that offered additional explanatory variables to a high-dimensional set of potential factors.

Existing methods are handling long-term factor relationships. The problem with factor crashes is that they appear relatively fast (in a few months or even days), requiring a framework without long sample analysis or forecasting. An example is a characteristic-based benchmark to measure factor loadings provided by Daniel et al. (1997). This metric is based on triple-sorting factor portfolios. However, in this framework, the sequence of factor sorting sufficiently influences performance. Another example is the active share ratio by Cremers and Petajisto (2009), which defines unique fund positions related to fund benchmarks. On average, managers from higher active share quantiles have positive and sustainable alpha to four-factor model (Carhart, 1997), whereas the lowest active share quantile shows negative alpha for all tracking error control groups.

3. Data and methodology

3.1. Data

Data included stock prices and market capitalization from major stock exchanges in 10 countries: Brazil, China, Hong Kong, India, Indonesia, Malaysia, Russia, Taiwan, Thailand, and Vietnam. I use the recent research by Hanauer and Lauterbach (2019) as the benchmark for data offloading and processing. Consistent with the cited study, I use Datastream as the data source. Instead of Hanauer and Lauterbach (2019), I take leading exchange data from countries, not countries alone. I also use only common stocks in local currency, excluding fund stocks, REITs, and depositary receipts for foreign stocks. The period for all indicators is the end of the month.

Identifying liquidity for emerging markets 20–30 years ago is complicated. Like Hanauer and Lauterbach (2019), I apply a filtration by market capitalization. Before each portfolio rebalancing, I sort all available stocks by capitalization in descending order and left 97% of all market capitalization. The filter used significantly reduces the stock universe. The average available stocks across all 10 markets dropped from 6813 to 3267 or by 52%. On average, 48% of the companies cover 97% of market capitalization in emerging markets.

Another procedure that significantly affects the content of the data and the results is deleting data cells in all tables if the data are initially missing in at least one table. All factors must operate in one stock universe. If this step is skipped, the momentum factor will select stocks from a broader universe than the size factor, which may explain the significant difference in results with other studies (Cakici et al., 2013; Hanauer

& Lauterbach, 2019; Zaremba & Czapkiewicz, 2017) on emerging markets.

The steps above describe processing stock closing prices and market capitalization data. Subsequently, this study uses data on the risk-free rate, the local currency to U.S. dollar rate, and inflation data. Where data are disclosed in the middle of the month (CPI), I shift it as if we were learning it at the end of the month. The rare missing values are filled in with the last available value. The risk-free rate is the monthly yield in the local currency of the shortest government bonds available in Datastream. Table.A1 provides details regarding each country's start date and other indicators.

3.2. Formation of size, volatility, and momentum sorted portfolios

Portfolio formation procedures are based on the simplified version of the standard approach (Fama & French, 2012). Each country's stocks are split separately into portfolios based on factor characteristics. For each anomaly for each country, I form a market-neutral winners minus losers (WML) portfolio. WML portfolios contain long positions in the top 30% of stocks based on factor characteristics and short positions in the bottom 30% of stocks. This rebalancing procedure repeats yearly, with holding a position for one year. The holdings in portfolios are weighted by market capitalization.

Due to the approach to distinguishing the unique source of risk, the main difference from the standard methodology is avoiding any control procedure to adjust factors by another factor. For each anomaly, I form a single WML portfolio without double sorting for an additional anomaly. Examples of this control are given in Fama and French (2012). The authors construct 25 momentum portfolios consistent with five pure momentum portfolios in each capitalization quantile. This double sorting should show that the performance of momentum is independent of simply buying a small stock. The method is reasonable when the intersection of portfolio holdings between two factors is relatively low; however, if the intersection rises, results can be biased, as shown in subsection 3.2.

Momentum (UMD) portfolio formation based on ranged stock price changes from t−1 to t−12 period without a lag. The long part consisted of the top 30% (UP) from a ranged list of available stock at each formation date, whereas the short part opposite contains bottom 30% (DOWN) stocks. The instrument does not participate in portfolio formation if a price for liquid stocks in period t−1 or t−12 is missing. The UMD forms are as follows:

$$UMD_t = \frac{1}{3}UP_t - \frac{1}{3}DOWN_t, \tag{1}$$

Size (SMB) portfolio formation is based on the range of the most recent companies' market capitalizations in period t−1 without a lag. The long part consisted of the bottom 30% (SMALL) from a ranged list of available stock at each formation date, whereas the short part contains top 30% (BIG) stocks. The instrument has not participated in portfolio formation if capitalization or the price for liquid stock in period t−1 is missing. SMB forms are as follows:

$$SMB_t = \frac{1}{3}SMALL_t - \frac{1}{3}BIG_t, \tag{2}$$

Low-volatility (VOL) portfolio formation based on the range of 12 months trailing standard deviation of stock price returns changes from t−1 to t−12 period without a lag. The long part consisted of the bottom 30% (LVOL) from a ranged list of available stock at each formation date. On the contrary, the short part contains top 30% of top (HVOL) stocks. The instrument does not participate in portfolio formation if a price for liquid stock in period t−1 or t−12 is missing. Missing values between t−1 and t−12 are not included in the computation of trailing standard deviation. VOL is formed as follows:

$$VOL_t = \frac{1}{3}LVOL_t - \frac{1}{3}HVOL_t, \tag{3}$$

3.3. Unique factors

The primary technique is to remove duplicate positions from each portfolio in a single period (Fig. 3). For example, for the Indian market stock, TAMO simultaneously offered for purchase in VOL and UMD portfolios for July 2010. In this case, TAMO will be unavailable for purchase (but available for short) from July 2010 to July 2011 for all three factors: VOL, UMD, and SMB. No other stock replaces deleted stocks. The weight is equally allocated among the remaining holdings.

In two extreme cases, any two or all three unique factors can include 0% or 100% of the number of stocks from the initial factor portfolios. As shown in the empirical section, both cases are extremely rare.

If this method is compared with the standard double-sorting procedure (Fama & French, 2012), the unique factor procedure can show the dynamic high holdings intersection. Double sorting contributes to the same portfolio with fewer stocks in the case of a 100% holding intersection of two factors. The unique factor procedure identifies similar strategies and provides close to zero stocks available for purchase. The last method decreases the unpredictable share of an initial number of instruments. Nevertheless, it can be adopted for allocating capital in three or more factors. Double sorting with 30% quantiles portfolios will result in only 9% stocks remaining from the stock universe.

The suggested method is free of look-ahead bias. It is complicated to control future return correlation yet relatively easy to drop replicated stocks in the portfolio formation procedure. Although removing repeats implies a declining future return correlation, returns on the remaining stocks are unknown and can still correlate.

4. Results

4.1. Factor performance and correlation in emerging markets

This subsection contains the following evidence.

1. Momentum and low volatility perform relatively poor in most countries compared to evidence in the related literature for emerging markets.
2. Simple correlation between factors cannot provide hidden risks of factor crashes. In most cases, multifactor portfolios regularly show months with negative returns. For some countries, the sequence of negative months can exceed four in a row.
3. Factors are also correlated between countries.
4. Periods of high correlation between factor returns can be characterized by lower volatility, positive market returns, and relatively higher portfolio holdings intersection.

The performance of momentum, size, and low volatility significantly differed from the evidence in the literature (Cakici et al., 2013; Hanauer & Lauterbach, 2019; Zaremba & Czapkiewicz, 2017). The momentum shows relatively poor results and performs well only in Hong Kong (Table 2). Positive and insignificant alphas are shown for India, Russia, and Vietnam. The last two markets have the lowest number of liquid stocks and sample periods. In contrast, India has the largest number of liquid instruments and an early start date. Other markets provide negative and insignificant alphas for momentum.

