Stability and Impact of Hedge Funds' Country Allocation in Emerging Markets

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This version: August 2010

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Abstract

I use return-based style analysis to estimate the exposures of emerging market hedge funds to individual countries. Long-only portfolios that mimic the funds' country allocations in the previous months generate abnormal returns that are comparable to the ones of the hedge funds. This supports the reliability of the estimation procedure and indicates the stability of hedge fund strategies. Further analysis shows that an increase in hedge fund investments is associated with a lower stock market volatility, while de-investments have no discernable effect on volatility. The study therefore fails to find evidence that hedge fund investments lead to market disruptions.

JEL classification: F3, G1, G2
Key words: emerging markets, hedge funds, country selection, market impact

1 Introduction

Since the financial crises of the 1990s, there are concerns that hedge funds might disrupt entire markets (see, e.g. Eichengreen et al, 1998). If hedge funds can exert significant pressure on a developed market like the UK (George Soros' speculative attack on the Sterling in 1992), it seems all the more conceivable that their investments and de-investments can influence emerging markets. While Fung and Hsieh (2000) as well as Brown, Goetzmann, and Park (2000) conclude that hedge funds should not be blamed for the 1997 Asian currency crisis, there is no broad study on the role of hedge funds in emerging markets that includes both normal and crisis times. Such a study seems all the more desirable as the volume of hedge funds investing in emerging markets has grown dramatically since the 1990s (see Abugri and Dutta, 2009).

In this paper, I aim to partially fill this gap by examining the stability and market impact of hedge funds' country allocations in emerging stock markets. I use return-based style analysis (Sharpe, 1992) to estimate the country weights of emerging market hedge funds. Despite the large number of countries and the low number of usable observations associated with a monthly return frequency, the estimates appear to capture the current hedge fund positions well. Portfolios that mimic the funds' country allocations in the previous months generate abnormal returns that are comparable to the ones of the hedge funds. Since the mimicking portfolios are constructed on an out-of-sample basis, the similarity in performance cannot be an artifact of in-sample overfitting. The finding also implies that hedge fund strategies are relatively stable — otherwise it would not be possible to replicate current returns based on past data. Further analysis shows that an estimated increase in hedge fund investments is associated with a decrease in stock market volatility, while de-investments have no discernable effect on volatility. The study therefore fails to find evidence that hedge fund investments lead to market disruptions.

The return-based style analysis builds on similar studies that have analyzed hedge fund returns through factor models, e.g. Fung and Hsieh (1997), Agarwal and Naik (2000), Brown, Goetzmann, and Park (2000) and Hasanhodzic and Lo (2007). These studies use top-level factors like major stock market indices (e.g. S&P 500, Emerging Market Index), commodities prices, or exchange rates to model hedge funds including funds with an emerging market focus. By contrast, I explain hedge fund returns through their exposures to individual emerging stock markets. Again departing from several existing studies, I impose a long-only constraint in estimating country weights. This seems sensible given that short-sale constraints are likely to prevail in emerging markets.[1] Another benefit of the restriction is that it tends to increase the robustness of the estimation procedure, which is important if many country weights are estimated with a relatively small number of returns. The two differences to prior literature can explain why the mimicking portfolios approximate hedge fund performance well, whereas other attempts to replicate superior performance of emerging market hedge funds have so far been unsuccessful (Hasanhodzic and Lo, 2007).

The remainder of the paper is structured as follows. In Section 2, I describe the data and the methodology. Section 3 analyzes the performance of portfolios that mimic past hedge fund behavior. Section 4 examines the link between market volatility and changes in hedge fund allocation, and Section 5 concludes.

[1] In the description of emerging market hedge funds included in their database, Hedgefund Research writes: “Emerging Markets funds invest, primarily long,…”, see http://www.hedgefundresearch.com/.

