Size Matters: *Tail Risk, Momentum, and Trend Following in International Equity Portfolios*

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In this article, we explore the small-firm effect using MSCI style indexes for both developed and emerging markets for the period since 1995 and show how overlaying relative momentum and trend following strategies can substantially enhance both absolute and risk-adjusted returns. For over 30 years, the size effect has been well documented in the finance literature, starting with Banz [1981] and Keim [1983]; the outperformance of small stocks relative to their large counterparts has been an accepted "anomaly" in asset pricing.[1] Indeed the "small minus big" factor is a key component of the Fama and French [1992] three-factor model. Arguments can be made, in much the same way as the value–growth debate, that small firms have higher returns to compensate their owners for bearing additional risk compared with large firms. This might take the form of lower liquidity or less balance sheet strength for example. Alternatively, one can argue that the small firm effect is an anomaly that is mispriced by the market. A key finding in our study is that a mid-cap effect dominates in emerging markets.

Another anomaly within stock markets, and indeed asset classes generally, is that of momentum. The classic equity strategy highlighted by Jegadeesh and Titman [1993] involves buying the "winners" over the past 6–12 months and selling the "losers" over the same period. This is frequently referred to as cross-sectional momentum or relative momentum by Antonacci [2012]. Studies by Erb and Harvey [2006] and Miffre and Rallis [2007] demonstrate the effectiveness of this approach within commodity markets.

An alternative type of momentum investing is where one is interested only in the direction of prices or returns rather than how they fare against their peer group. This type of activity is known as trend following (other names include time-series momentum and absolute momentum) and is frequently used by commodity trading advisors (CTAs) (see Szakmary, Shen, and Sharma [2010]). As examples, trend following rules may use the current price relative to a moving average (Faber [2007]) or the length of time that excess returns have been positive over a range of timeframes (Hurst, Ooi, and Pedersen [2012]). Indeed, Hurst, Ooi, and Pedersen [2012, p. 2] made the following distinction:

> The most basic trend-following strategy is time series momentum—going long markets with recent positive returns and shorting those with recent negative returns. The aim is always to trade in the direction of the prevailing price, i.e., when prices are rising long positions are taken and when prices are falling then cash or short positions are taken.

Evidence for the effectiveness of trend following strategies has been presented by Faber [2007], ap Gwilym et al. [2010], and Moskowitz, Ooi, and Pedersen [2012], among others. Clare et al. [2016] demonstrated that when relative momentum is compared with trend following, it is the latter that provides by far the more impressive investment performance enhancement for a variety of asset classes.

A few studies have considered combining relative momentum with other established equity strategies, such as value. Asness [1997] observes that momentum is present in both value and growth stocks in the United States but that the effect is larger in the latter. Similar results were observed by ap Gwilym et al. [2009] in the United Kingdom when momentum is combined with dividend yield. Clare et al. [2014] studied a variety of international markets and found that trend following enhances the risk-adjusted returns of both value and growth companies, but particularly the latter.

In this article, we seek to examine the relationship between size and momentum in an international context. We find the following:

- the size effect exists across a large range of international markets, both developed and emerging;
- relative momentum provides small improvements in risk-adjusted performance compared with standard equal-weight portfolios, although this has appeared to diminish in the last decade;
- trend following delivers substantial benefits in terms of considerably higher risk-adjusted returns and much lower maximum drawdowns; and finally,
- that *combining* trend following with relative momentum leads to higher levels of return although there is little improvement in risk-adjusted performance compared with trend following alone.

MOMENTUM AND TREND FOLLOWING

Momentum

Momentum is one anomaly in the financial literature that has been demonstrated to offer some explanatory ability of future returns. Many researchers, such as Jegadeesh and Titman [1993] and Grinblatt and Moskowitz [2004] have focused on momentum at the individual stock level, while others, such as Miffre and Rallis [2007] and Erb and Harvey [2006], have observed the effect in commodities. Asness, Moskowitz, and Pedersen [2013] found momentum effects within a wide variety of asset classes, while King, Silver, and Guo [2002] used momentum as a means of allocating capital across asset groups.

Typical momentum strategies involve ranking assets based on their past return (often the previous 12 months) and then buying the winners and selling the losers. Ilmanen [2011] argued that this is not the ideal approach and that investors would be better served by volatility weighting the past returns. Failing to do this leads to the most volatile assets spending a disproportionate amount of time in the highest and lowest momentum portfolios (see Asness, Moskowitz, and Pedersen [2013]).

Moskowitz, Ooi, and Pedersen [2012] found significant "time-series momentum" in equity index, currency, commodity and bond futures for each of the 58 liquid instruments considered. They found persistence in returns for 1 to 12 months that partially reverses over longer horizons, consistent with sentiment theories of initial underreaction and delayed overreaction.

