



Global real estate mutual funds: regional exposure and forecasting skill

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Abstract

Purpose – The purpose of this paper is to examine the risk-adjusted performance of US-based global real estate mutual funds (GREMFs) with emphasis on their ability to manage their domestic and foreign portfolios exposures.

Design/methodology/approach – The paper applies common econometric measures of portfolio performance and implements a non-traditional methodology called attribution returns to measure forecasting ability. In this setting the paper compares the actual monthly fund return to what would have been earned by the set of indices that best reflects the fund's investment strategy during the previous month. Performance and forecasting ability is examined during two different time periods: 2001-2005 and 2006-2010.

Findings – It is found that global real estate fund managers outperform the market and show good forecasting ability during the 2001-2005 time period. Good forecasting ability translates to positive risk-adjusted performance, as attribution returns are positively correlated with α .

Originality/value – Despite the significant growth in the number of US-based GREMFs and the ample coverage these funds receive in the popular press, few studies are solely devoted to the examination of these funds. In this study the paper empirically examines the ability of fund managers to successfully forecast country/regional political and economic conditions as well as fluctuations in currency exchanges rates brought about by the changes they made to their portfolios' domestic and foreign exposures.

Keywords Forecasting ability, Global real estate mutual funds, Mutual fund performance

Paper type Research paper

1. Introduction

The growth in real estate mutual funds (REMFs) has been impressive. Hartzell *et al.* (2010) and Shen *et al.* (2012) provide statistics that show that before the subprime financial crisis, REMFs were growing in both number and assets under management despite the apparent halt in the number of new real estate investment trusts (REITs). A new trend is the growth in international real estate mutual funds (IREMFs). Shen *et al.* (2012) provide evidence that IREMFs are becoming an important set of funds within the REMFs umbrella. In fact, based on the data provided by Shen *et al.* (2012) in 1998 IREMFs represented about 3 percent of the combined total net assets of domestic and IREMFs, and at the end of 2008, this number reached 22 percent. IREMFs include foreign REMFs, and global real estate mutual funds (GREMFs). Foreign REMFs invest in foreign REITs and either totally refrain or maintain only a minimal portion of their



portfolios in US-REITs. GREMFs invest in foreign REITs while preserving a significant portion of their portfolios invested in US securities.

GREMFs are especially attractive to US investors as they offer a straightforward way to diversify internationally. Although each GREMF is different, a typical fund will invest at least 80 percent in equity-related securities of real estate entities from around the world with as much as 60 percent in US securities. When selecting securities for the fund's portfolio, GREMFs' managers must find an optimal balance between the domestic (US) and foreign real estate markets. In this study we empirically examine the ability of GREMFs' managers to successfully forecast country/regional political and economic conditions as well as fluctuations in currency exchanges rates by the changes they made to their portfolios' domestic and foreign exposures. In sum, in this study we explore the link between risk-adjusted performance, forecasting ability, active management of portfolio's regional exposure, and the value provided to GREMFs' shareholders.

Our empirical approach is based on Sharpe (1992) style methodology and Gallo *et al.* (2000) examination of US-based REMFs. We first examine the risk-adjusted performance of GREMFs and then explore their regional exposure as a possible explanation for the evidence of outperformance. To measure forecasting ability, we calculate monthly attributions returns. An attribution return is defined as the monthly difference between each fund's actual return and the return that would have been generated by the fund portfolio's regional exposure in effect the previous month. A positive attribution return indicates that the fund manager successfully forecasted future market conditions and effectively altered the fund's portfolio mix to beat the previous month's investment strategy.

This paper is organized as follows. In Section 2, we present a brief literature review. In Section 3, we discuss the empirical methods, while in Section 4 we provide a description of the data used in our analysis. We report empirical results in Section 5 and the conclusion in Section 6.