2 Data and methodology

The hedge fund returns studied in the paper considered are returns on the Emerging Markets (Total) Index compiled by Hedge Fund Research.[2] Monthly data is available from January 1990 to December 2009, which defines the time period used in this study. Equity market data are from Datastream. I use the MSCI country indices (total return), denominated in US Dollar. The countries considered for hedge fund replication are the ones that are included in the MSCI Emerging Markets Index at the end of the previous year. This ensures that the countries considered for the hedge fund clone at time *t* are countries that investors at time *t* actually would have considered, thereby avoiding possible selection biases. Information on country membership is available in MSCI Barra (2008).[3] As risk-free rate, I choose the one-month T-bill rate, taken from Ken French's website.[4]

The analysis is based on a linear factor structure in which monthly hedge fund returns *HF* are explained by the risk-free rate R^f and up to *K* country indices $MSCI_i$:

$$HF_t = b_0 R_t^f + \sum_{i=1}^{K} b_i I_{it} MSCI_{it} + u_t \tag{1}$$

where I_{it} is an indicator variable which takes the value one if country *i* is included in the MSCI Emerging Market index at the end of the previous year, zero otherwise.

To determine the portfolio composition of a hedge fund clone based on style analysis as suggested by Sharpe (1992), one chooses an estimation period [t,t-a] and then finds the *b's* that minimize the variance of the u_t. In the base case, I impose the restriction that the exposures to the

[2] Data is available on http://www.hedgefundresearch.com/.
[3] Index changes after the publication of MSCI Barra (2008) are the deletion of Jordan, Argentina, and Pakistan. Information can be obtained from the www.mscibarra.com.
[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

country indices are non-negative, and that the estimated exposures sum to one. The estimated coefficients $\hat{b}$ can then be used to construct a portfolio which has no short positions in country indices. As the hedge fund indices are not published on the last trading day of month *t* but with a lag of several days, I allow for a one-month implementation lag in portfolio construction. A portfolio is implemented based on the coefficients estimated with data ending in the preceding month. Therefore, the returns of the hedge fund clone in month t, denoted by $StyleClone_t$, obtain as follows if studied out-of-sample:

$$StyleClone_t = \hat{b}_0^{t-2,t-a-2} R_t^f + \sum_{i=1}^{K} \hat{b}_i^{t-2,t-a-2} I_{it} MSCI_{it} \tag{2}$$

where the superscript *t-2,t-a-2* indicates the period used for estimating the *b*'s. Note that only information that is actually available at the time of portfolio construction is used. Studying out-of-sample returns is important to establish that similarities between the hedge fund index and the clones are not the result of overfitting the data in-sample.

In a variant of (2), I implement an equity-only portfolio. The country weights are the country exposures of (2), scaled with the percentage not invested in the risk-free asset:

$$StyleCloneEquity_t = \sum_{i=1}^{K} \frac{\hat{b}_i^{t-2,t-a-2}}{1-\hat{b}_0^{t-2,t-a-2}} I_{it} MSCI_{it} \tag{3}$$

This equity-only clone eliminates market-timing components in hedge fund returns that are reflected in time-varying exposures to the risk-free asset.

Finally, I also consider the route favored in the literature and estimate the exposures in (1) through a constrained linear regression without a constant;[5] the only constraint imposed is that

[5] Including a constant does not change conclusions.

the coefficients sum up to one. The returns of the clone constructed with these estimates will be denoted *RegClone*.

I consider estimation periods of 24 and 36 months for the style analysis with the long-only constraint. Unreported analysis show that using an estimation period of 48 months leads to results which are qualitatively similar. Given that the maximum number of countries included in the Emerging market index is 26 in the period under scrutiny, one might wonder whether 24 months can work at all. While a linear regression would be infeasible in such a situation, style analysis can work due to the non-negativity restrictions. Nonetheless, the degrees of freedom are very low, and one might question the reliability of the analysis. As noted above, studying out-of-sample returns provides a natural check against this problem. To further address concerns, I conduct a simulation in which I study how well style analysis uncovers the weights of an exemplary portfolio. Out of the 20 countries that qualify for portfolio inclusion throughout the period 1997-2009, I put together a hypothetical portfolio that is long in five countries (Korea, Mexico, Pakistan, Peru, Philippines), each with a 20% weight, short in another five countries (Poland, South Africa, Taiwan, Thailand, Turkey), each with a 10% weight, and has 50% in the risk-free asset. Table 1 summarizes the weights estimated through style analysis with a 36-month estimation period.[6] The estimated exposures clearly reflect the ordering. The average weight (pooled over time and countries belonging to a group) of countries with a positive weight is 9.37%, compared to 0.44% and 0.00% for countries with zero and negative weights, respectively.

