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Do the Managers of Global Real Estate Mutual Funds Have Skills?

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Abstract

We examine the performance of active, global real estate mutual funds (GREMFs), both at sector and individual fund levels. We apply a bootstrap procedure to separate genuine skills from luck. We find no evidence of skills, but find evidence of lack of skills in the bottom 10% of funds. We find that outsourcing has a *positive* effect on GREMFs but a *negative* effect on global mutual funds overall. We also find no evidence of skills in timing or in stock selection. Overall, our results suggest that there is no benefit to a U.S. domestic investor from investing in GREMFs.

Keywords: mutual fund performance, real estate, global investment, bootstrap

JEL Classification: R31, C14

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1 Introduction

The last three decades have witnessed a strong growth in global sector mutual funds, from 26 in 1992 to 291 in 2016, and a growth in assets under management from \$4.5bn to \$198bn. Of the 291, 196 were actively-managed and accounted for \$170bn of the assets. And, of the actively-managed sector funds, the real estate sector, with 82, had the largest number of funds and the second largest assets under management at \$41bn.[1]

For their supposed skills, actively-managed mutual funds charge much higher expenses than passive funds, with global real estate mutual funds (GREMFs), on average, charging the highest expenses (155 basis points) among different types of funds.[2] However, despite the importance to investors, there is limited published research on whether such expenses are justified by fund performance. Accordingly, it is appropriate to investigate the performance of actively-managed Global Real Estate Mutual Funds (GREMFs), and to establish whether international investment improves risk-adjusted returns.

Although identifying underpriced international equities could bring benefits in terms of return and geographical diversification of risk, significant efforts and costs are involved as different countries have different institutional contexts and different levels of market transparency and maturity. Therefore, it is possible that managers who are based in a local area have specialist knowledge and access to information, leading to information asymmetry between local and non-local investors, and enabling the former better to assess the value of securities. As the international real estate market is characterised by a high degree of market-specific, value-relevant, local factors, information about which is generally less accessible and transparent to outside investors, the information asymmetry is likely to be even more evident for GREMFs (Hung and Glascock, 2010). Accordingly, it may be more difficult for them to outperform local managers.

One approach to dealing with the difficulties of international real estate investment is to sub-contract to experts in local markets. However, Chen et al. (2013) concluded that outsourcing has a negative effect on mutual fund performance, and Chuprinin et al. (2015) found the same result for international mutual funds overall. Nonetheless, despite these results, given the nature of international real estate markets, it is not obvious that the same should be expected for GREMFs. Indeed, Bernile et al. (2015) found that institutional investors, which are located in the same area as the stocks in which they invest, earn superior returns on these local investments, and Coval and Moskowitz (2001) found that mutual funds that invest

[1]Healthcare was the largest by assets under management, with \$66.5bn in 2016 but only had 10 funds.

[2]Based on the expense ratio data from CRSP US Mutual Fund database, and from ICI (Investment Company Institute) 2016.

heavily in their local market do better. The results of these two studies suggest that the same might be possible for GREMFs, so the matter merits investigation.

We are also interested in whether fund managers have skills in choosing the right geographical areas at the right time or in picking quality stock. We develop an approach to assessing this. Also, as most funds have both institutional and retail share classes, we compare their performance.

We take two approaches to assessing performance and to comparing domestic and global real estate mutual fund performance. First, we consider several return:risk ratios, specifically the Sharpe Ratio, the Treynor Ratio and the Manipulation-Proof Performance Measure (MPPM) developed by Goetzmann et al. (2007) and applied to REITs by Alcock et al. (2013). Second, to assess outperformance, both gross and net of expenses, we employ the alpha measure, which has been widely used to examine fund performance, including in studies of domestic real estate mutual funds (DREMFs) and international equity mutual funds. Previous studies suggest that the results are sensitive to the choice of benchmarks (Cumby and Glen, 1990; Lin and Yung, 2004; Hartzell et al., 2010). Various benchmarks have been used, among which the most frequently used are asset pricing models based on the required returns of a passive portfolio. Accordingly, we test the appropriateness of a wide variety of potential benchmarks. We undertake our analysis for the GREMF sector as a whole and for individual funds. For the former, we also undertake rolling estimates of alpha to consider its time trend.

Although several recent studies show that some mutual funds may have talents (Kosowski et al., 2006; Fama and French, 2010; Berk and Van Binsbergen, 2015), identifying managers with skills is a non-trivial exercise because good past performance could simply be the result of luck. Moreover, even if managers are talented enough to generate gross outperformance, this could be cancelled by their expenses. Therefore, we address statistical issues that hinder the appraisal of performance, namely cross-fund dependency, auto-correlation and heteroscedasticity, and which have not previously been fully considered in the real estate literature. We implement the bootstrap approach of Kosowski et al. (2006), which accounts for the aforementioned issues and enables us more effectively to separate skills from luck.

This rest of the paper is organized as follows. Section 2 considers the literature on the performance of actively managed GREMFs. Section 3 then outlines the methodology and section 4 explains the data used in this study. Section 5 presents the empirical results, and section 6 summarises the main findings and draws conclusions.

2 Literature Review

There is a long-established literature on the performance of diversified active funds with a U.S. market focus (Grinblatt and Titman, 1989; Ippolito, 1993; Elton et al., 1993; Malkiel, 1995; Gruber, 1996; Carhart, 1997). The general conclusion is that, on average, active funds underperform passive alternatives.

More recent studies draw similar conclusions. Kosowski et al. (2006), in their examination of the returns of U.S. domestic equity mutual funds from 1975 to 2002, found that a minority of funds possessed genuine skills to produce outperformance when operating expenses were taken into account. Fama and French (2010) examined the net returns of active diversified equity funds from 1984 to 2006 and found that only the top three percentile funds could add enough value to cover expenses, and this was attributed to their stock-picking talents. Barras et al. (2010), in a study of net fund performance from 1975 to 2006, found that 10-15% of the 2076 funds were skilled during different periods before 1996 but none thereafter. They attributed this to increasing market efficiency, inadequate skills of fund managers, and the movement of skilled fund managers to the more lucrative sectors, such as hedge funds. These three papers all used bootstrap approaches.

There is also evidence that funds that concentrate in specific industries perform better than those that do not (Kacperczyk et al., 2005). This is explained by information asymmetry, which means that these managers know their sectors better than other types of fund managers (Kaushik et al., 2010). In contrast, studies which have considered sector funds (Dellva et al., 2001; Tiwari and Vijh, 2001; Eakins and Stansell, 2007; Kaushik et al., 2010; MacGregor et al., 2020) have found that some sectors, such as technology, health care and utilities, can outperform but only during specific periods. And Khorana and Nelling (1997) suggested that the overall risk levels of sector funds are indistinguishable from small-cap or aggressive-growth funds. The need to include a *sector-based index* in the established asset pricing benchmarks, to account for their sector specific investment styles, has been addressed by these studies.

As the largest sector among all mutual fund sectors, U.S. domestic real estate has been the most extensively studied. Earlier studies by Kallberg et al. (2000) and Gallo et al. (2000) found outperformance when real estate market returns were poor, which is attributed to real estate market inefficiency. However, more recent studies (O'Neal and Page, 2000; Lin and Yung, 2004; Rodriguez, 2007; Chiang et al., 2008; Chou and Hardin, 2014; MacGregor et al., 2020) have found little or no evidence to support significant outperformance attributable to real estate mutual fund (REMF) managers' superior skills, regardless of the benchmarks used for the market or the real estate sector.