2. Related literature

Our paper is similar in spirit to Gallo *et al.* (2000). Gallo *et al.* find that a sample of 24 REMFs outperformed the Wilshire Real Estate Security Index on a risk-adjusted basis from 1991 to 1997. They attribute the superior performance to property-type weighting strategies. REMFs managers added value to their investors by overweighting their portfolios in outperforming asset classes during the sample period. Kallberg *et al.* (2000) provide evidence in favor of active management and find positive performance by a sample of 44 REMFs during the 1986-1998 time period. The authors find that both standard and time-varying α 's are significantly positive and positively correlated to assets and turnover. O'Neal and Page (2000) evaluate the performance of a sample of 28 REMFs during the 1996-1998 time period and show that REMFs fail to outperform stock, bond, and real estate market indices. More recently, Lin and Yung (2004) evaluate the performance of REMFs from 1993 to 2001. Consistent with O'Neal and Page (2000), they find that these funds do not outperform either the stock market or the real estate market indices. The authors employed several performance evaluation models and risk factors standard in the equity mutual fund literature and found that these factors were related to fund performance. However, factor correlations disappear when a real estate market index is included as a control variable. Rodríguez (2007) examines the forecasting ability of REMFs during the 1999-2004 time period, and finds that REMFs managers as a group show no forecasting skill.

The aforementioned academic studies find conflicting evidence. Kallberg *et al.* (2000), and Gallo *et al.* (2000) provide evidence in favor of active fund management. O'Neal and Page (2000), Lin and Yung (2004), and Rodríguez (2007) find that REMFs do not outperform a series of stock or the real estate market indices. Chiang *et al.* (2008) explain the apparent contradiction in the academic literature about the performance of REMFs. They argue that REMFs generated higher returns than other mutual fund categories during their study period. However, under alternative risk-adjusted specifications the REMFs do not outperform their benchmarks, consistent with an equilibrium in which competition drives away abnormal returns. More recently, Shen *et al.* (2012) examine the performance of IREMFs in comparison to domestic REMFs during the 1998-2006 time period and report three major findings: IREMFs outperform domestic REMFs up until 2007; both IREMFs and REMFs fail to show market timing and stock selection ability; and IREMFs flows are mostly due to investors' return-chasing behavior. To the best of our knowledge, Shen *et al.* (2012) is the only study solely devoted to the examination of IREMFs, despite the significant growth in the number of IREMFs and the ample coverage these funds receive in the popular press. In this study we plan to add a significant contribution to the limited academic literature on GREMFs.

3. Empirical methods

Before examining the forecasting ability of GREMFs, we examine their risk-adjusted performance. To that end we estimate two well-known metrics, i.e. the Sharpe ratio and Jensen's α .

The Sharpe ratio (SR) for each fund i is computed as follows:

$$SR_i = \frac{\bar{R}_i - R_f}{\sigma_i} \quad (1)$$

where \bar{R}_i is the fund's average return, R_f is the risk-free rate for the period, σ_i is the return standard deviation of fund i .

The second risk-adjusted performance gauge we use is based on the work by Jensen (1968). Jensen's α is the intercept in the following linear model:

$$R_i - R_f = \alpha_i + \beta_i(R_B - R_f) + \varepsilon_i \quad (2)$$

where R_i is the fund's return, R_f is the risk-free rate, R_B is the return on the benchmark, α_i is the intercept of the equation and the measure of risk-adjusted performance, β_i is the coefficient of systematic risk, and ε_i is the unexplained component of the model. We estimate α for each fund with the FTSE EPRA/NAREIT world index as the benchmark. A positive value of α is indicative of mutual fund outperformance.

Now we want to focus our attention on answering the following question: do US-based GREMFs add value to investors by actively managing their domestic and foreign portfolio's exposures? We take a non-traditional avenue to answer the above question; examining the dynamics between GREMF's portfolio exposures to both the domestic (US) and the foreign real estate market by computing attributions returns. A fund's attribution return is defined as the difference between a fund's actual return and the return that would have been generated with the previous month fund's portfolio asset allocation. A positive attribution return indicates that the fund manager adds value by actively managing the weights of individual securities or asset classes

within the portfolio. In a way, each fund manager is being evaluated on a monthly basis by its own benchmark which is changing through time, resulting in a monthly time series of attributions returns which can be further analyzed. This measure is based on the performance metrics proposed by Ibbotson (1996), Myers *et al.* (2001), and Dor *et al.* (2003). Attribution returns are further explored in Rodríguez (2007) and Comer *et al.* (2009).