Trend Following

Trend following has been widely used in futures markets, particularly commodities, for many decades (see Ostgaard [2008]). Trading signals can be generated by a variety of methods, such as moving average crossovers and breakouts with the aim to determine the trend in prices. Long positions are adopted when the trend is positive, and short positions, or cash, are taken when the trend is negative. As trend following is generally rules based, it can aid investors because losses are mechanically cut short and winners left to run. This is frequently the reverse of investors' natural instincts. The return on cash is also an important factor either as collateral in futures or as the risk-off asset for long-only methods. Examples of studies on the effectiveness of trend following are those by, among others, Szakmary, Shen, and Sharma [2010] and Hurst et al. [2010] for commodities, and Wilcox and Crittenden [2005] and ap Gwilym et al. [2010] for equity indexes. Faber [2007] used trend following as a means of tactical asset allocation and demonstrated that it is possible to form a portfolio that has equity-level returns with bond-level volatility. Ilmanen [2011] offered a variety of explanations as to why trend following may have been successful

EXHIBIT 1
Equity Index Summary Statistics

	Developed Markets					Emerging Markets					All Markets				
	Large	Mid	Small	Large & Mid	All	Large	Mid	Small	Large & Mid	All	Large	Mid	Small	Large & Mid	All
June 1995–May 2013															
Annualized Return (%)	8.62	8.69	–	8.68	–	10.07	11.11	–	10.64	–	9.53	9.99	–	9.79	–
Annualized Volatility (%)	18.63	19.17	–	18.76	–	26.16	27.48	–	26.64	–	20.37	21.19	–	20.67	–
Sharpe Ratio	0.31	0.31	–	0.32	–	0.28	0.30	–	0.30	–	0.33	0.34	–	0.34	–
Maximum Drawdown (%)	58.40	60.89	–	59.64	–	62.86	67.04	–	64.96	–	58.16	61.19	–	59.69	–
Skew	–0.79	–0.88	–	–0.85	–	–0.47	–0.47	–	–0.48	–	–0.71	–0.75	–	–0.73	–
January 2002–May 2013															
Annualized Return (%)	7.72	10.17	12.97	8.96	10.32	17.99	21.22	19.79	19.63	19.73	11.61	14.38	15.63	13.00	13.90
Annualized Volatility (%)	19.87	20.98	22.80	20.33	21.02	23.30	25.15	25.86	24.11	24.56	20.62	21.93	23.47	21.21	21.86
Sharpe Ratio	0.31	0.41	0.50	0.36	0.42	0.70	0.78	0.70	0.75	0.74	0.49	0.58	0.60	0.54	0.56
Maximum Drawdown (%)	58.40	60.89	63.81	59.64	61.05	57.96	62.63	66.34	60.04	62.14	58.16	61.19	64.39	59.69	61.29
Skew	–0.82	–0.94	–0.82	–0.90	–0.89	–0.70	–0.77	–0.81	–0.75	–0.80	–0.82	–0.93	–0.87	–0.88	–0.90

Note: This table presents summary statistics for equally weighted combinations of the large-, mid- and small-cap indexes and combinations of these three, over the study period.

historically, including investor underreaction to news and herding behavior. Moskowitz, Ooi, and Pedersen [2012] referred to an equivalent of trend following as "time-series momentum."

Combining Trend Following and Momentum

A few studies have sought to combine some of the strategies previously discussed. Faber [2010] used momentum and trend following in equity sector investing in the United States. Antonacci [2012] used momentum for trading between pairs of investments and then applied a quasi-trend-following filter to ensure that the winners have exhibited positive returns. The risk-adjusted performance of these approaches has been a significant improvement on benchmark buy-and-hold portfolios. In a related study, these ideas were extended to the multi-asset context (Clare et al. [2016]) with the finding that although adding a momentum filter increases the level of return compared with equal weighting, the momentum portfolios are prone to large drawdowns. By contrast, Clare et al. found that trend following filters produce higher Sharpe ratios than the momentum-based equivalents and, crucially, much lower maximum drawdowns. Finally, Clare et al. [2016] found that the higher returns achieved by adding the trend-following filter cannot be explained by the Fama–French–Carhart four-factor model.

DATA, METHODOLOGY, AND RESULTS

In order to gauge the impact of both momentum and trend following on market-cap investment strategies, we used MSCI large-, mid- and small-cap indexes for 20 developed and 12 developing economies. The developed economy equity indexes were for Australia, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom, and United States. The developing economy equity indexes were for Brazil, Chile, China, India, Indonesia, Korea, Malaysia, Russia, South Africa, Taiwan, Thailand, and Turkey.