Ferreira et al. (2013) considered active mutual funds in 27 countries and used country-specific Carhart benchmarks. They sought to explain performance by a variety of fund and country factors and concluded that mutual funds underperform the market. However, they did not address the issue of non-normality in returns and did not use a bootstrap approach. Busse et al. (2013) also used country-specific Carhart benchmarks, which they aggregated into factors for developed and emerging markets, with both sets being used in the model. They implemented a bootstrap approach, in line with Kosowski et al. (2006) and Fama and French (2010), to examine active retail and institutional global mutual funds, and found little evidence of superior alphas. Although the extreme right tail of the distribution contains some large alphas, simulations suggest that they are produced more by luck than skills.

The performance of international property companies was examined by Eichholtz et al. (2011) during 1996-2007. Their results indicate that such companies underperformed local property companies in the earlier years because of the political environment, the level of economic integration and transparency of the target real estate markets. However, in later years, the underperformance of international property companies vanished, suggesting increased market transparency in the international real estate industry.

Shen et al. (2012) evaluated the performance of 59 U.S.-based GREMFs during 1998-2008 and used a variety of performance measures, including the Sharpe and Treynor ratios. They concluded that, before 2007, GREMFs outperformed DREMFs but this advantage disappeared thereafter. Alcock et al. (2013) considered REIT performance, also using traditional risk-adjusted return performance measures as well as the Manipulation-Proof Performance Measure (MPPM), developed by Goetzmann et al. (2007). They concluded (p460) that 'REIT managers may opportunistically employ leverage in order to game performance measures'.

Outsourcing is an important consideration. Chen et al. (2013, p. 530) reported that 'roughly 41% of [mutual fund] families outsource to some degree' and that 'a typical family on average outsources the management of 26% of its funds'. They considered mutual funds but explicitly removed international funds and sector funds from their analysis. They concluded that outsourcing has a negative effect on mutual fund performance, leading to underperformance of 'approximately 50bps' a year (p525). They attributed this to 'agency costs that make it more difficult ... to extract performance from an outsourced mutual fund' (p528). Chuprinin et al. (2015) found the same result for global mutual funds overall. They concluded that outsourced funds underperform by 85 basis points a year. They attributed this to 'preferential treatment of in-house funds via the preferential allocation of IPOs, trading opportunities, and cross trades' (p2275).

However, Coval and Moskowitz (2001) found that mutual funds that invest heavily in their local market do better, and Bernile et al. (2015) found, using U.S. states data, that there is a link between 'local exposure' and 'a geographic component in ... performance', and that 'the geographical distribution of information about firms' economic interests generates location-dependent information asymmetry that can explain institutional investors' portfolio decisions and performance' (p2042). Given the characteristics of international real estate markets, both of these studies suggest that outsourcing to experts in local markets could be an advantage to GREMFs, so the matter merits investigation.

Another issue that has been examined is the impact of team management compared to individual management. Bliss et al. (2008) pointed to a growth in team management of equity mutual funds, from 30% in 1993 to 56% in 2003. This, they suggested, could be because 'groups make better decisions' or to avoid the negative impact of 'stars' leaving (p110). They used the Fama and MacBeth (1973) method and the Carhart benchmark but found 'no statistically or economically significant differences between individually managed and team-managed mutual funds' (p.115). Massa et al. (2010) also considered the issue and again found no significant difference, using the CAPM and Carhart benchmarks. However, Patel and Sarkissian (2017), using a different dataset, concluded that team-managed funds have higher risk-adjusted annual returns by 30-40 bps. None of these explicitly considers global mutual funds.

The literature also suggests that factors other than outsourcing and team management, such as size, age, recent performance, capital flows, expenses, number of funds in the the fund family and size of the fund family, are linked to mutual fund performance (Bliss et al., 2008; Chen et al., 2013, 2004; Chuprinin et al., 2015; Ferreira et al., 2013; Massa et al., 2010; Patel and Sarkissian, 2017; Chou and Hardin, 2014) Thus, it is important to control for these factors.

We are also interested in whether fund managers have skills in investing in the right geographical areas at the right time and in picking quality stock. Kacperczyk et al. (2014) considered whether mutual fund managers have timing and stock selection skills and whether these are better in periods of expansion or contraction. They estimated measures of these skills and concluded that timing ability is higher in recessions, while stock picking is lower in recessions.[3] For GREMFs, Shen et al. (2012) also considered whether performance could be attributed to timing skills or stock selection skills. They did so by applying versions of the Treynor-Mazuy and Merton-Henriksson models.[4] They found no evidence of timing skills and some of stock selection skills.

There is ample empirical evidence to show the violation of the normality assumption (Kosowski et al., 2006; Fama and French, 2010; Cuthbertson et al., 2008), and that fund returns follow non-standard distributions. To control for this in our study of GREMFs, we employ a cross-sectional bootstrap approach and rely on inferences from this. This means that we can more effectively separate genuine managerial skills from luck in fund performance.

In this study we add to the literature on GREMFs in six main ways. First, we use the Manipulation-Proof Performance Measure (MPPM) and compare it with

[3]Kacperczyk et al. (2014, p. 1460) argue that a fund with timing ability overweights high beta stocks when the market is expected to rise and underweights when the market is expected to fall; and a fund with high picking ability overweights assets that have high idiosyncratic returns and underweights assets with low idiosyncratic returns.

[4]In both cases, additional variables are added to the CAPM: in the former, the market return above the risk free rate, multiplied by lagged instrument variables, representing public information, and with the square of the market return above the risk free rate, are added; in the latter, instead of the squared term, the first difference of the market return above the risk free rate, and this term multiplied by lagged instrument variables, are added.

more traditional measures. Second, we undertake formal assessments to determine appropriate benchmarks. Third, we assess fund performance for the sector and for individual funds, using a robust bootstrap approach. Fourth, we consider the impact of outsourcing on fund performance. Fifth, we assess whether fund managers have geographical timing or stock selection skills and which factors affect these. Finally, we consider both institutional and retail funds separately.

3 Methodology

3.1 Performance assessment

To assess and compare the performance of active mutual funds that invest either in domestic (U.S.) or foreign listed real estate equities, we use two different approaches. First, we use the well-known Sharpe and Treynor ratios, which relate fund return rates in excess of the risk-free rate to a measure of return rate risk. In the Sharpe ratio, risk is measured by the standard deviation of the return rates; in the Treynor ratio, risk is measured by the beta between fund and market return rates, see for instance Schulz et al. (2019). Both ratios consider only lower moments of return rate distributions. Fund managers could use strategies such as short selling and derivatives to improve the ratios at the cost of higher moments. Although extensive use of such strategies is not permitted for mutual funds, we use also the measure proposed by Goetzmann et al. (2007). This measure is similar to Morningstar's risk-adjusted return rate that is used in the investment industry and which is insensitive to moment manipulation.[5] Of the three measures, only the Sharpe ratio is related to an equilibrium in a competitive asset market.[6]

The second approach to assess the performance of funds uses a linear asset pricing model. In a competitive market, assets will be priced so that the expected return rate compensates for asset's risk exposure. As there are several candidates, we must choose the most appropriate asset pricing model. We motivate next the core regression equations *given* a linear asset pricing model and explain how we use the regressions to choose the asset pricing model for our benchmark. The first core regression equation is

$$r_{i,t} = \alpha_i + \mathbf{x}_t \boldsymbol{\beta}_i + \epsilon_{i,t} \tag{1}$$

[5]The measure assumes a particular utility function for investors and estimates effectively the welfare under the return rate distribution generated by a fund manager. The coefficient of relative risk aversion ρ acts as tuning parameter. One can be sceptical about a performance measure that can be tweaked and we will assess it for different plausible values of ρ.