The difficulty in implementing the attribution return methodology is driven by data limitations, i.e. the lack of portfolio holdings and country exposure on a monthly basis. To overcome this hurdle, the style methodology first introduced by Sharpe (1992) is used. Style analysis allows for the estimation of each fund's portfolio country exposure from publicly available daily fund returns. The country weights are the solution of a quadratic programming problem. These weights represent factor loadings on an index strategy that best replicates GREMFs returns. We assume that GREMFs' daily returns can be expressed as:

$$r_i = \sum_{j=1}^n w_{i,j} r_j + e_i \quad (3)$$

where r_i is the total return of fund i , $w_{i,j}$ is the exposure of fund i to index j , r_j is the total return of index j , and e_i is the unexplained component of the fund return.

The portfolio weights are the solution of a quadratic programming problem. These weights represent factor loadings on an index strategy that best explains fund returns:

$$\text{Min} \left[\text{var} \left(r_i - \sum_{j=1}^n w_{i,j} r_j \right) \right]$$

subject to

$$0 \leq w_{i,j} \leq 1 \quad \forall j \quad (4)$$

$$\sum_{j=1}^n w_{i,j} = 1$$

Gallo *et al.* (2000) applied the style methodology on REMFs to infer portfolio's allocations across property types. They argue that the source of outperformance reported in their study was due to the fact that, relative to their benchmark, fund managers allocated more to outperforming property types; specifically, fund managers allocated more assets to health care and apartments before these sectors outperformed other property types.

Given the estimated monthly portfolio allocation weights from the style analysis procedure, we can define an attribution return for a given fund i and month t as follows:

$$r_{att,i,t} = r_{i,t} - \sum_{j=1}^n w_{i,j,t-1} r_{j,t} \quad (5)$$

where $r_{att,i,t}$ is the attribution return for fund i and month t , $r_{i,t}$ is the fund i total return for month t , $w_{i,j,t-1}$ is the fund i estimated exposure to index j for month $t-1$, $r_{j,t}$ is the total return of index j for month t .

We use daily fund and index returns which allow us to estimate a time series of monthly portfolio weights and attribution returns. A positive average attribution return suggests positive forecasting ability. Forecasting skill comes from several sources like the ability to identify undervalued securities and/or to anticipate future market conditions. Rodríguez (2007) employed attribution returns to measure the forecasting skill of domestic REMFs and found that forecasting ability is fundamentally important for fund survivorship as non-surviving funds showed significantly poor forecasting ability.

Both Lin and Yung (2004) and Shen *et al.* (2012) argue that real estate indices are the only risk factors needed to examine REMFs, while Hartzell *et al.* (2010) advocate the use of a multiple-benchmark approach when evaluating REMFs. Their work motivates our choice to include only real estate indices in our multi-factor models. Although perhaps too simplistic, with the first index model we want to express GREMFs returns as linear combinations of three indices: US real estate market, the global (ex-US) real estate market, and cash. With this formulation we plan to examine the forecasting ability of GREMFs by looking at domestic/foreign portfolio's exposures.

In order to have a more detailed account of GREMFs' portfolios we consider a second multi-factor model. To better decide which factors to include in the second model, we checked the information regarding the regional exposure of our sample of GREMFs published on the *Morningstar* web site. Even though this information is just a point in time, it serves to motivate our second model. The data on GREMFs' regional exposure reveals that by far the dominating geographical regions on their portfolios are the USA, Asia, and Europe. On average, GREMFs' portfolios have 38 percent invested in the USA, 25 percent in Asia, and 18 percent in Europe. Given this information, the second index model includes a cash index plus indices for the real estate markets of the USA, Asia, and Europe. This four-factor model gives us the opportunity to better examine the regional portfolio exposure of GREMFs. With this in mind, we include indexes from NAREIT and FTSE EPRA/NAREIT for Developed World, World ex US, US, Europe, and Asia regions. Also, daily and monthly index prices are collected from Bloomberg. The Lehman Short Treasury daily index is used as the cash factor.