For countries except China, Taiwan, and Thailand, momentum shows a win rate in portfolio holdings higher than 50%. The lowest part of the portfolio provides a highly negative performance. For most countries, momentum correlation with the general market is nearly zero. In comparison, other factors are most strongly negative. In most cases, momentum has the highest turnover from 36% to 57% across other

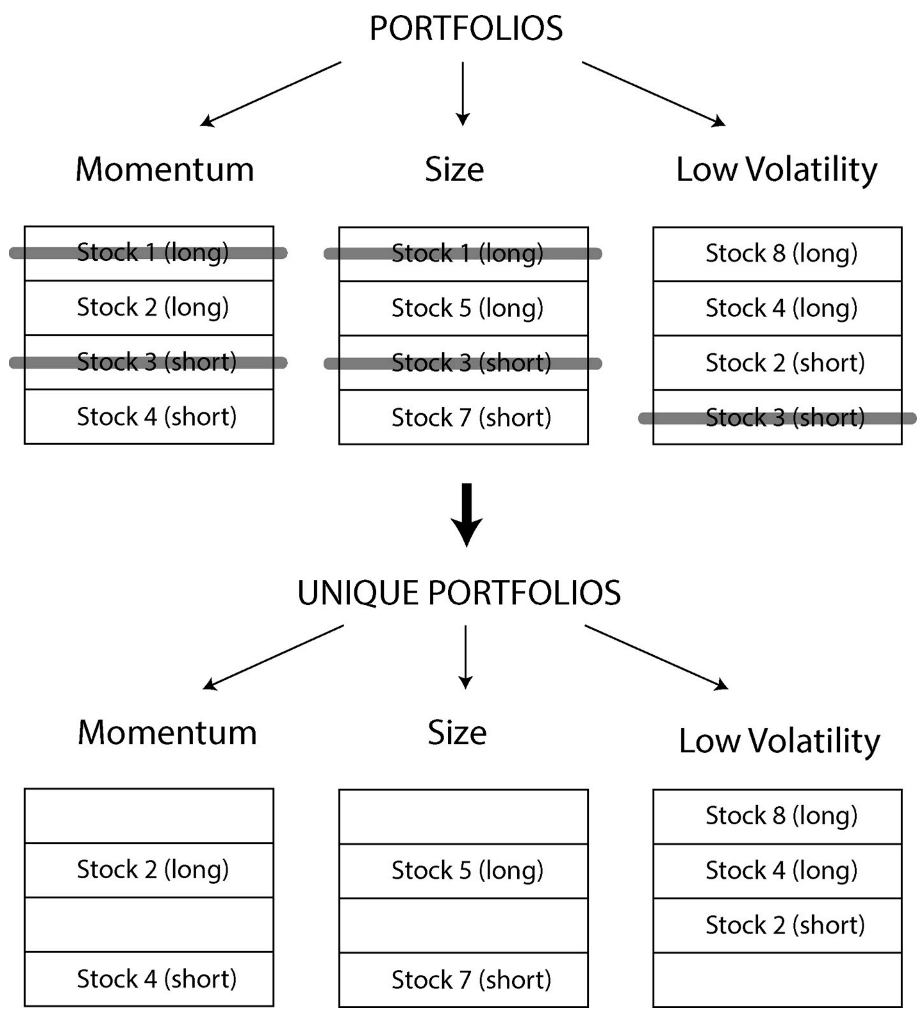

Fig. 3. Unique factor technique. Portfolio holdings are compared between each factor for all periods. Repeatable positions in two or three portfolios are replaced for the period. No other stock replaces deleted stocks. The weight is equally allocated among the remaining holdings. Received unique portfolios contain only non-repeatable holdings. The number of stocks in the unique portfolio ranges from 0% to 100% of the original portfolio.

factors. In practice, results will be the weakest in emerging markets due to relatively higher transaction costs.

In most cases, size has a confusing combination of the highest alphas and lowest share of profitable positions. Brazil and China have the most significant advantages of small versus large stocks. According to further results in this subsection, Brazil is the more vulnerable market due to the hidden risk of factor crashes. Hong Kong is the worst market in terms of size and the best for trending stocks. For all markets except Malaysia, size provides high and insignificant alphas. Small and big companies retain their capitalization due to lower turnover than momentum and low volatility.

Low volatility, in general, does not provide negative alphas, and significance is slightly lower than the threshold. India is the only market with significant performance. Nevertheless, this anomaly has only one market with negative and insignificant alpha—Thailand. In other metrics, low volatility is in the middle between size and momentum.

The survey of factor correlation starts with the procedure of finding minimum, mean, and maximum values (Table 3). The mean correlation shows an illusion that factors are independent and provide a different source of risk and returns. The maximum monthly correlation between the three-factor pairs exceeds 0.5 for each country except India. This is related to the results of Geertsema and Lu (2020) for the U.S. market. As expected, correlation spikes for emerging markets are even stronger. Geertsema and Lu (2020) provided a high correlation inside clusters based on similar economic ideas: trends, relative valuation, low risk, and 25 other groups. In this study, all factors are based on different economic ideas.

Nevertheless, correlation spikes can be related to positive factor returns. To show the hidden risk of the factor investing in emerging markets directly, I conduct tests focused on negative returns (Table 3). Based on the number of months, the last three columns of Table 3 are when the excess return for all anomalies is negative. The total share of returns of negative months from 0% to 100% allows us to compare countries for unexpected risks of the multifactor model. This ratio exceeds 5% for all markets except for China and Vietnam. The markets with the highest negative ratio are Brazil with 15.2%, and Thailand with 12.4%. The average value for emerging markets is 8.1%. There is no straight link between the three correlation measures and the hidden risk of negative return. Taiwan has the highest maximum correlation and the average ratio of negative periods.

The maximum number of subsequent factor crashes shows the longest months with negative performance. Three or four straight periods with negative returns can be critical for leveraged funds. Four out of 10 markets pass this line. On average, emerging markets have a mean streak of 2.3 months. There is a clear link between the share of negative periods and the longest streak for all countries except Malaysia. Only two markets, China and Russia, show no sequence with two or more periods in raw. China is the second market with available liquid stocks, and Russia is the last.

The columns with the total number of subsequent factors crashing for

Table 2

Performance of momentum, size, and low-volatility anomalies in emerging markets. Table 2 contains individual results of a market-neutral portfolio for each factor for emerging markets as a group. The time series of monthly excess returns over risk-free rates in local currency is provided for each factor in each country. These data are then used with the local benchmark for calculating CAPM annual alpha and beta, the correlation with the market, the share of profitable positions, and mean turnover. The correlation with market returns includes the same country benchmark. The share of profitable positions shows the mean value of stocks from 0 to 100% with a positive cumulative return before the next formation procedure. The mean turnover presents the ratio of new stocks rebalancing from 0 to 100% in the next year.