[6]The Sharpe ratio is the slope of the capital market line of the CAPM. This model results if investors have mean variance preferences. The CAPM results also in an expected utility framework *if* return rates follow particular distributions (Chamberlain, 1983). However, if fund managers can manipulate return rate distributions, the less restrictive derivation is no longer appealing and so is the Sharpe ratio.

and relates the return rate of asset i in excess of the risk-free rate to a constant, a row vector $\mathbf{x}_t$ of traded risk factor realisations multiplied with the factor loadings, and a noise term. Asset i can be a fund or a portfolio of funds. The chosen asset pricing model determines the elements in $\mathbf{x}_t$. If a set of funds is managed passively, then we have $\boldsymbol{\alpha} = \mathbf{0}$ under the correct asset pricing model. As a passive manager takes risk, but does not try to outsmart the market, an alpha of zero simply implies that the expected return rate will compensate for the risk taken. If a set of funds is managed actively, then some funds may have $\alpha_i > 0$, but other may have $\alpha_i \leqslant 0$. We will use the time series regression in Equation 1 in several places in this paper.

The second core regression equation is

$$\mathbf{r}_t = \mathbf{B}_t \boldsymbol{\lambda}_t + \boldsymbol{\alpha}_t \tag{2}$$

and relates the cross section of return rates in excess of the risk-free rate to the expected premiums $\boldsymbol{\lambda}_t$ for the risk factors in period t. Row i of the matrix $\mathbf{B}_t$ contains the factor loadings of asset i with respect to the risk factors of the candidate pricing model. The loadings in $\mathbf{B}_t$ are estimated with observations from previous periods.[7] The $\boldsymbol{\lambda}_t$ are estimated for each period separately. As $\mathbf{B}_t \boldsymbol{\lambda}_t$ corresponds to the required return rates for the assets, the vector $\boldsymbol{\alpha}_t$ contains the pricing errors. For the correct asset pricing model, we expect $\mathrm{E}[\boldsymbol{\alpha}_t] \equiv \boldsymbol{\alpha} = \mathbf{0}$ for a set of passively managed funds. We will use the cross sectional regression in Equation 2 in several places in this paper.

As should be clear from the discussion above, the correct pricing model will have alphas for passive funds that are indistinguishable from zero.[8] To find this model, we perform two types of tests. Firstly, we use time series of return rates of portfolios of passive funds and stack the regression in Equation 1 for all i and t. We run this system for the different candidate factor models and test whether all elements in the estimated vector $\boldsymbol{\alpha}$ are jointly zero.

Secondly, we use a robust covariance matrix that allows for heteroscedasticity, autocorrelation, and cross-sectional correlation of errors between assets. To obtain further evidence on the asset pricing models, we use Equation 2 to estimate the pricing errors $\hat{\boldsymbol{\alpha}}_t = \mathbf{r}_t - \mathbf{B}_t \hat{\boldsymbol{\lambda}}_t$ for the different candidate models, followed by the panel regression

$$\hat{\alpha}_{i,t} = \sum_{j=1}^{I} \alpha_j 1_j(i) + \nu_{i,t} \tag{3}$$

The indicator function $I_j(i)$ becomes one if $j = i$ and zero else. We test whether the α_is are zero for all i, where we use again a robust covariance matrix estimator

[7] Each row corresponds to the transpose of the estimated vector of factor loadings from the regression $r_{i,\tau} = a_i + \mathbf{x}_\tau \mathbf{b}_{i,t} + e_{i,\tau}$ with $\tau \leqslant t-1$. We use data from the 36 months preceding t for estimation.

[8] Obviously, the same should hold true for individual stocks. However, throughout our analysis, we work with fund return rates.

that allows for heteroscedasticity and autocorrelation of $\nu_{i,t}$ over time and for cross correlation of the errors in a given month between assets i and j, $i \neq j$.

3.2 Performance of fund cross sections

We assess the performance of the cross sections of individual funds that invest in domestic and foreign listed real estate separately with the bootstrap approach of Kosowski et al. (2006).[9] The basic idea of the approach is intuitive: given a cross section of funds, we could run Equation 1 for each fund separately and estimate the $\hat{\alpha}_i$.[10] We can then rank the funds based on the $\hat{\alpha}_i$ estimates. Such a relative ranking is always possible and will give, for instance, a best and a worst fund. But this does not necessarily mean that the best fund is also a *good* fund. The manager of the best fund could have been just lucky.

In our context, it could happen that a larger share of global than domestic funds seems to perform well simply due to luck. Inference is complicated by the facts that financial return rates are heteroscedastic and non-normal and that funds can enter and exist the cross section. Kosowski et al. (2006) suggest a bootstrap approach to simulate the distribution of t-statistics under the null that no fund manager has skill and that the funds are ranked by their measured performance. These simulated t-statistic distributions under the null are then used to assess the significance of the actual t-statistics.

The bootstrap approach works as follows. First, using the estimated $\hat{\boldsymbol{\beta}}_i$ and the residuals from the regression in Equation 1, return rate histories $r^b_{i,t} = \mathbf{x}_t\hat{\boldsymbol{\beta}}_i + \hat{\epsilon}^b_t$ are simulated for each fund i, where $\hat{\epsilon}^b_t$ is drawn randomly (with replacement) from the set of actual residuals for this month.[11] Observe that the null of no skill is imposed on the simulated return rates. The simulated return rate history is then used in regression Equation 1 as the dependent variable which results in estimates of $\hat{\alpha}^b_i$, $\hat{\boldsymbol{\beta}}^b_i$ and new residuals. We are only interested in the t-statistic of $\hat{\alpha}^b_i$, generated under the null. For given b, this leads to I t-statistics, which can be ranked by size. Repeating this simulation B times, we end up with B realisations of the largest t-statistics, B realisations of the second largest t-statistic and so on, each generated under the null. This simulated null distribution, which takes ranking into account, allows the appropriate p-values for testing.

[9] We implement the extended version which allows for cross-sectional correlation in the errors, see section C. in Kosowski et al. (2006, IV.) for details.

[10] We will focus in the empirical implementation on the t-statistics for the estimated alphas as these have better statistical properties and take a fund's risk taking into account, see Kosowski et al. (2006, p. 2558).

[11] We estimate individual equations here, because fund histories cover different time periods.

3.3 Fund performance and characteristics

Given the pricing errors $\alpha_{i,t}$ of actively managed funds, are there characteristics that help explain the magnitude of these errors? We examine this with the panel regression[12]

$$\hat{\alpha}_{i,t} = \alpha_i + \mathbf{z}_{i,t}\boldsymbol{\theta} + \nu_{i,t} \tag{4}$$

The dependent variable for a fund is computed as the monthly return rate of the fund in excess of the risk-free rate minus the required return rate estimated from a portfolio of funds that have a similar size with respect to assets under management. $\mathbf{z}_{i,t}$ contains a list of explanatory variables, such as *outsourcing* and *team-management.* The robust standard errors allow for possible heteroscedasticity, autocorrelation, and cross correlation in the $\nu_{i,t}$s.