Monthly data for these price and total return indexes begin at end of May 1994 for the large- and mid-cap indexes and from the end of December 2000 for the small-cap indexes, unless otherwise indicated. The final month for all data is May 2013.

Equally Weighted Long Portfolios across Markets and Sizes

Exhibit 1 shows the summary statistics for the large, mid, and small caps, and combinations of the three, over the study period. The results are presented in two periods: June 1995–May 2013, the whole data period, and January 2002–May 2013, the period that small caps are introduced.[2] All portfolios are equally weighted and rebalanced monthly. First, we note that over the whole period from 1995 in developed markets (see Exhibit 1), large and mid caps delivered essentially the same performance. In emerging markets mid caps returned around 1% per annum more with slightly higher volatility. In the later period beginning 2002, however, mid caps outperformed large caps by over 2% per annum for developed markets and 3% per annum for emerging markets. Volatility was somewhat higher but not enough to diminish the relationship on a risk-adjusted basis. Small caps delivered the highest risk-adjusted returns within developed markets with a Sharpe ratio of 0.5 over the shorter period compared with 0.31 for large caps and 0.41 for mid caps; however, there was no similar outperformance shown by emerging small caps, with the mid-cap sector offering the highest absolute and risk-adjusted returns with a Sharpe ratio of 0.78, the highest among the strategies in Exhibit 1.

Over the whole period beginning in 1995, the risk-adjusted performance of developed and emerging markets was very similar, with Sharpe ratios of around 0.3. In the later period, emerging markets outperformed considerably. Returns were some 10%–11% per annum higher for emerging mid caps than for the developed markets, albeit with volatility around one-fifth higher too. The maximum drawdowns for each strategy are the numbers usually associated with long-only equity strategies, with a very painful 60%+ being commonplace; we note that any investors creating long–short strategies possibly with leverage may well have been wiped out, rendering the existence of many "anomalies" questionable (Gray and Vogel [2013]).

Ranking by Volatility-Adjusted Returns for Different Size Categories—Relative Momentum

We next consider the interaction of relative momentum and size. Following the method of Ilmanen [2011], we rank markets according to their prior 12-month return and then volatility weight these by dividing by the standard deviation of returns over the same period. Portfolios are held for one month and then recalculated with the momentum portfolio being the top quarter of available assets.

Exhibit 2 reports that over the whole period, returns for the momentum portfolio are around 2% to 3% per annum higher for both large- and mid-cap developed markets than for all developed markets in Exhibit 1 with similar volatility. Within emerging markets, however, the performance of large-cap momentum is very poor, with an annual compound return of just 1.2% versus about 11% for all markets. In the lower panel of Exhibit 2, we see that mid-cap momentum for emerging markets has slightly higher risk-adjusted and absolute returns than all markets, but the strategy of taking the highest momentum indexes from the large- and mid-cap combined emerging market universe is still below the base-case scenario risk-adjusted return (lower panel, Exhibit 1).

Over this shorter period in Exhibit 2, we observe some benefits to relative momentum within developed small caps, but this is offset by underperformance within emerging small caps with the mid-cap segment showing notably superior performance. There is little other evidence found to support the case for relative momentum during the second time frame. Sharpe ratios are very similar with or without momentum. It should be noted that the maximum drawdowns experienced by all of these portfolios are very severe. Every size category had to endure a maximum drawdown of at least 60%, with some portfolios, such as small-cap emerging, suffering even deeper falls.

Overlaying Trend Following on the Equally Weighted Size Portfolios: Does It Help?

Thus far, we have examined the relationship between relative momentum and size. We next consider the performance of trend following, or absolute momentum, in the same context. The concept of trend following is not new; Ostgaard [2008] provided a description of trend-following activities that date back across several centuries. Hurst et al. [2012] demonstrated that trend following has been a profitable strategy to adopt across equities, bonds, currencies, and commodities as far back as 1902.

Following on from the work of Faber [2007], we use a 10-month moving average to define the trend.[3] Specifically, if the current index price is above a simple 10-month moving average of the prices, then a long position in the asset is adopted. If the current price is below the moving average, then the asset is sold and a

