Economic Relevance of Concentration for Emerging Markets Funds Performance

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The ultimate strategy to improve equity mutual fund performance has been a source of academic debate for decades. In this article, we focus on the vast literature that analyzes the relationship between performance and a portfolio's concentration of mutual funds. A recent study based on U.S. global equity funds by Huij and Derwall [2011] provides evidence that the performance of mutual funds with concentrated holdings is superior to that of funds that exhibit lower levels of tracking error. Moreover, Kacperczyk, Sialm, and Zheng [2005], who studied fund concentration based on industry sector loadings, provided evidence that managers who accentuate the weight of specific industries tend to outperform those with broadly diversified funds, revealing that the superior performance of concentrated aggregates is mainly a result of stock selection ability. Our research is also related to that of Baks, Busse, and Green [2006], especially in explaining the role of funds' style decision on returns, and to the work of Cremers and Petajisto [2009], who showed that the greatest chance for excess return relative to an index is provided by managers with the highest levels of *active share*, the measure of how much a portfolio's holdings differ from the benchmark index's constituents. Examining four regions (North America, Europe, Japan, and Asia Pacific), Fama and French [2012] found that local factor market models provide passable descriptions of local average returns for portfolios formed on size and value versus growth, but they are less successful when used with portfolios formed on size and momentum.

The argument put forward in this article is twofold. First it is worth understanding whether there is any evidence that mutual fund managers produce superior performance through concentrated investment strategies through examining different samples of equity funds investing in different geographical areas (the United States, Europe, and emerging markets). Although the literature on funds usually focuses on the U.S. mutual fund industry, both the growth of mutual fund weight and the evidence of important differences in the determinants of mutual fund performance in the United States and elsewhere in the world motivated us to broaden our analysis to include funds with a focus on European and emerging markets. We think that the focus on emerging markets is significant as this mutual fund segment has experienced sharp growth over the last 20 years and has played a major role in the growth of assets under management; moreover, the segment shows dissimilarities across funds that can be related to different dominant styles.

The ultimate aim of this research is to test the robustness of the results on different time span subsamples, thereby shining a light on the impact of the economic crisis of 2007 to draw some in-depth conclusions about the role of the strategy for different segments of funds. To our knowledge, our research is the first comprehensive study on the topic that focuses on funds with a country specialization and looks into the robustness of the results on different sample periods. The breaking of the sample in two subsamples aimed at avoiding the aftermath of the 2007 crisis enables us to investigate the impact of the recession on the relationship between performance and mutual fund concentration.

The remainder of the article is organized as follows. In the first section, we describe the dataset employed and explore the issue of survivorship bias in the samples. In the second section, we present the methodology and the empirical results of the analysis of the relationship between fund performance and the breadth of the underlying strategies for the sample of funds investing in emerging and developed markets. The third section analyzes the periods of crisis, with a replication of the analysis for the subperiod beginning in June 2007. The concluding section summarizes our results and describes the implications for the asset allocation process, both for professional fund managers and private investors.

SURVIVORSHIP DATA AND THE DATASET EMPLOYED

In this study, we used a comprehensive dataset provided by Bloomberg that includes the monthly prices for all open-end global mutual funds, with a geographic focus on investment decisions in U.S., European, and emerging markets, for the period from January 2000 to December 2012. In detail, the sample consists of 3,030 equity funds with holdings concentrated on the U.S. market, 4,180 on European market, and 3,030 on emerging markets. To estimate the monthly loadings of funds, we required all funds in the sample to have at least 36 consecutive returns. These exclusion criteria reduced the sample to 1,448 equity funds for the U.S. market, 1,936 for the European market, and 1,670 for the emerging market sample. As investors tend to be uninterested in analyzing the data of funds that no longer exist, commonly employed datasets of mutual funds data often show the past records of all portfolios currently in existence. This could result in significant biases in the sample returns, as described in Brown et al. [1992] and Brown and Harlow [2009] because funds that accept a great amount of risk and win tend to persist in the samples whereas those aggregates that lose their bets are removed from the sample. This suggests that analysis performed only on surviving portfolios could overrate funds' returns. Because the present analysis covers all funds that existed during the minimum time span of 36 months required by our sampling procedure and included funds that were closed at any point during the sample period, many of the typical sources of *selection bias,* or *survivorship bias,* are reduced or eliminated.