3.4 Regional timing and picking skills

Skilled fund managers will generate return rates above those generated by the average investor by investing in the right regions at the right time (regional *timing*) and by investing in the right stocks within the regions (regional *picking*). To examine this, we follow Kacperczyk et al. (2014) and decompose the relative return rate generated by fund i to a benchmark, into a regional *timing* and a regional *picking* component.

$$Timing_t^i = \sum_{k=1}^{K}(w_{k,t}^i - w_{k,t}^m)\mathbf{x}_{t+1}\boldsymbol{\beta}_{k,t} \tag{5}$$

and

$$Picking_t^i = \sum_{k=1}^{K}(w_{k,t}^i - w_{k,t}^m)(r_{k,t+1} - \mathbf{x}_{t+1}\boldsymbol{\beta}_{k,t}) \tag{6}$$

where K denotes the number of regional markets in which fund i and the benchmark could have invested in, such as U.S., Pacific Asia, Europe, Middle East and Africa, Latin America, and others. $w_{k,t}^i$ is the weight invested in region k by fund i at t. $w_{k,t}^m$ is the weight in region k in the chosen benchmark at t. We assume that $w_{k,t}^i \geqslant 0$. $r_{k,t}$ is the return rate of assets in region k. To implement this decomposition, we estimate the betas with rolling windows (see footnote 7) and use $\mathbf{x}_{t+1}\mathbf{b}_{k,t}$ in Equation 5 and $r_{k,t+1} - \mathbf{x}_{t+1}b_{k,t}$ in Equation 6. We use the robust panel regression model of Equation 4 to explain the variation of these measures over time with fund characteristics in the same manner as Kacperczyk et al. (2014).

[12]We also implemented the Fama and MacBeth (1973) cross-sectional regression used in Chen et al. (2013) to derive robust inferences.

4 Data

4.1 Mutual Fund Data

We consider the monthly performance of GREMFs from January 1992 to December 2016. The data for GREMFs (or global funds) come from the survivor-bias free U.S. mutual fund database of the Center for Research in Security Prices (CRSP). This database provides a comprehensive coverage of mutual funds, including monthly return rates, size (total net asset values), expense ratio, turnover, and load. From December 2002 onward, the database also provides details of the security holdings in fund portfolios.[13]

In line with earlier studies, we start our sample in January 1992 and we cover the period up to December 2016. The focus of our study is an examination of the performance of U.S.-registered GREMFs. In the CRSP database, the GREMFs are classified by CRSP[14] as U.S.-based equity funds investing more than 25% of their assets in foreign real estate securities.[15] We only focus on the actively managed GREMFs, and exclude the passively[16] managed index funds from our data. To address the incubation bias (Evans, 2010), we exclude the returns from the period before a fund received a ticker[17] from NASDAQ. As for all funds, we do not impose an additional filter for fund size but require that a fund has been in existence for a minimum of three years to reduce the regression estimation error.

Mutual funds tend to offer different shareclasses[18] to investors, even though the returns come from the same portfolio. The data report net return rates for each fund shareclass separately. For each fund and month, we compute the weighted net fund return rate by averaging over the net return rates of a fund's different shareclasses using, as weights, the ratios of shareclass net assets to the fund's total net assets (TNA). The resulting net return rate is what the average investor receives when investing in the fund. Shareclass aggregation prevents newly-created shareclasses of a fund from causing duplication of return data that comes, effectively, from the

[13]The method used to identify portfolio holdings is explained in Appendix 1.

[14]CRSP mutual funds adopt the classification and codes provided by CRSP Style Code, based on the information from fund prospectuses and their investments.

[15]There are two types of GREMFs: Global Real Estate (GRE) and International Real Estate (IRE) defined by the proportions of real estate investment outside the U.S. GRE are funds that invest at least 25% but less than 75% of their equity portfolio in shares of companies engaged in the real estate industry that are strictly outside of the U.S. or whose securities are principally traded outside of the U.S. IRE are funds that invest at least 75% of their equity portfolio in shares of companies engaged in the real estate industry that are strictly outside of the U.S. or whose securities are principally traded outside of the U.S.

[16]We follow the procedure of Gil-Bazo and Ruiz-Verdu (2009) to identify passively-managed funds - details of the procedure are presented in A.2

[17]A ticker is an abbreviation used to uniquely identify publicly traded shares of a particular stock on a stock market.

[18]Shareclasses can differ regarding their front- and back-end loads paid to brokers, and the contribution to annual operating expenses of portfolio management.

same portfolio. We also repeat the same procedure to aggregate the institutional (and retail) share classes as institutional (and retail) funds.

The *Outsource* variable is defined using the same approach as Chen et al. (2013). We categorize a fund as being outsourced by comparing its family complex name to its investment advisory company(ies) name(s). There might be up to two advisors that manage a fund. If none of these names of advisors matches the fund family complex, we can identify this fund as being outsourced. Since some advisors with different names may still be affiliated, we also look into the form ADV for every family complex.

Table 1 shows, for each year of the sample period, the number of such active GREMFs (N_t), the total net asset value of GREMFs industry ($\text{TNA}_t = \sum \text{TNA}_{i,t}$), and the concentration in the GREMFs sector as measured by the Herfindahl Index.

$$H_t = \sum_{i=1}^{N_t} \left(\frac{\text{TNA}_{i,t}}{\text{TNA}_t} \right)^2 \tag{7}$$

The second and the third columns show that the number of funds and money under management were mostly increasing throughout the period. The growth of the sector also resulted in a less concentrated distribution of funds, implied by the decreasing figures for the Herfindahl Index. The GREMF investment by regions is shown in Table 2. Analysis of fund portfolio holdings using the information available since 2002 reveals that, on average, about 60% of funds' assets are invested in U.S. real estate securities, 20% in Pacific Asian markets, 15% in European markets and the remaining funds in the African, Latin American and Middle Eastern markets. It is evident that there is a shift of investments from the U.S. to Pacific Asian and European markets after 2010.

[Table 1 about here]

[Table 2 about here]

4.2 Real Estate Benchmark Data

The choice of a passive real estate benchmark against which to consider the performance of GREMFs requires an understanding of the risk exposure of their portfolios. As GREMFs hold predominantly global REITs and REOCs, we have two choices: the FTSE/EPRA/Nareit U.S. Real Estate Index with the FTSE/EPRA/Nareit Global Real Estate Index; and the Wilshire US Real Estate Securities Index (RESI) with the Wilshire Global RESI. We use the former, which is constructed to represent the real estate equities market in most developed regions worldwide, covering over 95% of the global markets and with a similar risk profile to GREMFs. These indices are available from the start date of our data in 1992, whereas the Wilshire Global RESI starts in 1993. However, we correlated the monthly returns for the two sets of indices and they are very close to one: from 1993-2016, the two global indices correlate at 93.8% and the two U.S. indices correlate at 99.6%; and from 1992-2016, the two U.S. indices correlate at 99.3%.

In section 5, we consider several benchmark pricing models, alone, with the U.S. domestic real estate index, and with both the U.S. domestic real estate index and a global index. In the last of these cases, we remove the U.S. component of the global index by regressing the global index on the domestic index and extracting the residuals as an orthogonalized international real estate factor.

Table 3 gives summary statistics for the value-weighted[19] and equal-weighted portfolios of global and domestic REMFs, and the global and domestic real estate indices, of monthly returns in excess of the risk-free rate from January 1992 to December 2016.

[Table 3 about here]

On average, DREMFs generated higher excess returns than their global counterparts, and the domestic real estate index beat the global real estate index. In addition to lower excess returns, the GREMF industry is less volatile than the DREMF industry, as indicated by its smaller standard deviation. This calls for a risk-adjusted measure for the performance of GREMFs.