Exhibit 2
Relative Momentum

	Developed Markets					Emerging Markets					All Markets				
	Large	Mid	Small	Large & Mid	All	Large	Mid	Small	Large & Mid	All	Large	Mid	Small	Large & Mid	All
June 1995–May 2013: Top Quarter															
Annualized Return (%)	11.06	10.83	–	11.22	–	1.18	10.47	–	8.67	–	10.97	14.66	–	12.52	–
Annualized Volatility (%)	19.35	19.83	–	19.15	–	29.46	31.17	–	28.40	–	21.01	21.51	–	20.83	–
Sharpe Ratio (2.77%)	0.43	0.41	–	0.44	–	–0.05	0.25	–	0.21	–	0.39	0.55	–	0.47	–
Maximum Drawdown (%)	60.28	64.85	–	60.62	–	77.46	73.93	–	69.47	–	64.97	67.91	–	66.48	–
Skew	–0.59	–1.09	–	–0.88	–	–0.41	–0.59	–	–0.63	–	–0.73	–1.05	–	–0.94	–
January 2002–May 2013: Top Quarter															
Annualized Return (%)	6.89	11.47	15.18	9.54	11.07	11.64	22.57	18.03	18.63	19.28	9.45	18.43	16.74	13.59	14.70
Annualized Volatility (%)	19.33	21.56	23.06	20.11	20.85	26.31	26.42	29.38	25.30	25.47	21.31	23.25	25.15	22.14	22.63
Sharpe Ratio (1.58%)	0.27	0.46	0.59	0.40	0.46	0.38	0.79	0.56	0.67	0.69	0.37	0.72	0.60	0.54	0.58
Maximum Drawdown (%)	60.28	64.85	68.69	60.62	63.83	69.73	69.96	80.18	69.47	71.06	64.97	67.91	71.50	66.48	68.02
Skew	–0.85	–1.22	–0.92	–1.06	–1.08	–0.47	–1.03	–1.28	–1.01	–0.95	–0.96	–1.21	–1.00	–1.07	–1.15
4-Factor Alpha	0.252	0.545	0.757	0.407	0.494	0.594	1.42	1.19	1.11	1.19	0.430	1.09	0.966	0.730	0.808
Newey–West *t*-stat	(0.91)	(1.61)	(1.89)	(1.36)	(1.47)	(1.00)	(2.13)	(1.74)	(1.83)	(2.01)	(1.01)	(2.71)	(1.82)	(1.57)	(1.68)
3-Factor World Alpha	0.211	0.560	0.835	0.405	0.520	0.693	1.46	1.16	1.18	1.20	0.455	1.10	0.991	0.752	0.825
Newey–West *t*-stat	(1.15)	(2.40)	(2.68)	(2.20)	(2.36)	(1.46)	(2.60)	(2.06)	(2.41)	(2.57)	(1.51)	(3.02)	(2.46)	(2.24)	(2.36)

Notes: Markets are ranked according to their prior 12-month return and then volatility weighted by dividing by the standard deviation of returns over the same period. Portfolios are held for one month and then recalculated with the momentum portfolio being the top quarter of available assets. The 4-Factor Alpha is the alpha coefficient from a four U.S. factor Fama–French model where the factors are the return to the CRSP value-weighted market portfolio in excess of the Treasury bill rate (RMRF), the small minus big (SMB) factor that is long the smallest half of firms and short the largest half of firms, the high minus low (HML) book-to-market value factor, and an up minus down (UMD) momentum factor. The 3-Factor World Alpha is the alpha coefficient from a three-factor broad world factor model where the factors are the return to the Goldman Sachs Commodity Market Index (GSCI); the return on the MSCI world equity market index (MSCI); the return on the Barclays Aggregate Bond Index (BAR)—each in excess of the U.S. Treasury bill rate. Newey–West t*-statistics are shown in parentheses.*

position in short-term Treasury bills is taken instead. The trend-following rule is calculated at the end of each month and no short selling is permitted.

Exhibit 3 reports trend-following results across the range of size portfolios. For the long period, we first note the substantial improvements in risk-adjusted returns compared with both the base case and the relative momentum equivalents. For developed markets, returns are around 2% per annum higher than the equally weighted portfolios, with volatilities around eight percentage points lower. Substantial outperformance is also observed within large- and mid-cap emerging markets over the same period. A further benefit to the trend-following approach is that maximum drawdowns are reduced from around 60% to close to 20% in all portfolios. Finally, we also find that portfolios become less negatively skewed. In the case of developed markets, these remain negative; however, the emerging markets and the portfolios containing both developed and emerging markets are both positive. This evidence is consistent with the findings of Koulajian and Czkwianianc [2010] for other managed futures and trend-following strategies.