THE METHODOLOGY: FUND PERFORMANCE AND THE BREADTH OF STRATEGIES

The concept of breadth as applied to the asset allocation decisions of a fund manager is crucial to our analysis. Since the publication of Grinold [1989] and Grinold and Kahn [2000], this measure has been widely used by the investment community as a tool to assess a portfolio manager's ability to add value. The productivity of active management, represented by the prospective information ratio (PIR) depends both on the manager's skill in forecasting exceptional returns (EC) and the breadth of his or her strategy (N), namely the extent to which his or her skill is applied: PIR = EC × Breadth. Breadth is therefore the dimension of the independent asset allocation decisions that a manager collects in a single period; in other words, breadth conveys the number of independent risks a manager takes in betting on risk dimensions. The rationale behind this approach supports the hypothesis that managers with superior information about specific market segments tend to use this advantage and consequently are induced to bet on market areas in which they have a real competitive advantage.

This section examines the empirical analysis of different single and multifactor models that explain funds' returns as a function of different factors and that are suitable to elucidate the relationship between portfolio concentration and fund performance. Following the prevalent literature on the topic (Brown and Harlow [2009], Huij and Derwall [2011]), we intend to test the hypothesis that funds with concentrated bets in specific risk factors deliver better performance, both in absolute and relative terms, than funds exhibiting less style consistency. The result can be explained purely by lower portfolio turnover and lower expenses.

We follow the methodology recently proposed by Amihud and Goyenko [2009] that identifies the measure of fund managers' inclination to take big bets in the R^2 value, obtained by regressing fund returns in a market model and in different multifactor models. The R^2, or *coefficient of determination*, defined as $R_{SQ} = 1 - \sigma^2(e_j)/\sigma^2(R_j)$, can be interpreted as the percentage of fund *j*'s return variability due to the benchmark's or fund's style decision for multifactor models. Consequently, we have ranked funds as a function of this figure. Following this approach, because lower R^2 reveals higher idiosyncratic risk relative to total risk, this indicator can be offered as a measure of selectivity or active management and as a reverse proxy for fund strategy breadth.

To test for the relationship between funds' risk factor specialization and performance, we look to the Jensen [1969] alpha α_i. This indicator is well known as a measure of abnormal performance in evaluating portfolios in which *abnormal performance* is defined as an expected return that exceeds the equilibrium risk adjusted rate. Excess return is estimated as the intercept of the equation of the market model relative to the used market proxy:

$$r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the excess return of fund *i* at month *t*, and $RMRF_t$ is the excess return of the market benchmark (MSCI U.S., MSCI Europe, and MSCI Emerging Markets) at month *t* (with the one-month U.S. T-bill rate from Bloomberg as a proxy for the risk-free rate in excess returns). All returns are in U.S. dollars, and they are net of fees and operating costs. We use MSCI U.S., MSCI Europe, and MSCI Emerging Markets indexes because they are widely representative of the investment styles in the geographical areas taken into account.