5 Empirical Results

5.1 Introduction

Our interest is in whether the managers of GREMFs have skills. First, we consider whether GREMFs provide diversification benefits over DREMFs. We are also interested in whether GREMFs, overall as a sector and as individual funds, can produce outperformance, both gross and net, against an appropriate risk-adjusted benchmark. For the sector as a whole, we examine the time pattern of performance by estimating rolling windows. We consider which factors explain performance, specifically we assess the effect of outsourcing. We extend this analysis to an examination of whether fund managers have skills in the timing of the geographical structure of their portfolios or in picking stock, and which factors explain each of these. And we are interested in both institutional and retail share classes.

[19] We use total net assets of each fund as the weights.

5.2 The Diversification Benefits of the GREMF Industry

We use net returns and consider three measures of risk-adjusted returns: the Sharpe Ratio, the Treynor Ratio and the Manipulation-Proof Performance Measure (MPPM). The last of these was developed by Goetzmann et al. (2007) because they assessed that most performance measures could be manipulated by managers to improve their apparent performance. For the MPPM, we use three different values of the parameter in line with Alcock et al. (2013). In Tables 4, 5, 6, we test for significant differences in the ratios between DREMFs and GREMFs, overall, and separately for institutional and retail funds.

The broad pattern is consistent across the measures. For all funds, 1993 was significantly better for GREMFs but 1992 and 1994 were significantly worse. Then, from the early 2000s until the Global Financial Crisis, GREMFs tended to do significantly better. Thereafter, with the exceptions of 2009 and 2012 for some measures, GREMFs consistently did significantly worse. The broad patterns are repeated when institutional and retail funds are considered separately. Overall, whichever ratio is used, for 1992-2016 as a whole, GREMFs always perform significantly worse. In comparison to Shen et al. (2012), who appear to use gross returns and only consider 1998-2008, the pattern of the signs of the differences is predominantly the same but the pattern of significance is different. Nonetheless, their overall conclusion is the same: GREMFs perform worse.

[Table 4, 5, 6 about here]

5.3 Choosing Benchmarks

We turn now to consideration of performance against benchmarks. The first stage is to choose an appropriate benchmark pricing model. If the pricing model explains the expected returns of an asset, the constant in the time series regression of the asset returns on the model factors should be zero. We undertook two tests on passively-managed global funds: a joint alpha test based on a GMM approach using time-series regressions for ten decile portfolios on risk factors (Fama and French, 2018); and a joint alpha test using a robust panel approach on pricing errors derived from Fama and MacBeth (1973) two-stage approach. We tested a wide range of possible international benchmarks: the CAPM, the Fama-French three-factor model; the Carhart four-factor model; the Fama-French five-factor model; and the Fama-French five-factor model with the Carhart momentum factor. We also tested each of these alone, then with the U.S. domestic RE index added, and then with the orthogonalized international index added; and we also tested the RE indices alone. The results are shown in Table 7. We required that, to be selected, a benchmark must pass both tests, with and without the RE indices. Only the CAPM and the Fama-French three-factor models pass, so we use only these for subsequent analyses.

[Table 7 about here]

5.4 The Performance of the GREMF Industry

5.4.1 Estimates of Alpha for the Full Period

We start by considering the GREMF sector as a whole. Table 8 presents the results for the CAPM and the Fama-French three-factor benchmarks, both with and without the RE factors, and using equally-weighted and value-weighted portfolios. The results are shown separately for institutional and retail funds. A number of patterns emerge:

- all of the gross figures for equally-weighted portfolios are positive, but they are never significantly different from zero;
- half of the net figures for equally-weighted portfolios are positive and half are negative, but they are never significantly different from zero;
- 14 of the gross figures for value-weighted portfolios are positive and four are negative, but they are never significantly different from zero;
- three of the net figures for value-weighted portfolios are positive and 15 are negative, but they are never significantly different from zero;
- taken together these last four points suggest that larger funds do worse;
- the outperformance is always lower when the real estate factors are included but it is never significantly different from zero; and
- there is no material difference between institutional and retail portfolios.

Thus, there is no evidence that, as a sector, GREMFs are able to produce risk-adjusted outperformance.

[Table 8 about here]

5.4.2 Rolling Window Estimates of Alpha

We also produce 36-month rolling window estimates of outperformance (alpha) and of the risk-pricing factors (betas). These are shown in Figure 1 for the Fama-French three-factor model. We might have expected some outperformance in the earlier period because, arguably, the underlying real estate markets were less efficient and transparent. However, it is clear that there was no significant out- or underperformance in any period, which is consistent with the previous result.

For the risk factors, the Fama-French size (SMB) and value/growth (HML) factors were very rarely priced. But the market beta was almost always priced and has a value of around 0.4. The domestic real estate factor was always priced but the orthogonalized international real estate factor was not consistently priced until around 2006. This suggests a maturing market and a greater awareness of a systematic risk that needed to be priced.

[Figure 1 about here]

5.5 The Performance of Individual GREMF Funds

5.5.1 Estimates of Alpha

Next, we consider the performance of individual funds. The results are presented in Table 9, for gross and net returns, and for all funds and, separately for institutional funds and retail funds. Again, there is no evidence of significant outperformance, even before expenses are deducted. But there is evidence of underperformance for the worst two funds and, at 10% significance, for the worst 10% of funds. When expenses are deducted, the bottom 10% of funds display underperformance. Thus, while we can find no evidence of performance driven by skills rather than good luck, we do find substantial evidence of poor performance as a result of lack of skills rather than bad luck.

[Table 9 about here]

5.5.2 Explaining Alpha

Now, we investigate the relationship between fund performance, as measured by fund net alpha, and outsourcing and team management. We adopt the basic approach of Chen et al. (2013). For each benchmark, we estimate two models: first with expenses, size, age, previous period's return and previous period's net inflow of funds; then we add the number of funds and the value of the funds in the fund family. The results are shown in Table 10.

We have one striking finding - outsourcing has a significantly positive effect on performance, at 5% in 10 of the models and 10% in the other two. These positive results are the opposite of those of Chen et al. (2013) for U.S. domestic mutual funds and Chuprinin et al. (2015) for global mutual funds, but are consistent with the findings of Coval and Moskowitz (2001) and Bernile et al. (2015) on the importance of local knowledge and information asymmetry in performance. Given the local nature of real estate markets, it is not difficult to see the greater importance of local knowledge and expertise in real estate investments compared to stocks in other sectors. The general negative effect of outsourcing has been attributed to a principal-agent problem by Chen et al. (2013) and to preferential treatment of in-house funds by Chuprinin et al. (2015). Whatever the merits of these arguments in the context of global real estate funds, they are outweighed by the benefits of specialist local knowledge from subcontracting.

None of the other variables is significant at 5% but there is some evidence at 10% in the CAPM models of team management having a positive effect and fund size having a negative effect. The lack of significant variables is, perhaps, to be expected given the small sample size.

[Table 10 about here]

We repeat the analysis using a panel approach, which allows us to incorporate the NBER recession variable to test whether performance is better or worse during recessions. The results are shown in Table 11. The key result of a positive effect on outsourcing now holds at 10% for 10 of the 12 models but the recession variable is never significant.

[Table 11 about here]

To be sure that the outsourcing result is not an artefact of our methods, we use the same approach to examine all global mutual funds. The results are shown in Tables 12 and Table 13 are very clear: for all global funds, in direct contrast to GREMFs, outsourcing always has a significantly negative effect for either approach. This is consistent with the results of Chen et al. (2013) and Chuprinin et al. (2015). Size tends to have a negative effect on performance, and fund family size always has a positive effect.