In the shorter period, for developed markets and the combination of all markets, we observe the standard relationship of returns increasing as size decreases, both with and without trend following. We again find that annualized returns are higher for developed markets using a trend-following strategy, although the reverse is displayed for emerging markets. The consistent properties are the substantial reduction in both volatility and maximum drawdowns across all markets and all size categories. As a result the Sharpe ratios for all the trend-following portfolios are considerably higher than their traditional buy-and-hold equivalents. As in the longer period, we also report a positive shift in skewness although the majority of portfolios remain mildly negative. The emerging market mid-cap Sharpe ratio in

EXHIBIT 3
Trend Following

	Developed Markets					Emerging Markets					All Markets				
	Large	Mid	Small	Large & Mid	All	Large	Mid	Small	Large & Mid	All	Large	Mid	Small	Large & Mid	All
June 1995–May 2013															
Annualized Return (%)	10.38	10.85	–	10.64	–	11.88	15.14	–	13.54	–	11.14	12.66	–	11.92	–
Annualized Volatility (%)	10.38	10.25	–	10.09	–	14.85	14.99	–	14.67	–	11.10	11.02	–	10.92	–
Sharpe Ratio (2.77%)	0.73	0.79	–	0.78	–	0.61	0.82	–	0.73	–	0.75	0.90	–	0.84	–
Maximum Drawdown (%)	19.32	18.78	–	17.18	–	20.67	20.20	–	18.42	–	18.73	14.95	–	16.71	–
Skew	–0.34	–0.29	–	–0.26	–	1.08	0.67	–	0.89	–	0.26	0.17	–	0.25	–
January 2002–May 2013															
Annualized Return (%)	9.36	12.16	15.05	10.77	12.21	15.29	20.73	19.60	18.01	18.56	11.66	15.42	16.87	13.54	14.66
Annualized Volatility (%)	10.10	10.91	12.32	10.33	10.83	14.87	14.99	14.96	14.73	14.69	11.24	11.71	12.49	11.36	11.64
Sharpe Ratio (1.58%)	0.77	0.97	1.09	0.89	0.98	0.92	1.28	1.20	1.12	1.16	0.90	1.18	1.22	1.05	1.12
Maximum Drawdown (%)	19.32	15.00	21.23	17.18	18.55	17.82	20.20	20.13	18.42	18.94	18.73	14.95	19.08	16.71	17.51
Skew	–0.18	–0.32	–0.15	–0.20	–0.19	0.15	0.03	–0.28	0.06	–0.06	–0.05	–0.15	–0.25	–0.08	–0.15
4-Factor Alpha	0.581	0.737	0.908	0.659	0.742	0.989	1.38	1.29	1.18	1.22	0.73	0.978	1.05	0.856	0.921
Newey–West *t*-stat	(2.18)	(2.52)	(2.94)	(2.39)	(2.62)	(2.55)	(3.29)	(3.09)	(2.97)	(3.04)	(2.47)	(3.09)	(3.20)	(2.81)	(2.97)
3-Factor World Alpha	0.579	0.770	0.997	0.675	0.782	1.01	1.38	1.31	1.20	1.24	0.74	1.00	1.11	0.871	0.952
Newey–West *t*-stat	(2.59)	(3.21)	(3.37)	(2.96)	(3.19)	(2.89)	(3.76)	(3.51)	(3.38)	(3.47)	(2.91)	(3.78)	(3.72)	(3.39)	(3.56)

Notes: Trend-following portfolios are formed as follows: If the current index price is above a simple 10-month moving average of the prices then a long position in the asset is adopted. If the current price is below the moving average then the asset is sold and a position in short-term U.S. Treasury bills taken instead. The trend-following rule is calculated at the end of each month and no short-selling is permitted. See Notes to Exhibit 2 for details on 4-Factor Alpha and 3-Factor Alpha. Newey–West t*-statistics are shown in parentheses.*

the lower panel of Exhibit 3 is noticeably high at 1.28. Indeed, the mid-cap Sharpe ratios are high for all our strategies, suggesting that emerging market mid-caps behave like developed country small caps.

Overlaying Trend Following on Volatility-Adjusted Ranked Assets or Overlaying Absolute Momentum on Relative-Momentum Portfolios

Thus far, the evidence presented clearly favors trend following over relative momentum in giving high risk-adjusted returns. This is consistent with evidence presented by Antonacci [2013]. To further test this, we now look at combining relative momentum with trend following. Portfolios are formed in the same fashion as Exhibit 2; however, for a long position to be taken, the trend must be positive for the asset using the rule described earlier. If the trend is not positive then the asset allocation is placed in cash instead.

Exhibit 4 displays the results of the combination of the two types of momentum. First, we observe that the overall level of return is higher through this combination strategy than the equivalent returns from trend following alone (Exhibit 3), relative momentum (Exhibit 2), or equally weighted (Exhibit 1). This is true of all size categories and particularly noticeable within developed markets. We also find, however, that volatility is now higher than trend following alone and that this cancels out the increase in return, such that Sharpe ratio levels are largely unchanged in aggregate. This supports the results of Clare et al. [2016]. In addition to the higher volatility, there is also an increase in the maximum drawdowns that most portfolios are forced to endure.