4. Data

We examine GREMFs during two consecutive (five-year) time periods: 2001-2005 and 2006-2010. The advantage of considering two samples of funds during two different time periods is twofold. First, these time partitions allow us to examine GREMFs during two very different market conditions: a, financially speaking, stable time period (2001-2005), and a time period which includes the most devastating financial crisis since the Great Depression (2006-2010). Second, by selecting the fund samples in two moments in time we can examine a larger number of funds. The fund samples include all GREMFs as defined by Lipper in the Center for Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database at the beginning of both 2001 and 2006. Since our focus is on the fund's regional exposure and fund manager forecasting ability, for funds with multiple classes we only include the class with the longest history. The data from CRSP includes daily fund returns and fund characteristics like total net assets, expense ratio, and turnover ratio.

Table I presents descriptive statistics for both GREMFs samples. Besides the usual fund characteristics, Table I also shows two risk-adjusted performance metrics: the annual average excess returns and the average Sharpe ratio.

	Sample 1	Sample 2
Time period covered	1/2001-12/2005	1/2006-12/2010
Number of funds	8	31
Average annual fund return	19.76%	3.08%
Average annual excess return	19.57%	0.431%
Average Sharpe ratio	0.4102	0.0111
Average total net assets	387 million	193.9 million
Median total net assets	108 million	44.30 million
Average expense ratio	1.47%	1.37%
Average turnover ratio	60.3%	82.0%

Table I.
Global real estate mutual
funds samples description

The first and second samples include eight and 31 unique funds, respectively. These funds are either the only GREMFs in a fund family or the fund class with the longest history for fund families with multiple classes of the same GREMF at the beginning of years 2001 and 2006, respectively[1]. The average annual return, average (median) total net assets, and average expense ratio are all higher for sample 1. However, more active trading is evident during the 2006-2010 time period as the average turnover ratio is higher for sample 2. It is important to highlight that sample 2 includes the recent financial crisis and a higher turnover might be the result of more trading in response to market turmoil. Finally, based on the two risk-adjusted metrics, sample 1 performed better than sample 2. The average annual excess return is 19.57 percent for sample 1, vs 0.431 percent for sample 2. Also, the average Sharpe ratio is 0.4102 vs 0.0111 for samples 1 and 2, respectively.

5. Empirical results

5.1 Risk-adjusted performance

As a first step in our examination of GREMFs performance and forecasting ability, Table II presents the results of the estimation of Jensen's α . We estimate α using as the benchmark the FTSE EPRA/NAREIT World index. Table II shows the results for the portfolio of GREMFs and both samples of individual funds. The portfolio α for sample 1 is 8.57 percent per year and statistically significant at the 1 percent level. Seven individual funds from sample 1 have seven positive α , four of them statistically significant. For sample 2 the results are inconclusive. The α for its portfolio of funds is 4.56 percent, but it is not statistically significant. Thirty funds attained a positive α , but

	Sample 1 2001-2005	Sample 2 2006-2010
Portfolio α	8.57***	4.56
<i>Individual funds</i>		
Count of positives (sig.)	7 (4)	30 (3)
Count of negatives (sig.)	1 (0)	1 (0)
Range	17.36	33.21
Minimum	-2.55	-2.40
Maximum	14.81	30.81

Notes: All α values are annualized and expressed in percentages. ***Statistical significance at the 1 percent level

Table II.
Jensen's α

only three are statistically significant. Later on, we explore in detail the relation between risk-adjusted performance and forecasting ability.