Of course, an exemplary study like the one conducted here is not sufficient to establish that the style analysis approach works satisfactorily well for the data at hand. However, it suggests that

[6] Note that the mean weights reported in Table 1 do not need to sum to one. What is required to sum to one is the means weighted with the country-months in each group.

the approach *can* work despite the low degrees of freedom. Exploring other exemplary portfolios does not seem worthwhile as the interpretation would always hinge on their closeness with actual hedge fund strategies, which are unknown.

To assess performance of the hedge fund index and its clones, I start with a standard CAPM regression with the MSCI Emerging Market Index as the market portfolio. When examining the performance of a fund index or clone with returns *R*, the regression equation is

$$R_t - R_t^f = \alpha + \beta\left(MSCI_{EM,t} - R_t^f\right) + \varepsilon_t \qquad (4)$$

To capture market-timing components in fund performance, I follow Henriksson and Merton (1981) and allow the down-market beta to differ from the up-market beta:

$$R_t - R_t^f = \alpha + \beta\left(MSCI_{EM,t} - R_t^f\right) + \gamma\left(MSCI_{EM,t} - R_t^f\right)D_t + \varepsilon_t \qquad (5)$$

where D_t is an indicator variable which takes the value *minus one* if the excess market return, $\left(MSCI_{EM,t} - R_t^f\right)$, is negative, zero otherwise. In specification (5), β is the up-market beta, while (β − γ) is the down-market beta. A positive γ therefore indicates market-timing ability.

Further, I use a multivariate factor model which controls for possible size, value, momentum, and reversal effects. The factors, which are all built on equally-weighted portfolios, are defined as follows:

> $LARGE\text{-}SMALL_t$ is the month *t* return on the portfolio of the five countries with the largest GDP, minus the month *t* return on the portfolio of the five countries with the smallest GDP. Until June, GDP figures are taken from the last but one calendar year; from July to December figures are from the previous calendar year

$VALUE\text{-}GROWTH_t$ is the month t return on the equally-weighted portfolio of the five countries with the lowest price-earnings (PE) ratios in month t-1, minus the month t return on the portfolio of the five countries with the highest PE ratios in month t-1.

$SWINNER\text{-}SLOSER_t$ is the month t return on the portfolio of the five countries with the largest return over the twelve-month period from t-13 to t-1, minus the month t return on the portfolio of the five countries with the smallest return over the twelve-month period from t-13 to t-1.

$LWINNER\text{-}LLOSER_t$ is defined in the same fashion as $SWINNER\text{-}SLOSER_t$, with the five winner and loser countries now selected based on the three-year return from t-37 to t-1.

3 Estimated country weights and the performance of mimicking portfolios

Figure 1 shows the estimated portfolio weights when the estimation imposes a long-only restriction for country weights; the estimation period is chosen to be 36 months. The figure starts in February 1993 as data from January 1990 to December 1992 are needed to estimate the portfolio weights, which are then implemented with a one-month lag. For the sake of clarity, the figure only shows detailed weights of the ten countries with the largest average weight across the observation period. Since the estimation periods overlap, one would expect some constancy in weights for intervals of up to 36 months. A look at Figure 1, however, suggests that periods in which a country is estimated to have a large or small weight can persist for more than three years. This constancy indicates that a mimicking strategy based on past returns can capture significant patterns in current allocation. On the other hand, there are instances (e.g. Israel) where the country weight changes fairly quickly, without being driven by an index inclusion or removal. This suggests that the approach can react timely to changes in portfolio weights. Finally, note that the estimated weight of the risk-free asset is positive throughout the observation period even though it was not constrained to be so. Cloning the hedge-fund strategy does not require leveraged positions at any time in the observation period.

One could study statistical measures of the variability in style weights but it would be difficult to gauge the economic implications of some stability measure. Performance analysis of hedge fund clones provides an alternative way of assessing stability. If *current* hedge fund returns can be well replicated based on their *past* country allocations, then hedge fund allocations can be said to be stable from the perspective of an outsider who does not have detailed knowledge about individual positions.

Table 2 summarizes the results of the performance analysis using the CAPM (Panel A) or the CAPM extended to capture market timing (Panel B). One might be concerned about possible heteroscedasticity and autocorrelation. Unreported analyses show that estimating standard errors using the Newey and West (1997) procedure results in somewhat higher t-statistics than OLS. I therefore choose to report the OLS statistics, which are more conservative here.