The evidence presented thus suggests that when relative momentum and trend following interact, it is the latter that is the dominant beneficial presence in terms of the investor's experience. We have seen that relative momentum added little in the way of portfolio gains across a range of markets and size categories. Trend following, by contrast, provided substantial benefits in terms of considerably reduced volatility, lower maximum drawdowns and less negatively skewed returns.

Furthermore, and somewhat surprisingly, we see that for emerging markets it is the mid-cap firms that

Exhibit 4
Trend Following and Momentum

	Developed Markets					Emerging Markets					All Markets				
	Large	Mid	Small	Large & Mid	All	Large	Mid	Small	Large & Mid	All	Large	Mid	Small	Large & Mid	All
June 1995–May 2013: Top Quarter															
Annualized Return (%)	14.79	12.97	–	13.80	–	9.37	15.07	–	14.43	–	14.15	17.49	–	15.47	–
Annualized Volatility (%)	14.91	14.30	–	14.16	–	22.91	25.24	–	21.63	–	15.90	15.90	–	15.47	–
Sharpe Ratio (2.77%)	0.81	0.71	–	0.78	–	0.29	0.49	–	0.54	–	0.72	0.93	–	0.82	–
Maximum Drawdown (%)	26.11	35.31	–	29.15	–	55.44	58.52	–	49.77	–	25.05	32.08	–	25.96	–
Skew	0.21	–0.37	–	–0.13	–	0.36	–0.18	–	0.10	–	–0.02	–0.28	–	–0.18	–
January 2002–May 2013: Top Quarter															
Annualized Return (%)	10.93	15.16	19.08	12.81	14.82	17.27	28.29	22.91	24.53	24.40	13.39	22.78	20.57	17.79	18.86
Annualized Volatility (%)	13.30	14.26	14.60	13.57	13.27	21.45	21.60	22.17	19.93	19.87	15.34	15.88	16.15	15.36	15.20
Sharpe Ratio (1.58%)	0.70	0.95	1.20	0.83	1.00	0.73	1.24	0.96	1.15	1.15	0.77	1.34	1.18	1.06	1.14
Maximum Drawdown (%)	19.97	21.70	23.21	20.98	19.34	28.36	35.19	39.93	29.21	29.70	22.53	26.06	24.81	25.09	24.09
Skew	0.22	–0.43	–0.27	–0.21	–0.36	0.23	–0.11	–0.69	–0.09	–0.32	–0.02	–0.16	–0.45	–0.09	–0.25
4-Factor Alpha	0.684	0.951	1.16	0.779	0.897	1.15	1.90	1.55	1.64	1.64	0.840	1.49	1.31	1.15	1.20
Newey–West *t*-stat	(2.23)	(2.58)	(3.42)	(2.25)	(2.70)	(2.18)	(3.13)	(2.45)	(3.19)	(3.18)	(2.25)	(3.67)	(3.01)	(2.98)	(3.04)
3-Factor World Alpha	0.658	0.955	1.27	0.779	0.937	1.18	1.90	1.55	1.66	1.64	0.849	1.49	1.35	1.15	1.22
Newey–West *t*-stat	(2.58)	(3.18)	(4.07)	(2.81)	(3.35)	(2.36)	(3.30)	(2.63)	(3.36)	(3.39)	(2.56)	(4.03)	(3.53)	(3.36)	(3.48)

Notes: This table shows the results of the combination of the two types of momentum simultaneously. See Notes to Exhibits 3 and 4. Newey–West t*-statistics are shown in parentheses.*

offer the best risk-adjusted returns—they are the small-cap equivalent of developed market companies.

The Search for Alpha

The properties of the investment strategies thus far are based upon unconditional returns. In this section of the article, we examine whether the excess returns can be explained by well-known and widely employed risk factors. The lower parts of Exhibits 3 and 4 present alpha estimates and related *t*-values for the trend-following portfolios and the trend following combined with momentum, respectively. These figures are calculated for the full set of both developed and emerging size portfolios and hence cover the shorter period. The alphas for each of the *j* investment strategies (α_j) were generated using Expression 1, as follows:

$$ER_{jt} = \alpha_j + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_{jt} \quad (1)$$

where ER_j is the excess return on investment strategy *j*; MKT, SMB, and HML represent Fama and French's three factors (market, size, and value, respectively); UMD is Carhart's momentum factor; and ϵ_{jt} is a white noise error term. We also show results for a three-factor model where the factors are more recognizable as "macro" factors, namely the Goldman Sachs' Commodity Index (GSCI), the return on the MSCI World equity index, and the return on the Barclays Aggregate Bond Index (BAR): all are expressed in excess of the U.S. Treasury bill rate. The Newey–West *t*-statistics are shown in brackets.