5.2 Regional exposure

As mentioned before, our focus is on the regional exposure of GREMFs portfolios as a source of outperformance and the forecasting ability of fund managers. To measure regional exposure we implement two models. The first model includes factors for the US real estate market, the real estate market for the rest of the world (world ex US), and a risk-free factor to represent the cash portion of the funds' portfolio. The second model includes the cash factor and real estate factors from the USA, Europe, and Asia.

To explore the reliability of our two models, we first construct an equally weighted portfolio of all the funds in existence on any given day during the two sample periods of the study. The daily return of this portfolio is the dependent variable in Equation (3) and Table III presents the results of the estimated factor loadings. Panel A of Table III shows the results for Model 1. Even with the restrictions imposed by the style methodology, the model works well. The adjusted R^2 is close to 90 percent for sample 1, which covers the 2001-2005 time period, and above 93 percent for sample 2, which covers the 2006-2010 time period. For both samples all the factor loadings are statistically significant at the 1 percent level, also for both samples, GREMFs has the highest exposure to the US market. The cash exposure in both cases is around 10 percent.

Panel B of Table III presents the results for Model 2. Again, the model does a good job in explaining the variability of the fund returns and the adjusted R^2 are practically the same to those of Model 1. Also, all factor loadings are statistically significant and the highest portfolio exposure is to the domestic real estate market. For sample 1, the second highest exposure is to the European real estate market followed by the Asian market. For sample 2, the second highest exposure is to the Asian market.

Not presented in Table III is the monthly detail of the estimation of GREMFs portfolios' regional exposures. The results for Model 1 sample 1 show that GREMFs have the highest exposure to the domestic real estate market for each month during the complete sample period. For sample 2, only during two months the exposure to the foreign markets was higher than the exposure to the domestic market.

	Sample 1 2001-2005	Sample 2 2006-2010
<i>Panel A: Model 1</i>		
USA	0.7586***	0.5614***
World no USA	0.1322***	0.3372***
Cash	0.1092***	0.1014***
Adjusted R^2	0.8989	0.9342
<i>Panel B: Model 2</i>		
USA	0.7563***	0.5564***
Europe	0.0980***	0.1622***
Asia	0.0378***	0.1706***
Cash	0.1079***	0.1108***
Adjusted R^2	0.8968	0.9348

Table III.
Portfolio exposures

Notes: This table presents the exposures of a portfolio of all the funds in each sample to each of the three factors (Model 1) and four factors (Model 2). ***Statistical significance at the 1 percent level

Model 2 gives us more information about the regional exposure of GREMFs. During both sample periods, the exposure to the domestic market was the highest. However, for 36 months during the 2001-2005 time period, the exposure to the European real estate dominated the exposure to the Asian market. Interestingly enough, during the 2005-2010 time period the complete opposite happened. For 36 months of the sample period, the exposure to the Asian real estate market was higher than the exposure to Europe. Finally, during 2008, the crucial year of the crisis, for seven months the exposure was higher to the Asian market.

5.3 Forecasting ability

In this section we examine the forecasting ability of both samples of GREMFs as measured by attribution returns. The attribution return methodology evaluates the monthly difference between the actual fund return and the return generated by the previous month's portfolio's exposures. We compute attribution returns from February 2001 for sample 1, and from February 2006 for sample 2. For the individual funds, we compute attribution returns during each full sample period or when they cease to exist[2]. The results are presented in Table IV and the values are annualized and expressed in percentages. For sample 1 the average attribution returns for Models 1 and 2 are 7.91 percent and 7.85 percent, respectively. Both of these averages are statistically significant. Also, regardless of the model, all the individual funds

	Sample 1 2001-2005	Sample 2 2006-2010
<i>Panel A: Model 1</i>		
Portfolio		
Average	7.91***	1.86
Median	8.85	0.27
SD	13.00	14.64
Individual funds (average)		
Count of positives (sig.)	8 (6)	28 (3)
Count of negatives (sig.)	0 (0)	3 (0)
Range	10.14	34.38
Minimum	4.28	-7.93
Maximum	14.43	26.45
Correlation with α	0.90***	0.91***
<i>Panel B: Model 2</i>		
Portfolio		
Average	7.85***	3.21
Median	8.73	3.65
SD	13.50	16.79
Individual funds (average)		
Count of positives (sig.)	8 (6)	29 (3)
Count of negatives (sig.)	0 (0)	2 (0)
Range	9.58	32.78
Minimum	3.70	-6.92
Maximum	13.28	25.86
Correlation with α	0.93***	0.94***