[Table 12 and 13 about here]

5.5.3 Geographical Timing and Stock Picking

We turn now to the issue timing and stock picking as examined by Kacperczyk et al. (2014). However, as we do not have details of fund holdings, we have adapted their method to consider geographical regions rather than individual stocks. We assess whether fund managers have skills in investing in the right region at the right time, and whether they have skills in picking good stock. Recall that Kacperczyk et al. (2014) argue that a fund with timing ability overweights high beta stocks (in our case high beta regions) when the market is expected to rise, and underweights when the market is expected to fall; and a fund with high picking ability overweights assets that have high idiosyncratic returns and underweights assets with low idiosyncratic returns. We are interested in the time patterns as well as in the overall effects. To ensure a large enough sample, we start the analysis in 2003. We undertake the analysis with the global RE-CAPM which utilized the global real estate index.[20] The results are shown in Table 14. When the regional timing is significant, with the exception of the Global Financial Crisis year of 2008, it is positive. In contrast, the significant effects of picking are evenly balanced between positive and negative. Overall, however, neither is significant in any of the models.

[Table 14 about here]

Finally, we use the approach of the analyses reported in Tables 10 and 12 to consider which factors explain the geographical timing and the stock picking. We add the NBER recession variable. The results are shown in Table 15. There are three significant results:

- picking skills are significantly greater for team management, perhaps suggesting the moderating effects of teams compared to individual decision-making;
- timing skills are significantly greater during periods of recession;
- at 10%, flow of funds is positively related to timing, which supports the smart money hypothesis of Gruber (1996), but could also be explained by greater opportunities to restructure portfolios when funds are flowing in.

These results differ from those of Kacperczyk et al. (2014) who, in their study of mutual funds, *excluding* sector funds, found that picking was poorer in recessions and that flow of funds was insignificant. They did not consider team management.

[Table 15 about here]

6 Conclusion

This paper has considered the performance of U.S.-registered, active, global real estate mutual funds (GREMFs) during 1992-2016 to establish whether the fund managers have genuine skills and can produce benefits from global diversification, or if their performance is the result of luck. We considered both the industry as a whole, and 76 individual funds, before and net of expenses, and we looked, separately, at institutional and retail share classes. We used the CRSP Mutual Fund database,

[20] We also used other benchmark models that passed the asset pricing tests, and found no material differences.

which is free of survivor biases, and we controlled for incubation bias. We applied a bootstrap procedure to separate genuine skills from luck.

First, to investigate the benefits from investing internationally, we compared GREMF performance to that of DREMFs using several ratios and found GREMF performance to be worse. Next, we tested a wide variety of benchmark models and only the CAPM and the Fama-French three-factor model passed the tests. We used these alone, then with a U.S. domestic real estate factor and, then, additionally, with an orthogonalized international real estate factor. We used these benchmarks to examine the performance of both the GREMF sector as a whole and of individual funds, and we used recursive estimates to consider the time trends in the performance of the sector. We found no evidence of outperformance for the sector during any time period. For individual funds, even *before* expenses are deducted we also found no evidence of skills, and evidence of lack of skills for the bottom two funds. When expenses are considered, we found evidence of lack of skills in the bottom 10% of funds but no real difference between institutional and retail funds.

We considered the impact on performance of outsourcing, team management and a variety of other variables. We find that outsourcing has a *positive* effect on GREMFs but a *negative* effect on global mutual funds as a whole. This is a new result in the literature. Then, we assessed whether fund managers have skills in the timing of geographical allocations and in stock selection. We found that, in those years in which there is an impact, it is generally positive for timing and equally positive and negative for stock selection but, over the full period, there is no evidence of skills in either. Finally, we showed that stock picking skills are positively associated with team, rather than individual management; and that timing is better during periods of recession and is positively associated with inflows on cash.

Thus, while GREMFs may be a convenient vehicle for international real estate investment, overall, our results suggest that there is no benefit to a U.S. domestic investor in investing in them.

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Table 1: U.S.-registered Active GREMFs Overview: Number and value of active GREMFs for the period 1992-2016. All numbers are for the respective year end. Total net asset value (TNA) is in millions of US dollars ($). Sector concentration of GREMFs is measured with the Herfindahl Index.

	All Funds			Institutional Funds		Retail Funds	
Year	Number	TNA	Concentration	Number	TNA	Number	TNA
1992	2	8.31	100.00	1	8.31		
1993	3	146.17	100.00	2	146.17		
1994	3	106.62	85.38	2	106.62		
1995	3	70.76	75.61	2	70.76		
1996	4	106.45	40.78	3	59.24	2	47.21
1997	7	634.40	48.81	6	217.63	3	416.77
1998	10	635.60	34.97	7	173.90	6	461.70
1999	10	962.70	43.08	7	106.90	6	855.80
2000	10	1057.00	48.00	8	92.70	6	964.30
2001	11	1250.90	33.95	8	205.50	7	1045.40
2002	11	1695.90	23.63	8	403.70	7	1292.20
2003	12	3061.50	20.25	8	857.90	8	2203.60
2004	15	5708.40	21.19	9	1447.70	11	4260.70
2005	19	8135.60	18.88	13	2461.50	14	5674.10
2006	34	17283.30	9.31	26	5960.60	28	11322.70
2007	52	23454.40	7.12	41	9987.00	44	13467.40
2008	69	15578.10	4.18	46	6274.20	57	9303.90
2009	71	20030.10	4.35	48	8430.40	59	11599.70
2010	65	24189.10	4.69	45	10420.40	55	13768.70
2011	68	24362.90	4.67	49	12239.70	59	12123.20
2012	66	33683.10	4.56	45	17723.40	56	15959.70
2013	70	38997.00	4.52	47	21063.50	60	17933.50
2014	77	45030.10	5.13	52	24550.60	66	20479.50
2015	82	44390.40	4.92	57	25755.80	67	18634.60
2016	82	40664.30	5.19	59	24485.20	67	16179.10

Table 2: U.S.-registered Active GREMFs Portfolio Decomposition by Regions: The table presents the percentage of regional risk exposure of the portfolio holdings of U.S.-registered active GREMFs during 2002-2016 (missing data pre-2006). The data are the averages over each year, presented in percentages.

		Regional Risk Exposure of Portfolio Holdings				
Year	U.S.	Pacific Asia	Europe	Africa	Latin America	Middle East
2002	86.09%	-	-	-	-	-
2003	93.80%	-	-	-	-	-
2004	89.85%	0.14%	-	-	-	-
2005	89.00%	-	-	-	-	-
2006	94.10%	1.99%	3.46%	0.45%	0.00%	0.00%
2007	82.84%	9.65%	6.73%	0.60%	0.18%	0.00%
2008	85.21%	6.99%	7.27%	0.24%	0.29%	0.00%
2009	93.65%	3.23%	2.73%	0.12%	0.28%	0.00%
2010	67.79%	17.81%	12.82%	0.78%	0.78%	0.02%
2011	51.72%	26.58%	19.78%	0.79%	1.05%	0.09%
2012	51.85%	29.34%	17.27%	0.74%	0.73%	0.06%
2013	49.84%	32.51%	16.56%	0.55%	0.49%	0.05%
2014	50.25%	30.20%	18.51%	0.50%	0.44%	0.10%
2015	54.06%	25.30%	19.60%	0.60%	0.28%	0.15%
2016	55.88%	24.94%	18.34%	0.50%	0.25%	0.11%

Table 3: REMF vs. Real Estate Stock Market Indices: This table presents summary statistics for monthly excess return rates of the value- and equal-weighted portfolio of active GREMFs, active DREMFs, the global real estate index (FTSE/NAREIT global countries index), and the domestic real estate index (FTSE/NAREIT U.S. real estate securities index), from January 1992 to December 2016.