We see in Exhibit 3 that the excess return for both the four- and three-factor models for developed countries rises monotonically as we progress from large to small portfolios, ranging from 0.579% to 0.997% a month. A similar pattern is seen for emerging countries, where the excess return rises from a low of 1.01% for large firms to a high of 1.38% a month for mid-size firms, with a value of 1.31% for small firms. All of these numbers are highly statistically significant, with Newey–West *t*-values of 2.89, 3.76, and 3.51, respectively. Clearly a very significant alpha remains even after the removal of factor components, and it is highest for small firms in developed and for mid-size firms in emerging economies.

The lower section of Exhibit 4 contains similar analysis but for size portfolios based on both trend following and the top quartile by prior performance (momentum). Here, we again see strong, well-determined excess returns for all developed markets' size portfolios (ranging from a low of 0.658% to a high of 1.27% a month), and for emerging country portfolios, the excess returns are well determined and highest for the mid-size firms, at 1.90% a month, whichever set of risk factors are used.

Both investment strategies analyzing the absolute and relative trend interaction with size as an investing style give a powerful message that tail risk/drawdowns can be managed to give attractive Sharpe ratios and substantial alpha. As regards transaction costs, we note that recent work by Frazzini, Israel, and Moskowitz [2012] has clearly shown, using a real data set from a large investor, that anomalies/styles such as value, growth and size survive transaction costs with much greater room to spare than generally thought; the same cannot be said for reversal strategies. Furthermore, the switching of assets and moving to T-bills occurs relatively infrequently, with one-way transactions taking place on average approximately every seven months.

EXPLAINING THE OUTPERFORMANCE OF TREND-FOLLOWING STRATEGIES

Continuation, Reversals, and Behavioral Finance

Trend following, often known as time-series momentum (although they are not necessarily synonymous, as we point out in the introduction), is closely related to the predictions of some behavioral and rational asset pricing theories, such as those of Barberis, Shleifer, and Vishny [1998], Daniel, Hirshleifer, and Subrahmanyam [1998], and Hong and Stein [1999]. The empirical findings of Moskowitz et al. [2012], among others, that for a wide range of asset classes there is positive time-series momentum that partially reverses over the long-term may well be consistent with initial underreaction and delayed overreaction; indeed, theories of sentiment can produce these return patterns (Baker and Wurgler [2006, 2007]).

Trend-following strategies work if price trends continue more often than not (e.g., see Hurst, Ooi, and Pedersen [2012]), but why should these trends continue? Much of our understanding of this is based on the work of Kahneman and Tversky [1979] and, in this context, is typically related to the behavioral biases involved in underreaction of market prices to new information. If prices initially underreact to either good or bad news, trends tend to continue as prices slowly move to fully reflect changes in fundamental value. These trends may continue further to the extent that investors chase the trend via herding behavior, which can lead to an overreaction in prices beyond fundamental value. Naturally, all trends will eventually come to an end as deviations from fair value cannot continue indefinitely. This is the domain of managed futures' investing and has been applied with some success across many asset classes (e.g., Hurst, Ooi, and Pedersen [2012]) and indeed with particular success during extreme up and down markets.

Moskowitz, Ooi, and Pedersen [2012] found that the dominant force to both time-series and relative momentum strategies is significant positive auto-covariance between a security's excess return next month and its one-year lagged return. This evidence is consistent with both initial underreaction and delayed overreaction theories of sentiment as the time-series momentum effect partially reverses after one year. They also investigate the link between time-series momentum returns and the positions of speculators and hedgers, finding that speculators profit from time-series momentum at the expense of hedgers, which is consistent with speculators earning a premium via time-series momentum for providing liquidity to hedgers.

So, we believe that the *raison d'etre* for the existence of trends lies firmly in the area of behavioral finance. A major shift in some fundamental variable driving an asset price is adopted into the market slowly, revealing an initial underreaction to the new information, possibly due to the slow diffusion of news (Hong and Stein [1999]); the trend in price then overextends due to herding effects and finally results in a reversal. Research has linked the initial underreaction to behavioral features and frictions that slow down the price discovery process, these include:

1. *Anchoring.* Barberis, Shleifer, and Vishny [1998], Edwards [1968], and Tversky and Kahneman [1974] found that historical data provide a natural anchor for people, and their views adjust slowly to new information: anchoring leads to underreaction to news.

2. *The disposition effect.* Shefrin and Statman [1985] and Frazzini [2006] noted that people tend to sell winners too early because they like to realize gains, thus slowing down the rise in price, and they hold losers too long because they wish to avoid realizing losses, hence slowing any downward move in prices. Barberis [2013] pointed out that this argument follows directly from prospect theory. Holding losers demonstrates risk-seeking behavior by investors when they make losses. This idea is developed further by Barberis and Xiong [2012].