Notes: All values are annualized and expressed in percentages. ***Statistical significance at the 1 percent level

Table IV.
Attribution returns

attained average attribution returns which are positive, six of them statistically significant at the 5 percent level.

For sample 2, which covers the financial crisis, the results are inconclusive. For both models, the average attribution return is positive but not statistically significant. The results for Models 1 and 2 are 1.86 and 3.21 percent, respectively. Twenty-eight and 29 of the individual funds in Models 1 and 2, respectively, have average attribution returns which are positive but only three are statistically significant at the 5 percent level. In sum, only during the 2001-2005 we find evidence of positive risk-adjusted performance (α) and good forecasting ability (attribution returns).

5.4 Forecasting ability and market conditions

To further explore the forecasting ability of GREMFs' managers, we examine attribution returns during different financial conditions in the domestic market. We partition both sample periods based on the performance of three different markets: REITs, stocks, and bonds. We use the NAREIT all REITs index to measure the performance of the REITs market and the S&P 500 index to measure the returns of the stock market. Finally, we use the BofA Merrill Lynch US Corporate Bond Market index returns to measure the performance of the bond market.

The results based on Model 1 are presented in Table V. For each partition we present the markets being compared and the number of months each market outperformed the other. For the first partition we compare the REITs market with the stock market. In sample 1 (2001-2005) the REITs outperformed the stock market during 40 months and in sample 2 (2006-2010) during 32 months. We find that, only during the 2006-2010 time period, GREMFs show better forecasting ability when the stock market performs better than the REITs market as the difference between average attribution returns is statistically significant.

The second partition considers the comparison between the REITs and the bond market. In this partition, for sample 1 and sample 2 the REITs market outperformed the bond market in 38 and 33 months, respectively. We find that, only during the

	Sample 1 2001-2005		Sample 2 2006-2010	
	Number of months	Average attribution return (%)	Number of months	Average attribution return (%)
<i>REITs vs stocks</i>				
Better	40	6.36	32	-4.56
Worse	19	11.28	27	9.60
Difference		-4.92		-14.16*
<i>REITs vs bonds</i>				
Better	38	9.84	33	-2.28
Worse	21	4.32	26	7.20
Difference		5.52		-9.48*
<i>Stocks vs bonds</i>				
Better	27	12.00	33	2.88
Worse	32	4.32	26	0.60
Difference		7.68*		2.28

Table V.
Attribution returns and market conditions

Notes: This table presents average attribution returns aggregated by market conditions. All values are annualized and expressed in percentages. *Statistical significance at the 10 percent level

2006-2010 time period, the average attribution return is higher when the bond market outperforms the REITs market and the difference is statistically significant.

The last partition is based on the comparison between the stock and the bond market. During the 2001-2005 time period, the stock market did better than the bond market during 27 months. While during the 2006-2010 time period, the stock market outperformed the bond market during 33 months. The results show that during the 2001-2005, the average attribution return is higher when the stock market do better than the bond market and the difference between average attribution returns is statistically significant. Although not presented in Table V, the results based on Model 2 are qualitatively similar and let us reach the same conclusions.

5.5 Forecasting ability and risk-adjusted performance

The results of the previous sections provide evidence of good forecasting ability by GREMFs during the 2001-2005 time period. Attribution returns provide a way to examine forecasting ability but not risk-adjusted performance. A manager can have positive attribution returns and still underperform the benchmark or their peers. In this section we explore the relation between forecasting ability and risk-adjusted performance.