Equation (1) is estimated for each constituent of the sample on the fund's whole return history. In line with Chincarini and Kim [2006] and Huij and Derwall [2011], we approximate breadth by considering the number of factors to which our funds are exposed in a predictive model, thus allowing us to verify, at the same time, whether simultaneous exposition to multiple risk factors can contribute to improvements in performance. According to Huij and Derwall [2011] fund alphas were normalized and Winsorized to remove extreme outliers as follows:

$$z\_alpha_i = min\left[3, \max\left(-3, \frac{\alpha_i - \mu_\alpha}{\sigma_\alpha}\right)\right] \tag{2}$$

We then take into account the variability of the error terms in Equation (1), computing a modified version of Equation (2) that is analogous to the information ratio (see Goodwin [1998]) and which incorporates fund-specific $\sigma_{\varepsilon,i}$ as follows:

$$z\_alpha\_adj_i = min\left[3, \max\left(-3, \frac{\frac{\alpha_i}{\sigma_{\varepsilon,i}} - \mu_{\frac{\alpha}{\sigma_\varepsilon}}}{\sigma_{\frac{\alpha}{\sigma_\varepsilon}}}\right)\right] \tag{3}$$

where μ_α is the average alpha of the global market model and σ_α is the model's standard deviation; and $\mu_{\frac{\alpha}{\sigma_\varepsilon}}$ is the average ratio of funds' alphas divided by σ_ε and $\sigma_{\frac{\alpha}{\sigma_\varepsilon}}$ is the ratio's standard deviation.

Although very unlikely to have the best fit, given past research, the fit of the traditional capital asset pricing model–based Single Index Model in Equation (1) provided a baseline for comparison with more complex models. As observed by an impressive amount of literature, funds' excess returns can be affected by other types of return drivers, like country, sector, and style, which represent the funds' structural bets and the managers' investment strategies. The identification of these drivers allows us to capture distinctive market segments and to identify specific dimensions of risk. Multifactor approaches based on the identification of different investment styles are widely acknowledged by the financial community. Cooper, Gulen, and Rau [2005] reported that some mutual funds strategically change their names to more appealing terms (while remaining the same in size and value-growth dimension). Kumar [2009] and Froot and Teo [2008] showed that retail and institutional investors tend to allocate their capital at a style level between the dimensions of size and value-growth characteristics. Moreover, Kacperczyk, Sialm, and Zheng [2005, 2007] found that funds concentrated in a few industries provide superior performance compared with funds with a broad industry spectrum, even after controlling for differences in expenses, turnover, fund age, and fund size. Indeed, a body of literature suggests that the size of a fund affects its ability to outperform the benchmark. In a theoretical paper, Berk and Green [2004] introduced a model with rational agents. In this work, because of a competitive market for capital provision and when returns have been decreased to scale in active management, fund managers do not tend to outperform passive benchmarks after deducting expenses. In a related empirical study, Chen et al. [2004] found that, on average, smaller funds outperform larger funds because of diseconomies of scale.

Based on all these findings, we propose two different multiple factor models, the first based on styles (market capitalization and valuation multiples) and the second based on market sectors (industries). Equation (4) presents the Fama and French [1992, 1993] multifactor asset pricing model, which is a useful tool to explore the role of different factors in the cross-section of equity returns:

$$r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{2,i} HML_t + \varepsilon_{i,t} \quad (4)$$

where SMB_t is the difference in return between the MSCI (U.S., Europe, or emerging markets) Market Small Cap index and the MSCI (U.S., Europe, or emerging markets) Market index at month *t*, and HML_t is the difference in return between the MSCI (U.S., Europe, or emerging markets) Market Value index and the MSCI (U.S., Europe, or emerging markets) Market Growth index at month *t*.

The second multifactor model measures fund exposures to sectors:

$$r_{i,t} = \alpha_i + \sum_j \beta_{j,i} \mathrm{SECTOR}_{j,t} + \varepsilon_{i,t} \quad (5)$$

where $\mathrm{SECTOR}_{j,t}$ is the excess return on sector *j* at month *t* for the following MSCI (U.S., Europe, or emerging markets) Market Sector indexes.

We estimated the multifactor models in Equations (4) and (5) for each fund. To measure the explicative power of the funds' exposures to styles and sectors, we took the incremental adjusted R^2 values of the two multifactor models with respect to the market model as represented in Equation (1). Exhibit 1 reports the distribution of funds' adjusted R^2 values from the unique factor and the multifactor style and sector models. Because both of the two multifactor models produce regression R^2 values that are, on average, slightly higher than the R^2 from a market model, we conclude that style and sector exposures have a little incremental explanatory power to describe our sample fund returns.