	Global All Funds		Domestic All Funds		Index		Global Institutional		Global Retail	
	VW	EW	VW	EW	Global	Domestic	VW	EW	VW	EW
Mean	0.61	0.68	0.73	0.69	0.85	1.04	0.61	0.70	0.62	0.67
Median	0.74	0.97	1.02	1.02	1.16	1.31	0.83	0.93	1.01	0.96
Maximum	19.84	18.75	26.17	24.92	16.33	31.02	19.70	18.62	19.70	18.14
Minimum	-26.05	-25.91	-28.88	-28.44	-33.53	-31.67	-26.81	-25.86	-25.48	-25.38
Std. Dev.	4.87	4.84	4.96	4.83	5.19	5.46	5.09	4.90	4.92	4.94
Skewness	-0.69	-0.76	-0.78	-0.88	-1.07	-0.77	-0.67	-0.74	-0.77	-0.84
Kurtosis	6.64	6.66	10.06	10.15	9.49	11.41	6.31	6.45	7.31	6.82

Table 4: Global Diversification: This table presents the difference of risk-adjusted net returns between all GREMFs (GRE) and DREMFs (DRE) averaged over the year, including Sharpe ratio ($SR = \overline{r_i}/\sigma_i$), Treynor ratio ($TR = \overline{r_i}/\beta_i$), and Manipulation Proof Performance Measure ($MPPM = (1/(1-\rho)\Delta t)ln\left[1/T\sum_{t=1}^{T}((1+r_{i,t})/(1+r_f))^{1-\rho}\right]$), where ρ represents the chosen parameter of constant relative risk aversion, and has a value between 2-4 for market portfolios (Goetzmann et al., 2007).

	Sharpe Ratio			Treynor Ratio			MPPM(2)			MPPM(3)			MPPM(4)		
	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff
1992	0.14	0.37	-0.23***	0.51	1.35	-0.84**	2.26	3.14	-0.88	1.82	2.94	-1.12	1.37	2.74	-1.37
1993	0.88	0.40	0.473***	2.81	1.72	1.09*	16.45	4.14	12.31***	16.12	3.83	12.30***	15.79	3.51	12.29***
1994	-0.40	-0.13	-0.27***	-1.16	-0.93	-0.23	-7.75	-2.89	-4.86***	-8.06	-3.23	-4.83***	-8.36	-3.56	-4.80***
1995	0.22	0.26	-0.04	0.82	1.74	-0.91	3.86	4.67	-0.81	3.35	4.45	-1.11	2.84	4.24	-1.40
1996	0.64	0.74	-0.10	3.72	3.62	0.10	14.87	9.65	5.22	14.63	9.48	5.15	14.39	9.32	5.07
1997	-3.28	0.51	-3.79	1.31	2.79	-1.48	5.65	6.66	-1.01	5.19	6.37	-1.18	4.74	6.07	-1.34
1998	0.15	-0.39	0.54	-1.46	-3.11	1.64**	-8.15	-8.88	0.72	-8.90	-9.45	0.55	-9.68	-10.03	0.35
1999	-0.08	-0.14	0.06	-0.29	-1.32	1.03**	-2.59	-3.35	0.76	-3.11	-3.75	0.64	-3.60	-4.13	0.53
2000	0.28	0.34	-0.06	1.31	3.08	-1.76***	4.70	6.64	-1.93	4.25	6.24	-1.99	3.79	5.84	-2.05
2001	0.13	0.14	-0.01	0.81	1.21	-0.39	3.07	2.60	0.47	2.67	2.29	0.38	2.27	1.97	0.29
2002	0.10	0.08	0.02	0.44	0.63	-0.19	1.35	1.01	0.34	0.95	0.70	0.25	0.55	0.38	0.17
2003	1.15	1.11	0.04	3.34	4.09	-0.74***	15.39	13.18	2.21**	15.17	13.03	2.14**	14.94	12.87	2.07**
2004	0.65	0.51	0.14	3.07	3.73	-0.66	13.64	10.80	2.84*	12.95	9.92	3.03**	12.21	8.96	3.25**
2005	0.28	0.21	0.07*	1.16	0.97	0.20	5.16	3.27	1.90*	4.81	2.84	1.97*	4.45	2.40	2.05*
2006	1.02	0.74	0.28**	2.47	2.79	-0.32	12.30	10.72	1.59*	12.08	10.46	1.62*	11.86	10.21	1.66*
2007	-0.50	-0.28	-0.22	-1.80	-1.93	0.12	-10.75	-10.35	-0.40	-11.26	-11.03	-0.23	-11.77	-11.72	-0.05
2008	-0.54	-0.44	-0.10***	-5.44	-5.15	-0.29	-38.17	-38.93	0.75	-41.70	-44.17	2.47	-45.27	-49.50	4.23
2009	0.36	0.31	0.05	2.94	2.91	0.03	10.84	7.27	3.57***	8.20	3.53	4.67***	5.50	-0.27	5.77***
2010	0.27	0.33	-0.06***	1.51	1.98	-0.47***	6.34	8.14	-1.81***	5.48	7.36	-1.88***	4.62	6.57	-1.95***
2011	-0.09	0.03	-0.12***	-0.63	0.31	-0.94***	-5.48	-0.74	-4.74***	-6.49	-1.70	-4.79***	-7.50	-2.66	-4.84***
2012	0.60	0.55	0.05**	2.28	2.22	0.05	11.26	8.29	2.98***	10.88	7.99	2.89***	10.49	7.69	2.80***
2013	0.06	0.13	-0.07*	0.19	0.60	-0.40	0.31	0.73	-0.43	-0.14	0.32	-0.47	-0.60	-0.09	-0.50
2014	0.33	0.49	-0.16***	1.06	2.14	-1.08***	4.76	7.83	-3.07***	4.52	7.57	-3.05***	4.28	7.30	-3.02***
2015	0.00	0.06	-0.06***	0.00	0.45	-0.46*	-0.58	0.12	-0.67***	-0.85	-0.25	-0.60***	-1.12	-0.62	-0.50**
2016	0.06	0.13	-0.07***	0.27	0.74	-0.47***	0.49	1.68	-1.19***	0.08	1.23	-1.16***	-0.33	0.80	-1.12***
1992-2016	0.08	0.12	-0.04***	0.44	1.03	-0.59***	0.29	1.16	-0.86**	-0.73	0.08	-0.81**	-1.81	-1.07	-0.73*

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: Global Diversification: This table presents the difference of risk-adjusted net returns between institutional GREMFs (GRE) and institutional DREMFs (DRE) averaged over the year, including Sharpe ratio ($SR = \overline{r_i}/\sigma_i$), Treynor ratio ($TR = \overline{r_i}/\beta_i$), and Manipulation Proof Performance Measure ($MPPM = (1/(1-\rho)\Delta t)ln\left[1/T\sum_{t=1}^{T}((1+r_{i,t})/(1+r_f))^{1-\rho}\right]$), where ρ represents the chosen parameter of constant relative risk aversion, and has a value between 2-4 for market portfolios (Goetzmann et al., 2007).