We begin by computing the correlation between the average attribution return and α . For both samples of GREMFs, we found that forecasting ability is strongly correlated with risk-adjusted performance. Table IV shows that for sample 1, the correlation between average attribution returns and α is 0.90 for Model 1 and 0.93 for Model 2. Both correlation coefficients are statistically significant at the 1 percent level. We find similar results for sample 2. Based on Model 1, the correlation between attribution returns and α is 0.91, and 0.94 for Model 2. Again, both correlations are statistically significant.

As a second step in our analysis, we examine the relation between risk-adjusted performance and regional exposure. The basic idea is to examine the regional exposure of outperforming GREMFs as a source of positive performance. Perhaps, outperforming GREMFs overweighted (underweighted) outperforming (underperforming) regional markets in comparison with the underperforming funds.

To explore this possibility we estimate the exposure of outperforming and underperforming funds to each of the regional factors on Models 1 and 2, and compare the exposure to regions with good performance. The results are presented in Table VI. Panel A of Table VI provides the results for Model 1 and panel B for Model 2. In each panel we also present the average return for each geographical region during the specified time period. We find evidence consistent with the results presented in the previous sections. It is only during the 2001-2005 time period that we find that the regional exposure of outperforming funds might provide some explanation for their significant risk-adjusted performance. Panel A of Table VI shows that the best performing region during 2001-2005 time period is the foreign market. The average monthly return of the US market is 11.91 percent vs 13.37 percent for the foreign market. Also, the results in panel A show that funds with positive and significant α 's have higher exposure to the foreign market (24.3 vs 4.77 percent), than funds with positive but insignificant α 's.

Panel B of Table VI shows the results for Model 2. In Model 2, the outperforming region during the 2001-2005 time period is Europe, with an average monthly return of 16.6 percent. Again, during 2001-2005 the average exposure to Europe (the outperforming region) is higher for funds with positive and significant α 's. The

	Sample 1 2001-2005			Sample 2 2006-2010		
	Market returns (%)	Positive	Positive and significance	Market returns (%)	Positive	Positive and significance
<i>Panel A: Model 1</i>						
Cash	2.11	0.02140	0.17470	2.18	0.09618	0.22090
USA	11.91	0.93085	0.58195	9.81	0.56048	0.40048
No						
USA	13.37	0.04775	0.24335	2.41	0.34335	0.37862
<i>Panel B: Model 2</i>						
Cash	2.11	0.02144	0.15305	2.18	0.10499	0.22937
USA	11.91	0.94465	0.58130	9.81	0.55654	0.39868
Europe	16.66	0.02189	0.16566	-0.35	0.15807	0.15917
Asia	10	0.01202	0.10000	6.97	0.18040	0.21278

Notes: This table presents the average monthly exposures to each factor included in Model 1 and Model 2, of the funds with positive and significant α vs funds with positive but insignificant α . The significance level is 5 percent

Table VI.
 α and portfolio exposures

average exposure to Europe for funds with positive and significant risk-adjusted performance is 16.5 vs 2.18 percent for funds with positive but insignificant α 's. As with the results presented in the previous sections, during the 2006-2010 time period the evidence is inconclusive.

6. Conclusion

This paper empirically examines the risk-adjusted performance and forecasting ability of US-based GREMFs during two time periods, 2001-2005 and 2006-2010. We find that only during the 2001-2005 time period global real estate funds outperform a globally diversified real estate index. We also find that the risk-adjusted performance of these funds is highly correlated with forecasting ability. To measure forecasting ability, we compute a monthly attribution return which is defined as the difference between the monthly mutual fund return and the return that would have been generated by the regional exposure in effect the previous month. As in the case of risk-adjusted performance, we find that US-based GREMFs show good forecasting ability only during the 2001-2005 time period. Based on our examination of funds' regional exposure, we show that outperforming funds have higher exposure to the geographical region with the best performance.

Notes

1. For further details see Livingston and O'Neal (1998) and O'Neal (1999).
2. To avoid the survivorship bias problems presented in Elton *et al.* (1996), all non-surviving funds are included in the analyses.

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