The hedge fund index shows a positive alpha of 0.0042 per month, significant on the 0.1% level. In accordance with prior studies (Fung, Xu and Yau, 2002), there is no evidence of market-timing ability. On the contrary, the estimated γ coefficient is significantly negative, implying that the down-market beta is higher than the up-market beta. When controlling for market-timing, the selectivity coefficient alpha increases to a highly significant value 0.0092, suggesting that it is indeed promising to follow the country allocation of emerging market funds.

A clone that mimics the exposures using an estimation period of 36 months leads to an alpha which is smaller than the one of the original index but which is still significant at the 5% level.

StyleCloneEquity, which imitates the country allocation of the hedge fund index but neutralizes variation in the exposure to the risk-free asset, even matches the alpha of the cloned index. In the CAPM regression, its alpha is 0.0041, significant on the 1% level. Note that the finding is in stark contrast to prior literature. Hasanhodzic and Lo (2007) clone emerging market hedge funds through linear regression with global factors and obtain significant performance gaps between funds and clones.

The clones in the present paper also inherit the negative market-timing component of the fund index. This may be surprising as *StyleCloneEquity* neutralizes variation in the percentage invested in the risk-free asset. Unreported analyses show that there are differences in up-market betas across countries and that the heavily weighted countries tend to have low up-market betas.

Results are robust to the choice of the length of data utilized for style analysis. Equity-only clones based on an estimation period of 24 months perform even better than the 36-months base case. *RegClone*, the clone based on linear regression, however, fails to deliver a significant positive alpha. The reason is likely to be that the standard linear regression is more sensitive to the estimation error problem because it imposes fewer constraints.

When a multi-factor model is fitted to the data (see Table 3), estimated alphas are only slightly different from the CAPM alphas. For the hedge fund index and the style clones, estimated exposures to the size, value and momentum factors are mostly insignificant. There is no instance in which coefficients for one factor bear different signs and are both significant. This confirms the finding from Table 2 that the style clones match the current performance characteristics of the hedge fund index well.

The analyses conducted so far have established that hedge fund clones that mimic hedge funds' country allocation provide a good approximation of abnormal hedge fund returns. Table 4 answers the question whether this also translates into a high return correlation. In Panel A, the table reports the correlation of hedge fund returns with the out-of-sample returns of clones. For this analysis, weights for clone returns in time *t* are estimated with data ending in t-2. The correlation of clones with hedge fund returns comes close to the correlation of hedge fund returns with the emerging market index, but do not surpass it. In Panel B, the estimation also uses return information from the current month. Specifically, weights for clone returns in time *t* are the ones from the estimation period ending in *t*. Correlations with hedge fund returns are now significantly higher, between 95.9% and 97.8%. The highest correlation is obtained for StyleClone (24m), the clone that imposes a long-only constraint and uses an estimation period of 24 months.

In the analysis of the next section, country weights estimated over the period [*t*, *t*-a] will be taken as an estimate of the country allocation at time *t*. Correlations in Table 4 show how well they approximate hedge fund returns, while the out-of-sample analysis from Tables 2 and 3 dissipates possible concerns that the procedure overfits the data.

4 Hedge fund allocation and market volatility

The results of the previous section suggest that hedge fund country weights estimated through style analysis provide a good approximation of actual hedge fund allocation. With such estimates at hand, it is possible to test whether changes in hedge fund country allocation can impact a country's stock market. To measure the impact, I propose to study the association between the volatility of a country's index return and changes in that country's weight in hedge fund portfolios.

I choose the style weights estimated with a 24-month estimation window and the long-only constraint − StyleClone(24m) − because this clone exhibits the largest correlation with the hedge fund index and because it leads to more independent observations than the 36 month window. Unreported analyses show that results are very similar when the equity-only clone is used.