As introduced previously, to approximate the breadth of the underlying fund strategies, we considered the number of factors to which the funds are exposed in a predictive model. For the two multifactor models, we measured funds' exposures to styles and sectors, taking the average incremental adjusted R^2 values of two multifactor models. We then computed the differences in adjusted R^2 values between styles and sectors for all funds.

According to this rationale, to gain further insight into the factors that generate outperformance of active funds, we allocated funds to three groups based on the selection of the model with the best explicatory power. Group 1 contains funds for which the R^2 value of the market model is higher than the (adjusted) R^2 values of the two multifactor models; funds in this group reveal a passive or indexing style management, in line with the objective to minimize the tracking error of the fund's benchmark.

Group 2 contains funds for which one of the two multifactor models produces a higher adjusted R^2 value than the single-factor market model. Group 3 contains funds for which both of the multifactor models produce higher adjusted R^2 values than the market model; this group includes funds that adopt the largest number of distinctive concentrated strategies. The earlier segmentation of funds based on the breadth of styles and sectors—or, to state it simply, on the number of strategies they pursue—allows us to move forward and test the hypothesis of different risk-return behavior. The comparison among the three geographical focus samples (U.S., Europe, and emerging markets) is measured as the difference in their average normalized alpha values (z-alpha adjusted). The results of the analysis are summarized in Exhibit 2.

Our results indicate that, on average, the emerging market mutual funds with the highest factor specialization exhibit overperformance resulting from Jensen alphas when compared with U.S. and EU groups. The results of Exhibit 2, Panel A validate the assumption that the increase in strategy breadth is a significant driver of performance for the emerging market funds sample (the average excess alpha value of 0.12 is the highest positive and statistically significant value). The results of the same test in Panel B (emerging market versus European group) show an improvement in the risk-adjusted performance (on average, emerging market alphas are again higher than European ones), but the relationship between the breadth of strategies and performance is not clearly defined: The *t*-statistic at 1.29 is an important limitation and suggests interpreting the results of this group

EXHIBIT 1

Adjusted R^2 Values of the Market Model and the Style and Sector Model (mutual funds benchmark markets)

	Market	Style	Sector	Model vs. Style	Model vs. Sector	Style vs. Sector
Panel A: U.S. Funds						
Average	0.72	0.75	0.76	–0.03	–0.03	–0.01
Standard error						
Percentile %	0.21	0.21	0.20	0.00	0.01	0.01
10	0.21	0.20	0.21	0.01	0.00	–0.01
20	0.44	0.46	0.49	–0.02	–0.05	–0.03
50	0.70	0.74	0.74	–0.05	–0.04	0.00
80	0.89	0.92	0.91	–0.03	–0.02	0.00
90	0.92	0.94	0.94	–0.02	–0.02	0.00
Panel B: European Funds						
Average	0.76	0.79	0.79	–0.03	–0.03	0.00
Standard error						
Percentile %	0.17	0.18	0.17	0.00	0.01	0.01
10	0.13	0.11	0.18	0.03	–0.05	–0.08
20	0.57	0.59	0.61	–0.02	–0.04	–0.02
50	0.75	0.79	0.78	–0.04	–0.03	0.01
80	0.89	0.91	0.90	–0.03	–0.01	0.02
90	0.92	0.93	0.93	–0.01	–0.01	0.01
Panel C: Emerging Market Funds						
Average	0.77	0.77	0.77	0.00	0.00	0.00
Standard error						
Percentile %	0.18	0.18	0.18	0.00	0.00	0.00
10	0.16	0.15	0.16	0.01	0.00	–0.01
20	0.71	0.72	0.72	–0.01	0.00	0.00
50	0.75	0.76	0.76	0.00	0.00	0.00
80	0.9	0.9	0.89	0.00	0.01	0.01
90	0.94	0.94	0.94	0.00	0.00	0.00