	Factors	CAPM alpha, %	Beta	Market correlation	Share of profitable positions, %	Mean turnover, %
Brazil	Momentum	−0.02 (−0.00)	0.10	0.08	51.01	45.50
	Size	7.05* (1.90)	−0.35	−0.42	49.66	42.38
	Low Volatility	3.07 (0.73)	−0.41	−0.43	51.35	42.66
China	Momentum	−3.15 (−0.88)	−0.01	−0.01	45.99	44.24
	Size	7.65** (2.18)	0.03	0.05	58.33	35.51
	Low Volatility	2.54 (0.81)	−0.16	−0.26	53.70	40.22
Hong Kong	Momentum	6.30** (2.09)	−0.05	−0.06	59.14	47.08
	Size	−4.36 (−1.62)	−0.08	−0.13	46.88	42.95
	Low Volatility	4.81 (1.59)	−0.26	−0.34	50.54	44.01
India	Momentum	4.70 (1.10)	−0.03	−0.04	52.76	43.26
	Size	5.10 (1.54)	−0.03	−0.05	51.10	35.71
	Low Volatility	9.09** (2.09)	−0.39	−0.43	53.59	36.17
Indonesia	Momentum	−2.84 (−0.49)	−0.06	−0.05	53.67	57.34
	Size	2.66 (0.62)	−0.27	−0.29	48.59	57.74
	Low Volatility	3.93 (0.82)	−0.06	−0.06	54.80	53.45
Malaysia	Momentum	−2.23 (−0.68)	−0.08	−0.09	52.68	53.47
	Size	−0.32 (−0.12)	0.16	0.23	48.78	45.09
	Low Volatility	3.28 (1.25)	−0.53	−0.63	52.68	47.44
Russia	Momentum	1.85 (0.38)	−0.25	−0.27	51.63	36.07
	Size	4.94 (1.25)	−0.31	−0.39	49.02	28.08
	Low Volatility	2.93 (0.68)	0.03	0.03	52.94	33.70
Taiwan	Momentum	−1.52 (−0.50)	−0.04	−0.06	47.01	44.82
	Size	3.53 (1.19)	−0.07	−0.11	53.26	33.64
	Low Volatility	1.70 (0.54)	−0.36	−0.46	48.10	38.88
Thailand	Momentum	−0.01 (−0.00)	−0.18	−0.20	48.99	52.20
	Size	4.95 (1.60)	−0.33	−0.48	50.76	50.18
	Low Volatility	−1.53 (−0.46)	−0.47	−0.58	51.01	49.18
Vietnam	Momentum	4.90 (0.73)	−0.29	−0.28	54.30	49.20
	Size	3.89 (0.73)	−0.19	−0.23	51.66	43.97
	Low Volatility	6.32 (1.08)	−0.29	−0.31	52.98	47.56

Table 3

Correlation of anomalies in emerging markets. The first three columns show each country's minimum, mean, and maximum correlation between the monthly returns of all factor pairs (momentum, size, and low volatility). The last row shows the average of all the columns. The share of periods with factor crashes represents the percentage of months when returns of all three factors are negative from the total amount. The last column shows the total number of subsequent factor crashes for two or more periods.

	Factors correlation			Share of periods with factors crashes, %	Max series of subsequent factors crashes	Total number of subsequent factors crashes for two or more periods
	Min	Mean	Max			
Brazil	−0,38	0,011	0,603	15,203	4	6
China	−0,421	−0,211	0,521	4012	1	0
Hong Kong	−0,466	−0,147	0,67	7097	3	4
India	−0,415	−0,148	0,314	8564	2	3
Indonesia	−0,447	−0,166	0,505	5932	2	1
Malaysia	−0,456	−0,185	0,574	6585	3	1
Russia	−0,407	−0,106	0,413	8497	1	0
Taiwan	−0,471	−0,177	0,762	8424	2	4
Thailand	−0,462	−0,025	0,692	12,374	3	5
Vietnam	−0,429	−0,149	0,639	4636	2	1
Across all countries	−0,435	−0,13	0,569	8132	2,3	2,5

two or more periods show how often multifactor portfolios have two or more negative months in a row. Emerging markets have a mean number of 2.5 of this series. Brazil and Thailand provide similar related results in the previous two columns. Taiwan has a relatively small maximum streak of two that repeated approximately two times higher than average. In other cases, the countries with the highest negative series provide them more often.

A comparison of the results between factor performance in Table 2 and correlation in Table 3 may be confusing. There is no linear relation with historical performance measured with alpha to CAPM and the sequence of periods with negative returns. Size and low volatility generally perform well in Brazil, the riskiest market according to all measures (Table 3). Thailand's second riskiest market for factor investing is the market with the lowest alpha. China and Russia exhibit the lowest number and length of negative sequences for multifactor returns. At the same time, nothing special is found in factor performance in these markets compared to others. It is possible that factor crashes are unobservable for measures based on portfolio returns.

Nondiagonal values in Table 4 show that a correlation between anomalies exists between and inside countries. Diagonal values contain mean correlation between three-factor pairs inside countries. China has the lowest correlation between factors and countries, which is consistent with the evidence in the previous table. In contrast, Russia is highly correlated with other countries, especially Brazil, which is inconsistent with previous evidence. Similar to China, Russia provides the lowest risk of factor crashes in the sample.

Table 4

Correlation of factor returns between countries. The correlations of the volatility-scaled mean returns of momentum, size, and low volatility between countries are given in the table, except for diagonal values. Diagonal values show the correlation between momentum, size, and low volatility inside the country. Factor returns are given in U.S. dollars to capture the correlation between countries.

	Brazil	China	Hong Kong	India	Indonesia	Malaysia	Russia	Taiwan	Thailand	Vietnam
Brazil	0,01	−0,11	0,07	0,14	0,07	−0,01	0,27	0,09	0,13	0,01
China	−0,11	−0,21	0,11	0,07	0,11	−0,06	0,04	0,07	−0,05	0,1
Hong Kong	0,07	0,11	−0,15	0,17	0,1	0,2	0,15	0,2	0,2	0,33
India	0,14	0,07	0,17	−0,15	0,14	0,15	0,2	0,23	0,15	0,24
Indonesia	0,07	0,11	0,1	0,14	−0,17	0,21	0,17	0,13	0,16	0,26
Malaysia	−0,01	−0,06	0,2	0,15	0,21	−0,19	0,16	0,05	0,29	0,31
Russia	0,27	0,04	0,15	0,2	0,17	0,16	−0,11	0,1	0,16	0,19
Taiwan	0,09	0,07	0,2	0,23	0,13	0,05	0,1	−0,18	0,26	0,17
Thailand	0,13	−0,05	0,2	0,15	0,16	0,29	0,16	0,26	−0.03	0,25
Vietnam	0,01	0,1	0,33	0,24	0,26	0,31	0,19	0,17	0,25	−0,15

Correlation between countries is an additional problem to factor comovement within the country. The mean factor pair correlation in factors is 0.14 (nondiagonal values). The mean values of raw factor correlations inside the country are −0.13 (diagonal values). This can be explained by emerging markets' currency comovement to the U.S. dollar. The exchange rate significantly impacts emerging markets' returns in U.S. dollars due to a high currency correlation of 0.21 between countries. After all, investors in emerging markets face independent factors and correlations, both within and outside the country.

The literature provides evidence that the probability of factor crashes in the U.S. market rises during periods of market rebounds (Arnott et al., 2019; Daniel & Moskowitz, 2016) and rising volatility (Barroso & Santa-Clara, 2015). Evidence for emerging markets is presented in Table 5. In periods with the highest general market return, the correlation between factors is higher on average. For some countries, this relation is not linear or even reversed (Hong Kong). The link between volatility and correlation is linear for all emerging markets. When the volatility of factor portfolios rises, they become more correlated across the countries. This effect is evident in Vietnam and opposite in Brazil.

Table 5 contains an additional column to test correlation factors in periods that intersect between low, neutral, and high portfolio holdings. Compared with the measures from previous columns, this metric provides the sharpest decrease in average correlation. Volatility has a correlation difference of 2.5 times in low and high periods. The market return and holdings intersections are 1.6 and 6.5, respectively.

4.2. Unique factor performance and correlation in emerging markets

The subsection contains the following evidence.

1. Most factor spikes of correlations and sequences of negative returns were eliminated. Unique factors produce a different source of risk and opportunities for factor timing.
2. The correlation between countries decreases for all pairs.
3. The portfolio filtration procedure, on an average, discards 45% of the holdings of the initial portfolio.

Unique factors cannot contain positions that differ from the initial portfolio, meaning that new portfolios cannot be more diversified or present new sources of risk. In an extreme case, a unique portfolio can contain the same positions as an initial portfolio, whereas in the opposite severe case, the unique portfolio can hold zero positions if the sample includes two similar anomalies; however, neither situation existed for the emerging market (Fig. 4). They are infrequent even in the decomposition of momentum (Fig.A1), size (Fig.A2), and low volatility (Fig. A3) for every emerging market in the sample. On average, momentum loses 45% of duplicated portfolio holdings, size loses 43%, and low volatility is 47%. Discarding is sufficient. Meanwhile, investors in emerging markets still have an average of 3267 liquid stocks as investment opportunities.