In the analysis, the standard deviation $\sigma(MSCI_i)$ of country *i*'s index return, estimated over 24 months, is explained with the lagged standard deviation as well as with the change in estimated hedge fund weights from the previous 24-month period to the current one. This change in estimated weights is split up into positive and negative changes as it can be surmised that large-scale selling can have an influence different from large-scale buying.

$$\begin{aligned}\sigma(MSCI_i)^{t,t-24} &= a_0 + a_1\sigma(MSCI_i)^{t-24,t-48} \\ &\quad + a_2 \max(0, \hat{b}_i^{t,t-24} - \hat{b}_i^{t-24,t-48}) + a_3 \min(0, \hat{b}_i^{t,t-24} - \hat{b}_i^{t-24,t-48}) + u_i\end{aligned} \tag{6}$$

where superscripts such as *t,t-24* indicate the estimation period. In a variant of regression (6), the change in country weights is also lagged. In another variant, I interact the negative change in weights with the dummy variable SMALL, which takes the value one if the index capitalization of a country is below the median index capitalization of countries belonging to the index at time *t* – 1, and zero otherwise. The interaction term is meant to test whether small markets are more vulnerable to hedge fund activity than large ones.

There are several possible explanations for a negative association between volatility and changes in hedge fund weights: (i) to keep their risk budget, hedge funds reduce exposure if volatility rises, and vice versa; (ii) hedge fund managers correctly predict volatilities and reduce (build up) positions in markets with high (low) volatility, in order to improve their risk-adjusted performance; (iii) given that returns and volatility tend to be negatively related, one would also expect a negative relation between weights and returns if hedge fund managers are able to predict returns; (iv) hedge fund selling (buying) leads to an increase (decrease) of market volatility.

Therefore, negative coefficients a_2 and a_3 make it difficult to interpret the findings. In the absence of alternative explanations for positive coefficients, however, non-negative coefficients can easily be interpreted as evidence against disruptive effects of hedge fund behavior.

Before moving on to the estimation, an appropriate statistical estimation procedure needs to be chosen. Estimation of standard errors should be robust to cross-sectional correlation (errors in explaining volatility of country i could be correlated with errors in explaining volatility of country j). It should also be robust to autocorrelation so that overlapping observation periods can be used, e.g. the standard deviation estimated from 01/2000 to 12/2001, the standard deviation estimated from 02/2000 to 01/2002, and so forth. In order to cope with these difficulties, I use a Fama-MacBeth (1973) procedure. For each month, a cross-sectional regression is run along (6). The resulting coefficient estimates are averaged; their standard errors are estimated using the Newey and West (1997) procedure with a lag length of 24 months.

Table 5 reports the results. Unsurprisingly, the lagged standard deviation helps explain the current one. Increases in weights show the expected negative association with volatility, making it impossible to discern whether the effect is due to forecasting ability, hedge funds reacting to market changes, or hedge funds causing lower volatility. The coefficient estimated for decreases in country weights is much smaller and not significant. Therefore, there is no evidence that a reduction of hedge fund investments in a country's stock market leads to an increase in that market's volatility. Also, as evident from the regression using the lagged changes in weights (regression III in Table 5), past changes in country allocations do not influence future volatility. The coefficient on the interaction term in regressions II and IV are positive but not significant.

The possible premise that smaller markets are more vulnerable to de-investments is not borne out by the data.

5 Conclusion

Hedge funds are often suspected to destabilize markets. The fact that information on hedge fund positions is very limited makes it complicated to test the validity of such concerns. In this paper, I first show that a return-based style analysis can approximate the country allocation of emerging market hedge funds surprisingly well. For example, the out-of-sample abnormal return of a mimicking portfolio matches the abnormal return of the mimicked hedge fund index. The finding also indicates that hedge fund country allocations are relatively stable. Return-based clones can only succeed if past allocation is representative for current allocation.

With the estimated country weights at hand, I examine the relation between a country's stock market volatility and changes in estimated hedge funds' country weights. Increased hedge fund investments are associated with lower volatility. While it is unclear whether the association reflects a causal relationship, this evidence does not support concerns about hedge funds because lower volatility should be welcome to most market participants. Reductions in hedge fund weights, on the other hand, do not have a significant impact on volatility. Therefore, this study of hedge funds' country allocation obtains no evidence that hedge funds have a negative impact on the stability of emerging stock markets.

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Table 1: Estimated weights of an exemplary emerging market portfolio

At the start of each month, the exemplary portfolio has a weight of 20% in five countries, -10% in another five countries, and zero weight in the remaining countries; 50% are invested in the risk-free asset. Weights are estimated for all 36-month periods in the data set, applying a long-only constraint for country exposures. The table contains summary statistics of estimated weights that have been pooled over time and countries belonging to one group.