Panel D: Groups, Fund Number and Mean R^2

Entire Sample 2000–2013	U.S.		European		Emerging Markets	
	# Funds	Rsq_Market	# Funds	Rsq_Market	# Funds	Rsq_Market
Group Market Model	124	0.74	209	0.76	420	0.79
Group Low Factor specialization	369	0.66	548	0.76	920	0.76
Group High Factor specialization	955	0.75	1,179	0.76	330	0.76

Note: This exhibit reports the distribution of funds' adjusted R^2 values from multifactor style, country, and sector models:

$$r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{2,i} HML_t + \varepsilon_{i,t}$$

where SMP_t is the difference in returns between the MSCI U.S. Market Small Cap and MSCI Europe Market indexes, and HML_t is the difference in returns between the MSCI World Value and MSCI World Growth indexes:

$$r_{i,t} = \alpha_i + \sum_j \beta_{j,i} sector_{j,t} + \varepsilon_{i,t}$$

where $sector_{j,t}$ is the excess return on sector j based on MSCI U.S. Market (or European) sector indexes: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, IT, Telecom and Communication Services and Utilities.

with some caution. Conversely, when compared with EU funds, the emerging markets products in Group 2 (Low Factor Specialization) show the maximum increase in the risk-adjusted performance with a good level of statistical significance (t-statistic 4.85).

On the other hand, results from the test on Group 1 show a negative relationship between the incremental average alpha value of emerging market products and the breadth of strategies. In other words, for the aggregates in Group 1, the funds in the U.S. and European markets beat the emerging market funds in terms of average adjusted alpha generation. As funds in the group under examination are allegedly more passive and indexed than the components of the other two aggregates, this finding is consistent with the academic literature (e.g., Huij and Post [2011]) that documents less activity in the behavior of funds focused on developed areas because these markets present better opportunities for active managers to find abnormal returns.

It is important to recognize that although the main results in Exhibit 2 are significant, the incremental explanatory power of the different models is sometimes negligible. This lack of explanatory power induced us to reproduce the regressions of Exhibit 2, imposing a minimum threshold level (2.5% in Panel A and 5% in Panel B) for models' incremental explanatory power. The definition of a more consistent cut-off point provides a better segmentation of the three groups by requiring the adjusted R^2 values of a model to exceed the others by a significant amount (i.e., 2.5% and 5% are the thresholds according to which we obtain new clusters). The results of these analyses are presented in Panels A and B of Exhibit 3.

On average, the signs of the coefficient remain the same as we move from Exhibit 2 to Exhibit 3. Statistical significance favors the intermediate group (Group 2) whose alpha differentials are always positive and significant when the threshold is 2.5%. Conversely,

EXHIBIT 2

Fund Performance and the Breadth of Strategies for Mutual Funds Benchmark Markets (full sample period)

	Z–Adjusted alpha coefficient	*t*-statistic
Panel A: EM vs. U.S.		
Group 1 (Market Model)	–0.23***	–3.67
Group 2 (Low Factor specialization)	0.05	1.33
Group 3 (High Factor specialization)	0.12***	3.02
Panel B: EM vs. EU		
Group 1 (Market Model)	–0.46***	–5.67
Group 2 (Low Factor specialization)	0.22***	4.85
Group 3 (High Factor specialization)	0.08	1.29

Note: We allocated each fund to one of following three breadth groups: Group 1 contains funds for which the R^2 value of the market model is higher than the (adjusted) R^2 values of the three multifactor models; Group 2 contains funds for which one of the three multifactor models produces a higher adjusted R^2 value than the single-factor market model; and Group 3 contains funds for which two of the three multifactor models produce higher adjusted R^2 values than the market model. In Exhibit 2, we report adjusted alphas (Z_Alpha_adj) for each group, along with their respective t-statistics and P-values, based on the full-sample period (2000–2012).