Minimum, mean, and maximum values of correlation decreased at different times. The minimum value for all markets decreased slightly from −0.44 to −0.46 (Table 6). The mean change is sharper from −0.13 to −0.3. The most significant correlation change observed in maximum values, from 0.57 to 0.04 in general or more than 10 times for China and India, was that the maximum correlation became even negative.

The average share of periods with factor crashes decreases two times. An extreme decline was observed in India, Brazil, and Thailand. The mean length of the longest negative series became shorter by 50%. For three out of 10 markets, these series differ from one. The most significant

Table 5

Factor correlation in different periods of market returns, factor return volatility, and holding intersection. The mean correlation between monthly returns of all factor pairs (momentum, size, and low volatility) inside each country is shown in this table for different market return periods and for the intersection of factor return volatility and portfolio holdings. The last row shows the average of all columns. Factor volatility represents the mean twelve months trailing standard deviation for momentum, size, and low volatility. A portfolio holdings intersection is defined as an average intersection between holdings of all factor pairs. Market returns for each country are given in the local currency from the value-weighted index with liquid stocks. Periods with low (high) values for all columns are defined as the bottom (top) 5% number of periods ranked by the volatility of factors, holdings intersection, and market return. Neutral periods include the remaining 90% of periods.

	Volatility of factors return			Markets returns			Portfolio holdings intersection		
	Low	Neutral	High	Low	Neutral	High	Negative	Neutral	Positive
Brazil	0,16	0,033	−0,129	0,073	0,008	−0,226	0,078	0,021	−0,252
China	−0,268	−0,266	−0,211	−0,283	−0,294	−0,039	−0,335	−0,279	0,291
Hong Kong	−0,205	−0,166	−0,15	−0,261	−0,117	−0,252	−0,339	−0,15	−0,077
India	−0,072	−0,165	−0,099	−0,194	−0,145	−0,177	−0,254	−0,16	0,027
Indonesia	−0,147	−0,225	0,032	−0,054	−0,184	−0,211	−0,221	−0,17	−0,234
Malaysia	−0,407	−0,247	−0,097	−0,198	−0,24	0,007	−0,317	−0,202	0,065
Russia	−0,383	−0,058	−0,286	−0,459	−0,104	−0,26	−0,027	−0,115	−0,112
Taiwan	−0,313	−0,132	−0,338	−0,329	−0,166	−0,21	−0,365	−0,134	−0,18
Thailand	−0,078	0,013	0,312	−0,045	−0,143	0,086	−0,188	0,07	0,084
Vietnam	−0,056	−0,163	0,31	−0,483	−0,152	−0,064	−0,401	−0,099	0,033
Across all countries	−0,177	−0,138	−0,066	−0,223	−0,154	−0,135	−0,237	−0,122	−0,036

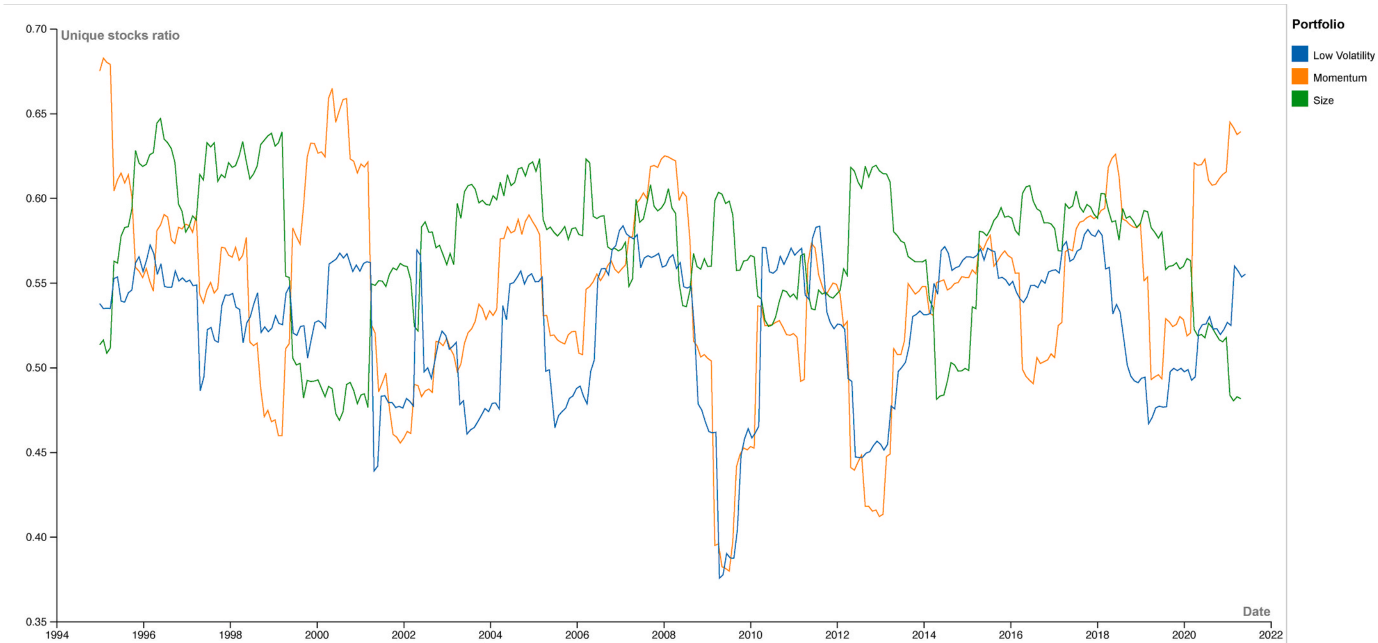

Fig. 4. Total share of holdings from the initial portfolio for unique momentum, size, and low-volatility portfolios across all countries. The orange line represents the share of the unique part of momentum portfolios across countries for each month. The unique part is defined as long (short) stock positions that are not included as long (short) in size or low-volatility portfolios in the same period. The green and blue lines represent the same unique size and low-volatility part. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 6
Correlation of unique factors in emerging markets. The first three columns show each country's minimum, mean, and maximum correlation between monthly returns of all unique factor pairs (momentum, size, and low volatility). The last row presents the average of all columns. The share of periods with factor crashes represents the percentage of months when returns of all three factors are negative from the total amount. The last column presents the total number of subsequent factor crashes for two or more periods.

	Factors correlation			Share of periods with factors crashes, %	Max series of subsequent factors crashes	Total number of subsequent factors crashes for two or more periods
	Min	Mean	Max			
Brazil	−0,442	−0,241	0,145	6419	1	0
China	−0,475	−0,392	−0,239	1543	1	0
Hong Kong	−0,476	−0,296	0,119	4731	2	1
India	−0,445	−0,332	−0,105	1105	1	0
Indonesia	−0,475	−0,259	0,095	4802	1	0
Malaysia	−0,487	−0,341	0,057	2683	1	0
Russia	−0,391	−0,217	0,01	11,765	3	5
Taiwan	−0,474	−0,355	−0,121	2446	1	0
Thailand	−0,48	−0,314	0,276	4798	3	1
Vietnam	−0,408	−0,225	0,189	3974	1	0
Across all countries	−0,455	−0,297	0,043	4427	1,5	0,7

Table 7
Correlation of unique factors returns between countries. The correlation of volatility-scaled mean returns of momentum, size, and low volatility between countries are given in the table except for diagonal values. Diagonal values illustrate the correlation between momentum, size, and low volatility inside the country. Factor returns are given in U.S. dollars to capture the correlation between countries.