	Mean	Standard deviation	Minimum	Maximum
Countries with long position	9.37%	6.20%	0.00%	29.34%
Countries with zero weight	0.44%	1.68%	0.00%	22.77%
Countries with short position	0.00%	0.00%	0.00%	0.03%
Risk-free asset	46.22%	7.90%	27.30%	63.17%

Table 2: Abnormal returns of hedge fund clones

The monthly returns of the HFR emerging market hedge fund index and out-of-sample clones of that index are first analyzed with the CAPM. Then a factor (the negative of the market excess return if excess return is negative) is added to capture market-timing ability. A positive γ indicates market-timing ability. Clones differ in the estimation period (36 or 24 months) used to derive the weights for country indices and the risk-free asset as well as in the restrictions imposed in estimation and implementation. In contrast to RegClone, StyleClone imposes a long-only constraint for country weights. StyleCloneEquity imposes a zero weight for the risk-free asset. OLS t-statistics in parentheses.

	α	β	γ	Adj. R^2	Obs
Panel A: CAPM					
HFR Index	0.0042	0.5372		0.808	203
	(3.23)	(29.15)			
StyleClone	0.0023	0.5541		0.860	203
(36m)	(2.06)	(35.23)			
StyleClone	0.0034	0.5953		0.824	203
(24m)	(2.45)	(30.76)			
StyleCloneEquity	0.0041	0.8965		0.881	203
(36m)	(2.48)	(38.70)			
StyleCloneEquity	0.0052	0.8925		0.876	203
(24m)	(3.06)	(37.72)			
RegClone	0.0028	0.6204		0.728	203
(36m)	(1.45)	(23.30)			
Panel B: CAPM extended to capture market-timing					
HFR Index	0.0092	0.4377	-0.1815	0.817	203
	(4.65)	(12.46)	(-3.30)		
StyleClone	0.0054	0.4922	-0.1131	0.863	203
(36m)	(3.16)	(16.21)	(-2.38)		
StyleClone	0.0061	0.5406	-0.0997	0.826	203
(24m)	(2.88)	(14.37)	(-1.69)		
StyleCloneEquity	0.0096	0.7866	-0.2006	0.885	203
(36m)	(3.83)	(17.70)	(-2.88)		
StyleCloneEquity	0.0089	0.8170	-0.1377	0.877	203
(24m)	(3.46)	(17.80)	(-1.91)		
RegClone	0.0046	0.5840	-0.0664	0.728	203
(36m)	(1.56)	(11.22)	(-0.81)		

Table 3: Abnormal returns of hedge fund clones: multi-factor analysis

The monthly returns of the HFR emerging market hedge fund index and out-of-sample clones of that index are analyzed with a multi-factor model containing the MSCI Emerging Market index (coefficient β), the return difference between large and small countries as measured by GDP (γ_1), the return difference between high-PE and low-PE countries (γ_2), the return difference between 12-month winners and 12-month losers (γ_3), and the return difference between 36-month winners and 36-month losers (γ_4). Clones differ in the estimation period (36 or 24 months) used to derive the weights for country indices and the risk-free asset as well as in the restrictions imposed in estimation and implementation. In contrast to RegClone, StyleClone imposes a long-only constraint for country weights. StyleCloneEquity imposes a zero weight for the risk-free asset. OLS t-statistics in parentheses.

	α	β	γ_1	γ_2	γ_3	γ_4	Adj. R^2	Obs
HFR Index	0.0042	0.533	-0.011	0.024	0.043	0.007	0.8110	203
	(3.17)	(23.69)	(-0.39)	(1.10)	(2.28)	(0.33)		
StyleClone	0.0021	0.573	0.045	0.010	-0.018	0.003	0.8612	203
(36m)	(1.83)	(29.68)	(1.93)	(0.55)	(-1.11)	(0.15)		
StyleClone	0.0027	0.629	0.079	0.047	-0.005	-0.025	0.8330	203
(24m)	(1.98)	(27.08)	(2.81)	(2.08)	(-0.26)	(-1.14)		
StyleCloneEquity	0.0036	0.923	0.067	0.035	-0.026	0.001	0.8834	203
(36m)	(2.17)	(32.64)	(1.96)	(1.26)	(-1.11)	(0.04)		
StyleCloneEquity	0.0041	0.940	0.111	0.071	-0.010	-0.047	0.8867	203
(24m)	(2.53)	(33.78)	(3.31)	(2.64)	(-0.43)	(-1.76)		
RegClone	0.0024	0.612	0.000	0.071	-0.018	0.048	0.7330	203
(36m)	(1.27)	(18.80)	(-0.01)	(2.23)	(-0.65)	(1.56)		