****denotes statistical significance at 1%; **denotes statistical significance at 5%; and *denotes statistical significance at 10%.*

EXHIBIT 3

Fund Performance and the Breadth of Strategies (Consistency Analysis – Mutual Funds Benchmark Markets – Full Sample Period)

	Z–Adjusted alpha coefficient	*t*-statistic
Panel A: EM vs. U.S. – Consistency Analysis		
Explanatory power above 2.5%		
Group Market Model	0.070	1.27
Group Low Factor specialization	0.13***	4.43
Group High Factor specialization	0.37	0.47
Explanatory power above 5%		
Group Market Model	–0.13	–0.04
Group Low Factor specialization	–0.08	–0.2
Group High Factor specialization	0.42***	4.65
Panel B: EM vs. EU – Consistency Analysis		
Explanatory power above 2.5%		
Group Market Model	0.54***	2.92
Group Low Factor specialization	0.06**	2.17
Group High Factor specialization	0.46***	3.34
Explanatory power above 5%		
Group Market Model	0.23	0.43
Group Low Factor specialization	–0.04***	–6.7
Group High Factor specialization	0.38	1.07

Note: We previously allocated funds to one of the three aforementioned groups based on the number of strategies they pursue, but now we require the adjusted R^2 values of the multifactor models to exceed the R^2 value of the market model by 2.5% and 5%. Next, we double-sort funds, first based on tracking error derived from Equation (1) into high and low tracking error groups, and then within each group based on the number of segments to which they are exposed (breadth). We report normalized fund adjusted alphas (Z-Alpha_Adjusted) over the period 2000–2012 for each group, along with their respective t-statistics and P-values.

****denotes statistical significance at 1%; **denotes statistical significance at 5%; and *denotes statistical significance at 10%.*

the 5% minimum value reinforces the results in Exhibit 3 Panel A (emerging markets versus U.S.) but biases the figures of Panel B (emerging markets versus Europe).

BREADTH OF STRATEGIES AND PERFORMANCE IN THE POST-CRISIS PERIOD

The last decade has seen a strong increase in the number of approaches to emerging markets investing, a rising integrated asset class that has gained considerable attention together with developed markets instruments. Because the traditional approach to emerging market investment has been concentrated on country selection (as a result of the fact that some countries are likely to grow faster than others), in recent years emerging market equity strategies have involved multiple dimensions of sectors and style.

Consideration of developments over recent years begs the question of whether the aftermath of the global financial crisis (GFC) could have further favored the emerging markets segment. This section describes the impact of the GFC that originated in the downturn of the U.S. housing market, known as the *subprime crisis*, and culminated with the bankruptcy of Lehman Brothers. The observation that emerging markets generally show a low integration with the rest of the world and that mutual funds focusing on this segment invest in financial instruments traded locally induced us to hypothesize that these markets were "insulated" from the effects of the crisis. Likewise, it is true that the sharpening of the crisis, which evolved in an international liquidity crunch, could have sinister effects on the stock markets of the whole world. The aim of this section is to separate the examination period into two subperiods to test the relationship between performance and breadth of strategies in periods of market stress. After all, the GFC has become a central point of investigation for a huge number of papers dealing with financial markets.

To evaluate any impact of the GFC effects, we replicate the analysis presented in Exhibits 2 and 3, focusing on the subperiod beginning with the onset of the crisis in June 2007. The main results of the analysis are shown in Exhibits 4 and 5. The regression analysis results for the post-crisis period in Exhibit 4 confirm the sign and the significance of the various results, with a relative increase of all coefficients and *t*-statistics in absolute terms. As the test is conducted on the average adjusted alpha differentials (emerging versus other markets), we can conclude that the outcome of the crisis generates a competitive advantage for those mutual funds invested in the emerging economies showing a style or a sectorial specialization.