	Brazil	China	Hong Kong	India	Indonesia	Malaysia	Russia	Taiwan	Thailand	Vietnam
Brazil	−0,24	−0,01	−0,09	0,1	−0,03	0,07	−0,08	0,06	0,05	−0,12
China	−0,01	−0,39	0,04	0,06	−0,05	0,01	−0,14	0,06	0,01	0,09
Hong Kong	−0,09	0,04	−0,30	−0,01	−0,01	0,12	−0,1	0,01	−0,01	0,05
India	0,1	0,06	−0,01	−0,33	0,09	−0,05	−0,05	0,02	−0,04	0,03
Indonesia	−0,03	−0,05	−0,01	0,09	−0,26	0,02	−0,16	−0,18	−0,1	−0,07
Malaysia	0,07	0,01	0,12	−0,05	0,02	−0,34	−0,14	−0,02	−0,12	−0,08
Russia	−0,08	−0,14	−0,1	−0,05	−0,16	−0,14	−0,22	0,02	0,02	0,03
Taiwan	0,06	0,06	0,01	0,02	−0,18	−0,02	0,02	−0,36	0,06	0,12
Thailand	0,05	0,01	−0,01	−0,04	−0,1	−0,12	0,02	0,06	−0,31	0,16
Vietnam	−0,12	0,09	0,05	0,03	−0,07	−0,08	0,03	0,12	0,16	−0,23

decline was observed for several negative series. The only exception in all cases is the Russian market.

Cross-country correlations mostly vanished as well (Table 7). The mean pair correlation between countries for unique factors is −0.01 (nondiagonal). The mean value of raw factor correlations inside the country is −0.321 (diagonal). Most countries became uncorrelated from each other in returns measured in U.S. dollars. The correlation between factor (diagonal) values in local currency is −0.02 for ordinary and −0.37 for unique factors.

However, unique factors do not produce higher alphas. In general, alphas became lower because nonunique stocks contain essential sources of return (Table.A2). The main advantage of the unique approach is that it is much easier to control holdings intersections in the portfolio formation stage rather than forecast future volatility and market returns (Daniel & Moskowitz, 2016; Barroso & Santa-Clara, 2015).

5. Robustness check

This section contains four additional tests to examine the persistence of vanished factor crashes and correlation for unique versions. The primary evidence of the subsections is as follows.

1. Varying portfolio holding percentages from the initial stock universe to form portfolios show no relation between portfolio diversification and the comovement of unique factors.
2. The second test distinguishes unique factor's performance from the most recent crisis periods: the Asian crisis in 1998, the GFC in 2008, and the COVID-19 pandemic in 2020. Unique factors are immune to comovement in all significant shocks.
3. Subsampling periods to excessively high or low CPI, local currency change, and the standard deviation of factor returns shows no change in the correlation between unique factors.
4. The last test shows the decomposition of portfolio holdings intersections between the long and short sides of portfolios. Shares are approximately identical for both sides. Unique portfolios are not biased in market directions.

The results of the percentile-varying procedure are included in Table 8. The test is based on a simple idea: a less diversified portfolio can be affected more deeply than more concentrated portfolios. I apply the same comovement metrics from the previous section to portfolios holding 10%, 20%, and 50% of liquid stocks from the investment universe. Nevertheless, all variations of the portfolio formation procedure after applying unique factor methodology show less vulnerability to factor crashes than original factors.

Table 9 examines factor crashes for unique portfolios during the most recent crisis in financial markets. Panel A in Table 11 includes the Asian financial crisis from July 1997 to December 1998. Panel B contains the GFC from December 2007 to June 2009. Panel C represents the COVID-19 pandemic period from February to April 2020. No negative series are observed for all countries in the latest pandemic crisis. In previous declining periods, the negative streak does not exceed one in all cases. For half of the sample, no factor crashes exist even in these periods.

Asset pricing and factor correlation in emerging markets can be

Table 8

Correlation of unique factors in emerging markets for portfolios with 10%, 20%, and 50% stocks from the investment universe. The first three columns show each country's minimum, mean, and maximum correlation between monthly returns of all factor pairs (momentum, size, and low volatility). The last row shows the average of all columns. The share of periods with factor crashes represents the percentage of months when returns of all three factors are negative from the total amount. The last column shows the total number of subsequent factor crashes for two or more periods.

	Min correlation	Mean correlation	Max correlation	Negative periods ratio, %	Max negative streak	Negative series num
Panel A: Portfolio holds 10% of liquid stocks from investment universe						
Brazil	−0,4	−0,089	0,4	7432	3	2
China	−0,462	−0,31	0,032	3395	1	0
Hong Kong	−0,445	−0,104	0,761	9032	4	5
India	−0,403	−0,156	0,486	6,63	2	2
Indonesia	−0,435	−0,157	0,32	8475	2	2
Malaysia	−0,439	−0,195	0,486	5122	2	2
Russia	−0,367	−0,075	0,395	8497	1	0
Taiwan	−0,433	−0,215	0,415	6522	2	3
Thailand	−0,455	−0,05	0,641	7071	3	1
Vietnam	−0,364	−0,025	0,408	9934	3	2
Across all countries	−0,42	−0,138	0,434	7211	2,3	1,9
Panel B: Portfolio holds 20% of liquid stocks from investment universe						
Brazil	−0,401	−0,182	0,405	5405	2	2
China	−0,483	−0,366	−0,204	0,926	1	0
Hong Kong	−0,464	−0,249	0,335	4946	2	1
India	−0,442	−0,266	0,17	4972	2	1
Indonesia	−0,453	−0,193	0,404	5932	2	1
Malaysia	−0,473	−0,257	0,492	4146	3	1
Russia	−0,332	−0,149	0,171	11,765	1	0
Taiwan	−0,462	−0,325	−0,14	3804	1	0
Thailand	−0,462	−0,178	0,33	5808	2	1
Vietnam	−0,437	−0,148	0,562	8609	2	1
Across all countries	−0,441	−0,231	0,252	5631	1,8	0,8
Panel C: Portfolio holds 50% of liquid stocks from investment universe						
Brazil	−0,374	−0,094	0,376	12,162	2	2
China	−0,448	−0,324	0,046	4938	2	2
Hong Kong	−0,426	−0,232	0,225	5591	3	3
India	−0,394	−0,189	0,602	9116	3	1
Indonesia	−0,447	−0,212	0,149	5085	1	0
Malaysia	−0,441	−0,276	0,19	3902	2	1
Russia	−0,372	−0,032	0,392	7843	2	3
Taiwan	−0,453	−0,267	0,29	5435	2	2
Thailand	−0,471	−0,231	0,285	5556	2	2
Vietnam	−0,419	−0,206	0,174	12,583	3	1
Across all countries	−0,424	−0,206	0,273	7221	2,2	1,7

Table 9

Unique factor crash in crisis periods. Panel A includes the Asian financial data. Panel B contains the GFC, and Panel C represents the COVID-19 pandemic period. The first three columns show each country's minimum, mean, and maximum correlation between monthly returns of all factor pairs (momentum, size, and low volatility). The last row shows the average of all columns. The share of periods with factor crashes represents the percentage of months when returns of all three factors are negative from the total amount. The last column shows the total number of subsequent factor crashes for two or more periods.