Of course, once a trend has become established a number of features can extend the trend:

3. *Herding.* Bikhchandani, Hirshleifer, and Welch, [1992], De Long et al. [1990], Hong and Stein [1999], and others argued that when prices start moving up or down for a while, then some traders will naturally join the bandwagon and the herding effect will feed on itself; this has been observed with equity analysts' forecasts and mutual fund investors.
4. *Confirmation bias/representativeness.* Tversky and Kahneman [1974] showed that people tend to look for information that they already believe and take recent price changes as representative of the future. Over-confidence and self-attribution confirmation biases are present (Daniel, Hirshleifer, and Subrahmanyam [1998]) as is the representativeness heuristic (Barberis, Shleifer, and Vishny [1998]), hence more investors join the trend: it becomes self-reinforcing. Of course, prices eventually extend far beyond underlying fundamental value, and the trend evaporates: Prices may move sideways for a period until new information moves prices once more.
5. *Rules-based investing strategies and behavioral finance.*

A key feature of both time-series and cross-section momentum investment strategies is that they can be implemented by applying simple rules. Ever since Michaud [1989] questioned the efficacy of combining asserts in mean–variance efficient portfolios, there has been interest in simple alternative approaches that do not involve generating expected returns, variances, and covariances: Simple rules may include equal dollar weights or, indeed, equal risk weights, so-called "risk parity." The latter has been especially popular of late, probably because of the low interest rate environment. Some researchers have compared such simple rules with more conventional rules due to Markowitz, both with and without perfect foresight, and found that the former are superior in terms of Sharpe ratio and other performance metrics (see, for example, Chaves et al. [2011]).

Why should such simple rules perform so well? We believe that the discipline of rules-based construction has clear advantages over attempting to forecast returns in a noisy world that also incorporates substantial behavioral biases: Overreliance on recent information is but one simple example of bias that could adversely affect such forecasts. Simple rules avoid behavioral biases in portfolio formation.

CONCLUSIONS

This article has investigated the relationship between size and momentum across a range of developing and emerging international equity markets. We particularly make the distinction between relative momentum, where assets are ranked based on their prior volatility-adjusted returns, and trend following, where assets are categorized according to the direction of recent price moves.

We find that the well-researched size effect has been present across a range of developed markets but *not* for emerging countries, particularly in the early part of the 21st century. Small- and mid-cap stocks have outperformed their large counterparts on both a risk-adjusted and unadjusted basis. The performance of equities over the period of study has been characterized by some periods of turbulence, such as the Asian crisis in the late 1990s, the dot-com boom and bust, and the housing boom and financial crisis that took place during the first decade of the new millennium. This activity was contemporaneous with substantial falls in equity prices, with many of the buy-and-hold portfolios in this study suffering drawdowns in excess of 50%.

When relative momentum was introduced, we found that over the whole period there were some small risk-adjusted gains to be had. These appear to diminish after 2001, however, when there became little difference from base-case portfolios. The introduction of trend following, however, was observed to offer substantial benefits across all size categories and both developed and emerging markets. Annualized returns were typically slightly higher, but the big gains were made in considerably lower volatility and maximum drawdowns compared with relative momentum and buy-and-hold portfolios. An additional property of trend-following portfolios is that returns were found to be less negatively skewed.

Finally, we combined relative momentum and trend-following strategies together. We observed that the level of return was higher than trend following alone but that this was accompanied by a commensurate increase in volatility, such that risk-adjusted returns were, on aggregate, little changed. We thus conclude that trend following is the dominant momentum effect.

When we expose these unconditional returns to both macro/financial and Fama–French factors in the search for alpha, we find that excess returns remain, especially for small stock portfolios in developed markets and for mid-sized firms in emerging economies.

ENDNOTES

[1]There has recently been a challenge to this perceived wisdom by Kalesnik and Beck [2014], who argued that there is an upward bias in size premium estimates due to inaccurate returns on delisted stocks in major databases and an inappropriate treatment of trading costs; also the statistical significance of the size premium estimates is likely overstated due to data mining and reporting bias. Furthermore, there is no statistical significance outside the United States and there is no risk-adjusted performance advantage attributable to the size factor. In contrast, Asness [2015] asserted that the small firm effect is stronger than ever once quality versus junk is accounted for amongst small firms.

[2]We use the first 12 months of data for momentum calculations in subsequent sections, hence the somewhat later start than might be anticipated based on the data section.

[3]Faber [2007] and Clare et al. [2016] reported that moving average lengths between 6 and 12 months perform similarly across a range of asset classes.

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