The apposition of a threshold minimum value for the incremental R^2 value among the groups emphasizes an improvement in the emerging market funds sample relative to the competitors on developed markets. On the other hand, results from the test on Group 1 show a change in the sign of the relationship between the incremental average alpha value of emerging market products and the breadth of strategies. Reading this result in conjunction with the output of the test on the entire sample (Exhibit 3), we reach the conclusion that the worst effects of the aftermath of the crisis centered on the segment of traditional mutual funds investing in developed markets with an almost passive strategy.

CONCLUSIONS AND FUTURE RESEARCH

In the last 25 years, emerging markets have taken a central role in modern global equity asset allocation portfolios. Because of the dynamic nature of this segment, the search for the best strategy approach is a crucial challenge faced by practitioners and investors. Although a large body of research has focused on the country allocation of emerging market portfolios, less attention has been paid to the role of other allocation strategies used by managers. The main goal of this study was to examine the role of the breadth of strategies as a driver of performance in the segment of emerging markets mutual funds as opposed to funds investing in more developed markets (i.e, U.S. and European). As most of the results from previous research do not include the post-crisis period and its influence on funds' performance, we also provide further insight regarding the impact of the GFC on the fund performance.

Using the recent contributions of the literature as a point of departure, we built our analysis on the acknowledged role of the breadth of the strategies used by more active managers as a driver of excess return for a sample of mutual funds investing in U.S., European, and emerging markets from January 2000 to December 2012. We measured funds' exposures to styles and sectors, taking the incremental adjusted R^2 values of two multifactor models, and allocated funds to three groups based on the selection of the model with the best explicatory power of returns in terms of adjusted R^2: Group 1 contains funds for which the market model is the best model,

EXHIBIT 4

Fund Performance, and the Breadth of Strategies – Mutual Funds Benchmark Markets – Global Financial Crisis (GFC) Period

	Z–Adjusted alpha coefficient	*t*-statistic
Panel A: EM vs. U.S.		
Crisis Full Sample: June 1, 2007–June 30, 2012		
Group Market Model	–0.12***	–2.7
Group Low Factor specialization	0.02	0.35
Group High Factor specialization	0.19***	4.41
Panel B: EM vs. EU		
Crisis Full Sample: June 1, 2007–June 30, 2012		
Group Market Model	–0.21***	–3.72
Group Low Factor specialization	0.22***	4.42
Group High Factor specialization	0.13**	2.21

Panel C: U.S. vs. EU vs. EM

	U.S.		EU		EM	
	# Funds	Rsq_ Market	# Funds	Rsq_ Market	# Funds	Rsq_ Market
Crisis Full Sample: 1 June, 2007 – 30 June, 2012						
Group Market Model	120	0.77	262	0.74	429	0.81
Group Low Factor specialization	363	0.79	639	0.67	855	0.78
Group High Factor specialization	961	0.8	1,026	0.79	382	0.79

Note: We allocated each fund to one of following three breadth groups: Group 1 contains funds for which the R^2 value of the market model is higher than the (adjusted) R^2 values of the three multifactor models; Group 2 contains funds for which one of the three multifactor models produces a higher adjusted R^2 value than the single-factor market model; and Group 3 contains funds for which two of the three multifactor models produce higher adjusted R^2 values than the market model. We report adjusted alphas (Z_Alpha_adj) for each group, along with respective t-statistics and P-values, based on the GFC period 2007–2012.

****denotes statistical significance at 1%; **denotes statistical significance at 5%; and *denotes statistical significance at 10%.*

EXHIBIT 5

Fund Performance, and the Breadth of Strategies. Consistency Analysis – Mutual Funds Benchmark Markets – Global Financial Crisis (GFC) Period Consistency Analysis