	Min correlation	Mean correlation	Max correlation	Negative periods ratio, %	Max negative streak	Negative series num
Panel A: Asian crisis 1997–1998						
China	−0,428	−0,4	−0,348	10,526	1	0
Hong Kong	−0,453	−0,377	−0,059	5263	1	0
India	−0,339	−0,281	−0,215	0	0	0
Indonesia	−0,376	−0,323	−0,249	5263	1	0
Malaysia	−0,465	−0,386	−0,314	0	0	0
Taiwan	−0,357	−0,327	−0,291	0	0	0
Thailand	−0,403	−0,349	−0,246	3509	1	0
Across all countries	−0,428	−0,4	−0,348	10,526	0,571	0
Panel B: Global financial crisis 2007–2008						
China	−0,384	−0,351	−0,31	0	0	0
Hong Kong	−0,442	−0,37	−0,28	5263	1	0
India	−0,412	−0,383	−0,352	0	0	0
Indonesia	−0,44	−0,271	−0,026	0	0	0
Malaysia	−0,422	−0,323	−0,196	10,526	1	0
Taiwan	−0,45	−0,402	−0,326	0	0	0
Thailand	−0,115	0,049	0,276	10,526	1	0
Across all countries	−0,381	−0,293	−0,173	3759	0,429	0
Panel C: COVID crisis 2020						
Brazil	−0,424	−0,404	−0,372	0	0	0
China	−0,446	−0,421	−0,393	0	0	0
Hong Kong	−0,308	−0,222	−0,155	0	0	0
India	−0,394	−0,351	−0,286	0	0	0
Indonesia	−0,374	−0,293	−0,217	0	0	0
Malaysia	−0,438	−0,381	−0,346	0	0	0
Russia	−0,185	−0,154	−0,143	0	0	0
Taiwan	−0,421	−0,381	−0,347	0	0	0
Thailand	−0,43	−0,407	−0,386	0	0	0
Vietnam	−0,228	−0,199	−0,135	0	0	0
Across all countries	−0,365	−0,321	−0,278	0	0	0

Table 10

Unique factor correlation in different states of factors volatility, CPI, and exchange rate. The mean correlation between monthly returns of all factor pairs (momentum, size, and low volatility) inside each country is shown for different periods of factor volatility, CPI, and local currency return to the U.S. dollar. The last row shows the average of all columns. Factor volatility represents the mean 12 months trailing standard deviation for momentum, size, and low volatility. CPI and currency return is based on Datastream data. Periods with low (high) values for all columns defines as the bottom (top) 5% number of periods ranked by the volatility of factor volatility, CPI, and local currency return to the U.S. dollar. Neutral periods include the remaining 90% of periods.

	Factors volatility			CPI			Currency rate to USD		
	Low	Neutral	High	Low	Neutral	High	Low	Neutral	High
Brazil	−0,383	−0,211	−0,329	−0,277	−0,248	−0,332	−0,228	−0,267	−0,147
China	−0,337	−0,423	−0,429	−0,381	−0,427	−0,333	−0,411	−0,43	−0,401
Hong Kong	−0,214	−0,329	−0,407	−0,31	−0,326	−0,214	−0,144	−0,33	−0,367
India	−0,323	−0,366	−0,318	−0,425	−0,354	−0,272	−0,428	−0,349	−0,419
Indonesia	−0,293	−0,295	−0,233	−0,134	−0,273	−0,361	−0,416	−0,263	−0,19
Malaysia	−0,206	−0,379	−0,366	−0,395	−0,373	−0,407	−0,29	−0,381	−0,384
Russia	−0,134	−0,207	−0,046	−0,099	−0,171	−0,292	−0,278	−0,192	−0,185
Taiwan	−0,311	−0,376	−0,349	−0,35	−0,385	−0,387	−0,358	−0,383	−0,36
Thailand	−0,341	−0,301	−0,386	−0,156	−0,327	−0,342	−0,244	−0,326	−0,332
Vietnam	−0,313	−0,243	−0,277	−0,229	−0,304	0,477	−0,328	−0,287	−0,26
Across all countries	−0,286	−0,313	−0,314	−0,275	−0,319	−0,246	−0,313	−0,321	−0,304

sufficiently different in periods of individual shocks, not based on global market falls. Therefore, in Tables 10 and I decompose the unique factor's performance into periods with the highest and lowest volatility, CPI, and exchange rate. This circumstance does not affect the negative correlation between countries. The only exceptions are periods of relatively high CPI in Vietnam, associated with a rising correlation close to 0.5.

The final robustness check test decomposes the intersections in a market-neutral portfolio into long and short positions. Diversification can be biased if a unique framework discards more holdings from one side. Intersection coefficients in Table 11 show that mean values are equal for long and short for two out of the three factors. Short intersections are close to two times higher in momentum-size pairs than long ones, meaning that small stocks are relatively higher and represent underperformance in past returns in emerging markets.

6. Conclusion

The simple correlation between factors cannot provide hidden risks of factor comovement. Multifactor portfolios for most markets regularly show the months with simultaneous negative returns. For some countries, negative months can exceed three in a row. Factor crashes are due to the rising level of portfolio holdings in both long and short positions. The unique factor technique presents a procedure for discarding duplicate positions from each portfolio in a single period. Unique portfolios

Table 11
Overlapping of portfolio holdings. The table provides long (Panel A) and short (Panel B) portfolio holdings separately overlapping between market-neutral portfolios of two-factor pairs. Values range from 0 (no overlapping in longs and shorts) to 1 (the same portfolios). Pairs with overlapping measures are formed from the three factors—momentum, size, and value.

	Momentum-Size Overlapping			Momentum-Low volatility Overlapping			Size-Low volatility Overlapping		
	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
Panel A: Long side of portfolio (30%)									
Brazil	0,145	0,417	0	0,34	0,667	0,143	0,231	0,462	0
China	0,153	0,4	0	0,249	0,44	0	0,311	0,458	0,182
Hong Kong	0,127	0,333	0	0,297	0,765	0	0,294	0,636	0
India	0,151	0,295	0,03	0,3	0,656	0,058	0,275	0,403	0,192
Indonesia	0,112	0,385	0	0,272	0,615	0	0,323	0,7	0,118
Malaysia	0,176	0,39	0,03	0,276	0,674	0,023	0,28	0,517	0,086
Russia	0,192	0,4	0,056	0,297	0,538	0,062	0,283	0,5	0,133
Taiwan	0,164	0,294	0	0,232	0,579	0,021	0,301	0,558	0,111
Thailand	0,136	0,311	0	0,256	0,615	0	0,355	0,552	0,191
Vietnam	0,183	0,316	0	0,309	0,7	0,103	0,335	0,568	0,115
Across all countries	0,154	0,354	0,012	0,283	0,625	0,041	0,299	0,535	0,113
Panel B: Short side of portfolio (30%)									
Brazil	0,292	0,5	0	0,399	0,833	0,125	0,227	0,417	0,071
China	0,306	0,502	0,13	0,239	0,442	0	0,335	0,569	0,227
Hong Kong	0,287	0,667	0	0,31	0,889	0,1	0,236	0,5	0,056
India	0,296	0,551	0,122	0,324	0,656	0,064	0,255	0,38	0,156
Indonesia	0,302	0,75	0	0,313	1	0	0,274	0,571	0
Malaysia	0,278	0,577	0,1	0,333	0,75	0	0,241	0,371	0,131
Russia	0,33	0,643	0,118	0,327	0,615	0,125	0,213	0,389	0,1
Taiwan	0,293	0,485	0,054	0,265	0,576	0,05	0,304	0,545	0,17
Thailand	0,324	0,667	0,077	0,341	0,682	0,027	0,334	0,529	0,212
Vietnam	0,318	0,476	0,192	0,291	0,571	0,071	0,34	0,477	0,161
Across all countries	0,303	0,582	0,079	0,314	0,701	0,056	0,276	0,475	0,128

for all three factors contain approximately half the number of stocks from the initial portfolios.

Evidence of vanished factor correlation is sustainable for the most recent crises: the Asian crisis in 1998, the GFC in 2008, and the COVID-19 pandemic in 2020. Periods of extremely high or low CPI, local currency change, and standard deviation of factor returns do not significantly influence the correlation between unique factors.

This research contributes to the area of empirical asset pricing. The unique factor framework allows for distinguishing hidden sources of factors in emerging markets. Rare events are known as crashes, with rising holdings overlapping with simultaneous negative returns for most sustainable factors. The suggested framework can be used for event study analysis of factor crashes and further decomposition of unique and nonunique risks in the factor zoo. Nonunique holdings of momentum, size, and low-volatility factors contain essential sources of returns for most periods in emerging markets.