Table 4: Correlations of monthly returns

Clones differ in the estimation period (36 or 24 months) used to derive the weights for country indices and the risk-free asset as well as in the restrictions imposed in estimation and implementation. StyleClone imposes a long-only constraint for country weights. StyleCloneEquity imposes a zero weight for the risk-free asset. In Panel A, weights for clone returns in time t are estimated with data ending in t-2. In Panel B, weights for clone returns in time t are the ones from the estimation period ending in t. All returns are in excess of the risk-free rate.

		StyleClone		StyleCloneEquity		MSCI Em
	HFR Index	(36m)	(24m)	(36m)	(24m)	Markets
Panel A: Clone weights estimated out-of-sample						
HFR Index	1					
StyleClone(36m)	0.900	1.000				
StyleClone(24m)	0.8750	0.966	1.000			
StyleCloneEquity(36m)	0.8983	0.991	0.957	1.000		
StyleCloneEquity(24m)	0.8753	0.967	0.984	0.972	1.000	
MSCI Em Markets	0.8982	0.928	0.908	0.939	0.936	1.000
Panel B: Estimation period includes current month						
HFRI Fund Index	1					
StyleClone(36m)	0.968	1.000				
StyleClone(24m)	0.978	0.989	1.000			
StyleCloneEquity(36m)	0.959	0.992	0.979	1.000		
StyleCloneEquity(24m)	0.964	0.980	0.984	0.986	1.000	
MSCI Em Markets	0.898	0.933	0.922	0.942	0.943	1.000

Table 5: Do changes in hedge fund weights lead to changes in stock market volatility?

The results are based on Fama-MacBeth type cross-sectional regressions. In each month *t*, the volatility computed over months [t, t-24] is regressed on a constant, the lagged volatility over [t-24,t-48] and changes in estimated country weights. Country weights *b* are estimated with a long-only constraint for country holdings and a 24-month estimation period. The changes in weights are split up into positive and negative components. In addition, the negative changes are interacted with the dummy variable SMALL, which is one for countries below the median market capitalization. Contemporaneous changes from t-24 to t and lagged changes from t-48 to t-24 are considered in separate regressions. T-statistics in parentheses are estimated by applying Newey-West with a lag length of 24 months to the estimated cross-sectional coefficients.

Dependent variable: $\sigma(MSCI_i)^{t,t-24}$

	I	II	III	IV
Constant	0.050	0.051	0.045	0.046
	(6.64)	(6.65)	(7.55)	(7.64)
$\sigma(MSCI_i)^{t-24,t-48}$	0.544	0.545	0.556	0.539
	(7.81)	(7.31)	(7.91)	(7.79)
$\max(0, \hat{b}_i^{t,t-24} - \hat{b}_i^{t-24,t-48})$	-0.188	-0.197		
	(-2.94)	(-3.12)		
$\min(0, \hat{b}_i^{t,t-24} - \hat{b}_i^{t-24,t-48})$	-0.002	-0.005		
	(-0.05)	(-0.06)		
$\min(0, \hat{b}_i^{t,t-24} - \hat{b}_i^{t-24,t-48}) \times$ SMALL		0.120		
		(1.33)		
$\max(0, \hat{b}_i^{t-24,t-48} - \hat{b}_i^{t-48,t-72})$			0.047	0.056
			(0.93)	(1.08)
$\min(0, \hat{b}_i^{t-24,t-48} - \hat{b}_i^{t-48,t-72})$			-0.029	-0.091
			(-0.46)	(-0.80)
$\min(0, \hat{b}_i^{t-24,t-48} - \hat{b}_i^{t-48,t-72}) \times$ SMALL				0.345
				(1.36)

Figure 1: Estimated style weights for HFR emerging market hedge fund index (36-month estimation periods)