	Z–Adjusted alpha coefficient	*t*-statistic
Panel A: EM vs. U.S.		
Explanatory power above 2.5%		
Group Market Model	0.287***	7.712
Group Low Factor specialization	0.0228	0.886
Group High Factor specialization	0.527***	6.218
Explanatory power above 5%		
Group Market Model	0.516***	12.742
Group Low Factor specialization	0.149***	4.939
Group High Factor specialization	0.628***	5.771
Panel B: EM vs. Europe		
Explanatory power above 2.5%		
Group Market Model	0.546**	16.478
Group Low Factor specialization	0.0627	1.256
Group High Factor specialization	0.363*	1.856
Explanatory power above 5%		
Group Market Model	0.608***	15.406
Group Low Factor specialization	–0.0115	–0.133
Group High Factor specialization	0.613***	4.770

Note: We allocated funds to one of the three aforementioned groups based on the number of strategies they pursue, but now we require the adjusted R^2 values of the multifactor models to exceed the R^2 value of the market model by 2.5% and 5%. Next, we double-sort funds, first based on the tracking error derived from Equation (1), into high and low tracking error groups, and then within each group based on the number of segments to which they are exposed (breadth). We report normalized fund adjusted alphas (Z-Alpha_Adjusted) over the GFC period 2007–2012 for each group, along with respective t-statistics and P-values.

****denotes statistical significance at 1%; **denotes statistical significance at 5%; *denotes statistical significance at 10%.*

Group 2 contains funds for which one of the two multifactor models produces a higher adjusted R^2 value than the single-factor market model, and Group 3 contains funds for which both multifactor models produce higher adjusted R^2 values than the market model. To emphasize the peculiarities of the emerging markets funds sample, we omit the results for the individual samples and report the differences between regression coefficients of the two groups: "Emerging Market versus U.S." and "Emerging Market versus Europe."

We can confirm that the number of strategies (Market, Value and Growth, Size and Sector Specialization) used by the manager has a great influence on the performance of emerging market funds, characterized by a larger amount of tracking error; conversely, the relationship between the concentration on the market factor alone is important for passive and indexed funds investing on developed countries' stocks. Although it has some shortcomings, the robustness test carried out to produce a more pronounced segmentation among the groups that define the degree of active management does not distort the sign of the relationships of the previous test (although in some cases it does modify the hierarchy of the models).

Because one of the main ideas behind investment in the emerging markets segment is that emerging-markets investments are better insulated from financial upheavals than developed ones, we offer proof on the evolution of results in the subperiod 2007–2012, which was characterized by financial turmoil and slower economic activity. We provide persuasive evidence that the association between strategy breadth and excess risk-adjusted return is confirmed and reinforced in the post-crisis period. Moreover, the apposition of a threshold minimum value for the incremental R^2 value between the groups strongly emphasizes these relationships, showing an improvement of the alpha for the emerging market funds sample relative to its competitors in Group 1 that aggregate funds for which the prevalent factor is the market. These results lead us to conclude that the worst effects of the aftermath of the crisis affected the segment of traditional mutual funds investing in the developed markets with an almost passive strategy.

We believe that our findings contribute to the existing literature in several ways. First, our results offer new insights into the drivers of emerging market fund performance via comparison with the same aggregates investing in developed markets. Moreover, the focus on the post-crisis period reveals the competitive advantage of emerging market funds within all the groups that aggregate funds based on the number of strategies they pursue. Our results are consistent with the literature that validates the hypothesis that emerging markets are less efficient than developed markets and that these markets present greater opportunities for active managers.

In summary, and in agreement with previous research on U.S. and global equity funds, we find that emerging Asian (e.g., Japan) markets perform better than funds with less diversified portfolios, especially when the specific concentration in multifactor style holdings is considered. In particular, when we perform a double-sort rank procedure, first based on tracking error and then based on the exposure to market segments, we observe a positive relationship between the number of segments to which a fund is exposed and its performance. As a result, we offer a caveat for fund selectors: Whether one is a manager or an investor, when choosing emerging market equity funds, both during normal conditions and during periods of stress, one must watch the number of holdings in multiple market segments as well as the tracking error.

In the light of this framework, we find implications for further research, especially in deepening the relationship between specialization and performance by taking into account a number of control variables, usually considered effective in predicting mutual fund returns.

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