The unique factor methodology can enhance the toolbox of factor identification (Daniel et al., 2020; Feng et al., 2020; Harvey et al., 2016; He et al., 2023) and portfolio performance evaluation. Due to the cyclical nature of factor returns (Dimson et al., 2017), new discoveries should not be discarded if they fail an out-of-sample test or reduced rank approach (He et al., 2023). If a new low overlapping factor is provided in periods of factor crashes, it can be reasonable to keep it for diversification.

Smart beta practitioners can apply the suggested methodology to provide diversified multifactor portfolios. Active managers can switch between unique and nonunique components of persistent factors to avoid rising correlation. As it is not possible to simultaneously apply the unique methodology to all existing factors, most instruments will be discarded. It can be reasonable to compare core factors from different groups (trends, fundamentals, sentiment) with each other. Newly discovered characteristics of similar economic ideas (fundamentals) might be compared with basic implementation (P/BV ratio for value).

The unique procedure can also be applied to fund managers of algorithmic strategies to manage the risk. Managers possibly provide uncorrelated results most of the time, although their portfolio holdings do not differ much. In periods of changing market correlation structures, excess risks of comovement may be provided. Due to calculation simplicity, the unique ratio can be calculated in real time.

The existing literature provides instruments for avoiding factor comovement in periods of negative returns with knowledge of future market rebounds or volatility spikes. The suggested framework applies to the portfolio formation (rebalancing) stage and does not require any forecasting. At the same time, discarding rarely exceeds half of the liquid stocks from emerging markets.

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Declaration of competing interest

None.

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Appendices.

Table.A1
Data description. The table shows a sample of stocks from each emerging market. The total number of stocks reflects the number of liquid stocks available for purchase in at least one period. The number of periods includes the months when portfolios were collected for each factor. Start and end dates reflect the market tracking period, subject to the condition of having at least 50 liquid stocks. The mean annual market return reflects the average annual return in U.S. dollars for the value-weighted portfolio of all available liquid stocks for each country market. The min and max number of stocks reflect the minimum and maximum number of stocks available for purchase in a particular period. The mean number of stocks shows the average number available for trade over the entire interval. The mean market cap shows the average market capitalization of liquid companies in each market in U.S. dollars for the whole period. Mean monthly volatility shows the average annual standard deviation of value-weighted market portfolio returns.

	Brazil	China	Hong_Kong	India	Indonesia	Malaysia	Russia	Taiwan	Thailand	Vietnam
Stock Exchanges	BSE	SSE, SZSE	HKEX	BSE, NSE	IDX	KLSE	MOEX	TWSE	SET	HOSE
Total number of stocks	831	3776	2211	6089	944	1228	364	1208	1127	434
Number of periods (months)	296	324	465	362	354	410	153	368	396	151
Start Date	1997–01	1994–09	1982–12	1991–07	1992–03	1987–07	2008–12	1991–01	1988–09	2009–02
End Date	2021–08	2021–08	2021–08	2021–08	2021–08	2021–08	2021–08	2021–08	2021–08	2021–08
Mean Annual Market Return, USD %	12,07	11,48	10,58	11,54	7,9	7,82	1,75	5,54	8,37	3,88
Mean Number of Stocks	94	1098	250	520	123	304	64	381	205	129
Min Number of Stocks	32	55	47	240	48	117	51	110	50	49
Max Number of Stocks	164	2358	609	811	251	448	92	569	320	172
Mean Market Cap, USD billons	2,67	2,11	2,02	0,88	0,64	0,41	5,35	0,82	0,51	0,39
Mean Monthly Volatility	19,49	15,35	19,35	20,15	20,59	14,67	14,29	12,94	14,9	13,21

Fig. A1. Total share of holdings from the initial portfolio for a unique momentum portfolio for each country. This figure represents the share of the unique part of momentum portfolios for each month. The unique part is defined as long (short) stock positions that are not included as long (short) in size or low-volatility portfolios in the same period.

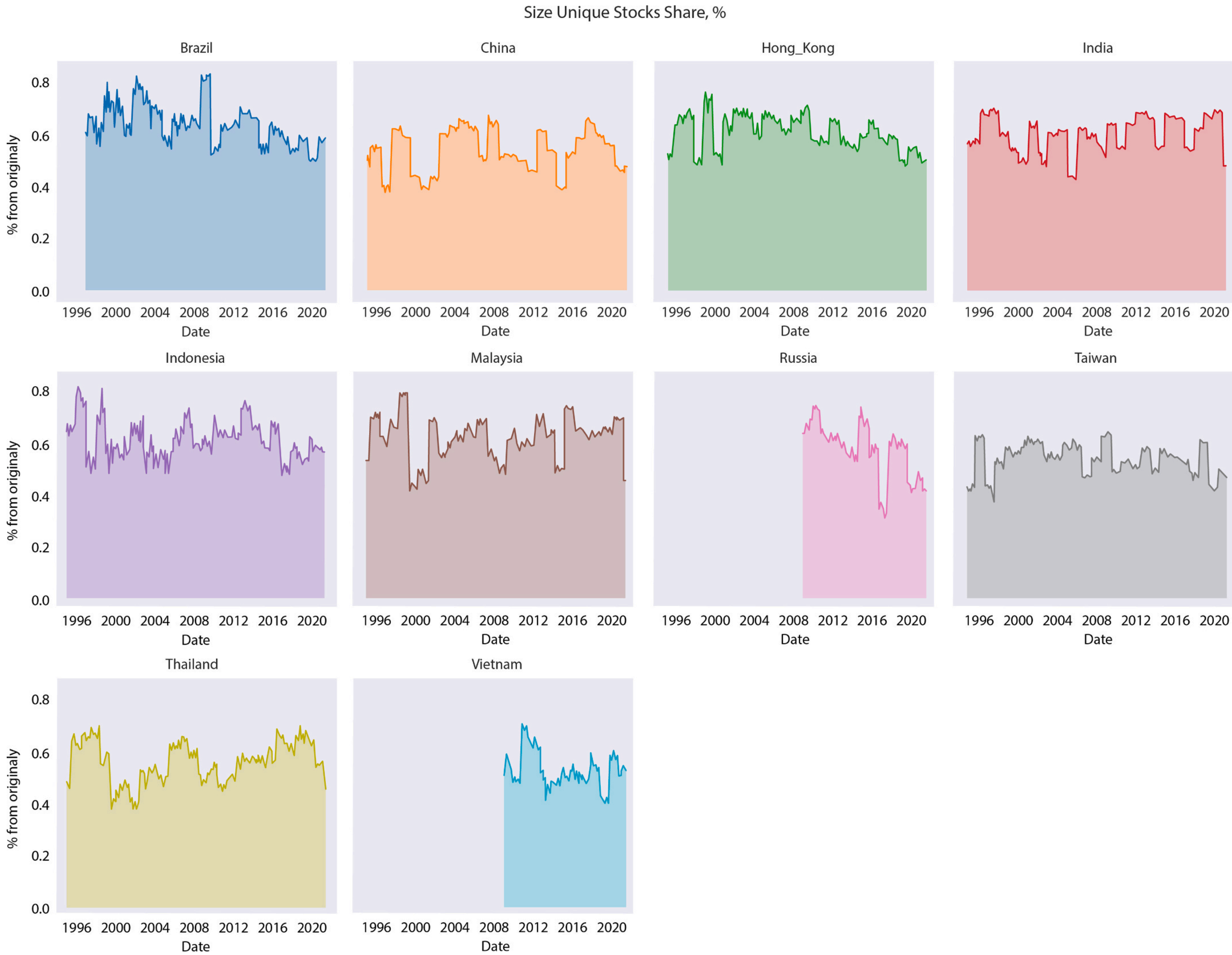

Fig. A2. Total share of holdings from the initial portfolio for a unique size portfolio for each country. This figure represents the share of each month's unique part of size portfolios. The unique part is defined as long (short) stock positions not included as long (short) in momentum or low-volatility portfolios in the same period.

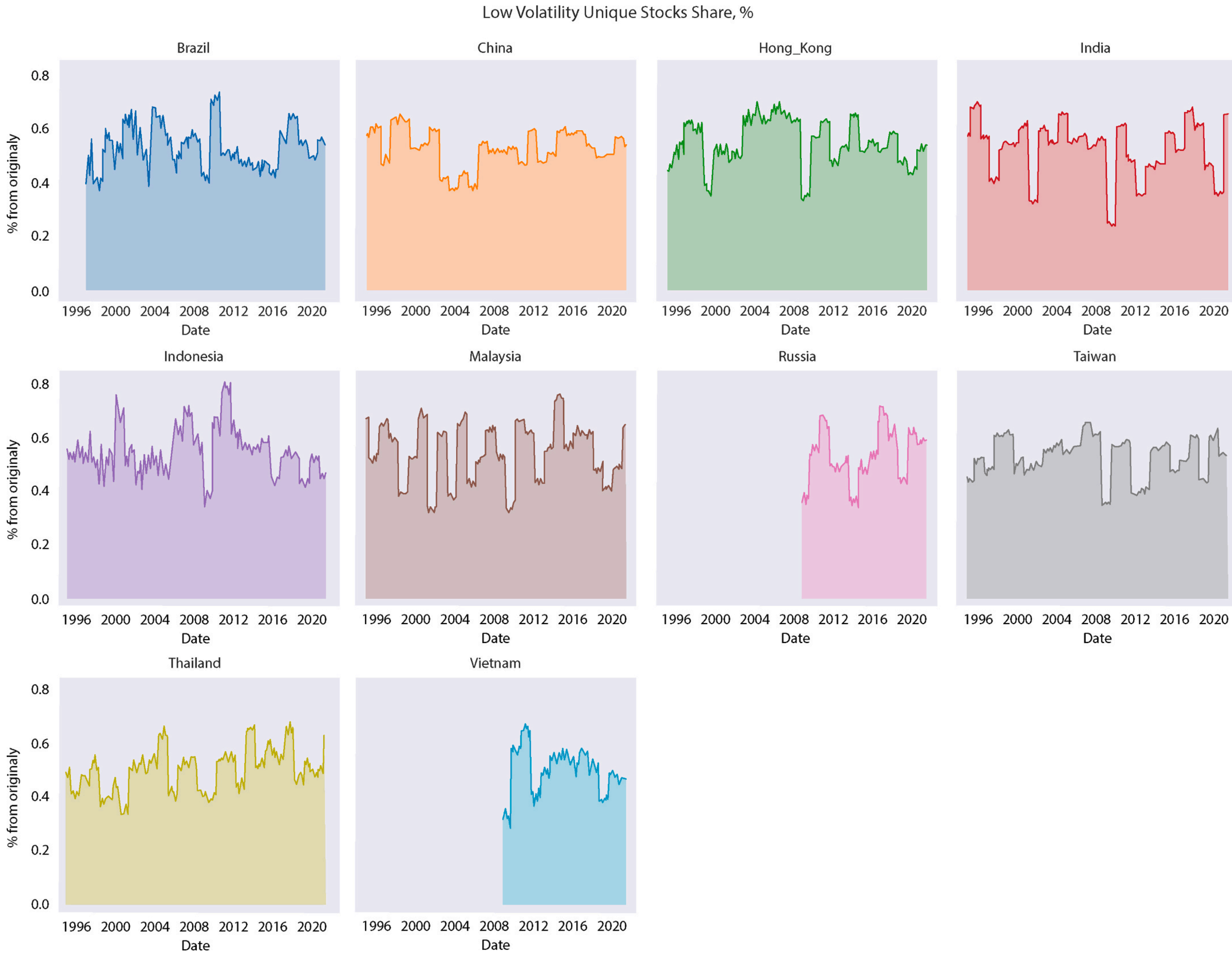

Fig. A3. Total share of holdings from the initial portfolio for each country's unique low-volatility portfolio. This figure represents the share of each month's unique part of low-volatility portfolios. The unique part is defined as long (short) stock positions that are not included as long (short) in momentum or size portfolios in the same period.

Table.A2

Performance of unique factors in emerging markets. A time series of monthly excess returns over a risk-free rate in local currency is provided for each factor in each country. These data are then used with the local benchmark for calculating CAPM alpha and beta, correlation with the market, the share of profitable positions, and mean turnover. As an explanatory variable, alpha and beta are calculated from linear regression with a value-weighted market return over a risk-free rate. Correlation with market returns includes the same country benchmark. Share of profitable positions shows the mean value of stocks from 0% to 100% with a positive cumulative return before the next formation procedure. Mean turnover presents the ratio of new stocks rebalancing from 0% to 100% next year.

	Factors	CAPM Alpha, %	Beta	Market Correlation	Share of Profitable Positions, %	Mean Turnover, %
Brazil	Momentum	−1.56 (−0.25)	0.40	0.30	51.01	51.64
	Size	2.53 (0.53)	−0.21	−0.21	47.97	50.93
	Low Volatility	0.35 (0.07)	−0.10	−0.10	48.65	52.79
China	Momentum	−7.67** (−2.15)	0.05	0.08	43.83	47.75
	Size	6.66* (1.70)	0.09	0.12	55.56	46.39
	Low Volatility	1.11 (0.28)	−0.13	−0.17	49.38	46.59
Hong Kong	Momentum	4.29 (1.30)	0.22	0.27	53.55	58.94
	Size	−9.21*** (−2.71)	−0.02	−0.02	41.08	52.10
	Low Volatility	7.42** (2.06)	−0.12	−0.14	53.12	52.69
India	Momentum	2.64 (0.63)	0.21	0.25	55.25	49.57
	Size	0.97 (0.24)	0.09	0.11	50.28	44.18
	Low Volatility	−2.30 (−0.56)	−0.24	−0.29	46.41	46.47
Indonesia	Momentum	−9.04 (−1.34)	0.05	0.03	49.72	73.95
	Size	−2.69 (−0.49)	−0.24	−0.21	43.79	64.01
	Low Volatility	8.03 (1.41)	0.10	0.08	57.63	64.41
Malaysia	Momentum	−1.51 (−0.46)	0.01	0.02	52.20	58.80
	Size	−1.98 (−0.58)	0.31	0.35	45.37	54.73

(continued on next page)

Table.A2 (*continued*)

	Factors	CAPM Alpha, %	Beta	Market Correlation	Share of Profitable Positions, %	Mean Turnover, %
	Low Volatility	−0.50 (−0.15)	−0.45	−0.48	48.78	55.29
Russia	Momentum	−8.50 (−1.18)	0.13	0.10	50.33	39.91
	Size	−5.82 (−1.16)	−0.16	−0.17	39.22	39.70
	Low Volatility	6.13 (1.01)	0.19	0.17	54.90	42.14
Taiwan	Momentum	−3.42 (−1.09)	0.13	0.18	45.65	47.93
	Size	4.10 (1.18)	0.09	0.12	53.53	44.96
	Low Volatility	3.86 (1.14)	−0.19	−0.25	52.72	45.30
Thailand	Momentum	1.76 (0.36)	0.25	0.25	53.03	59.64
	Size	7.99* (1.71)	−0.05	−0.05	51.77	56.74
	Low Volatility	4.89 (1.18)	−0.16	−0.19	54.80	60.03
Vietnam	Momentum	1.45 (0.19)	−0.02	−0.02	51.66	56.69
	Size	0.30 (0.05)	0.01	0.01	50.99	53.63
	Low Volatility	7.76 (1.05)	0.03	0.02	55.63	53.74

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