	Sharpe Ratio			Treynor Ratio			MPPM(2)			MPPM(3)			MPPM(4)		
	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff
1992	0.14	0.39	-0.25	0.51	0.59	-0.19	2.26	3.08	-0.82	1.82	2.75	-0.93	1.37	2.62	-1.25
1993	0.88	0.56	0.32	2.18	2.17	0.01	16.45	10.01	6.44	16.12	9.72	6.41	15.79	9.42	6.38
1994	-0.40	-0.19	-0.21	-0.92	0.67	-1.59	-7.75	-2.64	-5.12	-8.06	-3.03	-5.03	-8.36	-3.42	-4.94
1995	0.22	0.30	-0.08	0.68	1.31	-0.63	3.86	4.42	-0.56	3.35	4.13	-0.79	2.84	3.85	-1.01
1996	0.66	0.92	-0.26	2.72	6.13	-3.41	15.13	16.03	-0.90	14.89	15.89	-1.00	14.66	15.75	-1.10
1997	-3.25	-0.41	-2.84	1.07	2.91	-1.85	5.72	6.93	-1.21	5.26	6.64	-1.38	4.81	6.35	-1.55
1998	-0.31	-0.37	0.07	-1.57	-3.45	1.88**	-11.36	-9.67	-1.70	-12.35	-10.22	-2.13	-13.38	-10.79	-2.60
1999	-0.11	-0.14	0.03	-0.24	-1.08	0.84*	-3.09	-3.54	0.45	-3.69	-3.94	0.25	-4.26	-4.32	0.07
2000	0.19	0.39	-0.20***	0.73	3.27	-2.55***	3.33	7.41	-4.09***	2.82	7.01	-4.19***	2.32	6.60	-4.28***
2001	0.09	0.15	-0.06	0.35	1.21	-0.86***	1.17	2.43	-1.25	0.66	2.14	-1.48	0.14	1.84	-1.71
2002	0.13	0.18	-0.05	0.47	0.73	-0.25	1.99	1.47	0.52	1.51	1.16	0.35	1.02	0.84	0.18
2003	1.06	1.26	-0.20	2.74	4.41	-1.67***	16.48	13.81	2.66**	16.18	13.67	2.51*	15.89	13.53	2.36*
2004	0.65	0.47	0.18*	2.64	3.56	-0.92**	14.30	11.01	3.30**	13.58	10.10	3.48**	12.81	9.13	3.69**
2005	0.32	0.98	-0.66**	1.22	0.90	0.32	6.27	3.82	2.45	5.92	3.39	2.52	5.56	2.96	2.60
2006	1.15	0.80	0.35**	2.36	2.90	-0.54	13.03	11.45	1.58	12.82	11.20	1.62	12.60	10.95	1.66
2007	-0.57	-0.38	-0.19	-1.85	-1.88	0.03	-11.43	-11.01	-0.42	-11.92	-11.70	-0.22	-12.40	-12.38	-0.02
2008	-0.54	-0.37	-0.16***	-4.39	-3.76	-0.62	-31.84	-28.38	-3.46	-34.85	-32.91	-1.94	-37.99	-37.79	-0.20
2009	0.41	0.29	0.13*	3.09	3.00	0.09	12.33	8.09	4.24***	9.79	4.39	5.40***	7.19	0.62	6.57***
2010	0.26	0.34	-0.08***	1.41	1.89	-0.48***	6.08	7.87	-1.79***	5.20	7.09	-1.89***	4.31	6.30	-1.99***
2011	-0.45	0.04	-0.49	-0.73	0.24	-0.97***	-6.14	-1.14	-5.00***	-7.15	-2.09	-5.06***	-8.16	-3.05	-5.12***
2012	0.61	0.52	0.09***	2.27	1.98	0.29**	11.58	8.55	3.03***	11.18	8.25	2.93***	10.77	7.94	2.83***
2013	0.05	0.07	-0.02	0.16	0.30	-0.14	0.21	0.59	-0.38	-0.24	0.18	-0.42	-0.70	-0.23	-0.46
2014	0.31	0.47	-0.17***	0.98	1.89	-0.91***	4.44	7.33	-2.89***	4.20	7.07	-2.87***	3.95	6.80	-2.84***
2015	0.00	0.03	-0.03**	0.00	0.17	-0.17***	-0.62	-0.08	-0.54**	-0.89	-0.44	-0.45*	-1.17	-0.80	-0.36
2016	0.05	0.11	-0.06***	0.23	0.60	-0.37***	0.31	1.49	-1.17***	-0.09	1.06	-1.15***	-0.50	0.64	-1.13***
1992-2016	0.07	0.12	-0.05***	0.36	0.92	-0.56***	-0.04	1.00	-1.03**	-1.05	-0.10	-0.95*	-0.50	-1.29	-0.79*

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6: Global Diversification: This table presents the difference of risk-adjusted net returns between retail GREMFs (GRE) and retail DREMFs (DRE) averaged over the year, including Sharpe ratio ($SR = \overline{r_i}/\sigma_i$), Treynor ratio ($TR = \overline{r_i}/\beta_i$), and Manipulation Proof Performance Measure ($MPPM = (1/(1-\rho)\Delta t) ln \left[1/T \sum_{t=1}^{T}((1+r_{i,t})/(1+r_f))^{1-\rho}\right]$), where ρ represents the chosen parameter of constant relative risk aversion, and has a value between 2 and 4 for market portfolios (Goetzmann et al., 2007).

	Sharpe Ratio			Treynor Ratio			MPPM(2)			MPPM(3)			MPPM(4)		
	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff	$\overline{GRE}$	$\overline{DRE}$	Diff
1992		0.34			1.63			3.69			3.51			3.34	
1993		0.16			1.36			1.81			1.46			1.11	
1994		-0.08			-0.82			-1.90			-2.26			-2.61	
1995		0.31			1.91			4.93			4.71			4.49	
1996	1.48	0.65	0.83	10.01	3.55	6.46	38.52	9.98	28.54	38.21	9.80	28.41	37.91	9.62	28.28
1997	-10.65	0.69	-11.33	-0.73	2.58	-3.31	-4.54	6.15	-10.69	-4.72	5.86	-10.59	-4.90	5.58	-10.48
1998	0.46	-0.26	0.72	-1.12	-3.12	1.99*	-5.74	-8.74	3.00	-6.24	-9.32	3.09	-6.75	-9.92	3.17
1999	-0.09	-0.14	0.06	-0.36	-1.46	1.10***	-2.31	-3.48	1.17	-2.68	-3.85	1.17	-3.04	-4.21	1.17
2000	0.37	0.36	0.01	1.73	3.14	-1.41***	6.39	6.36	0.03	5.99	5.97	0.02	5.60	5.58	0.02
2001	0.12	0.15	-0.03	0.92	1.11	-0.19	3.65	2.36	1.30	3.42	2.03	1.39	3.19	1.71	1.48
2002	0.11	0.19	-0.08	0.47	0.82	-0.36	1.57	1.43	0.13	1.26	1.14	0.12	0.95	0.85	0.11
2003	1.20	1.21	-0.02	3.22	3.89	-0.67**	14.01	12.93	1.08*	13.83	12.78	1.05*	13.66	12.63	1.03*
2004	1.15	0.54	0.61	3.17	3.77	-0.59	14.22	11.00	3.22	13.59	10.13	3.46	12.91	9.19	3.72
2005	0.29	0.18	0.11**	0.99	0.85	0.14	4.25	2.89	1.37**	3.91	2.46	1.46**	3.57	2.02	1.55**
2006	1.06	0.73	0.33**	2.50	2.46	0.04	12.53	10.43	2.10***	12.33	10.18	2.15***	12.13	9.93	2.20***
2007	-0.55	-0.36	-0.20	-1.89	-1.95	0.06	-11.22	-10.35	-0.87	-11.71	-11.03	-0.68	-12.21	-11.70	-0.50
2008	-0.55	-0.42	-0.12***	-5.66	-5.48	-0.18	-39.62	-41.84	2.22	-43.10	-47.26	4.16	-46.59	-52.71	6.12
2009	0.31	0.24	0.07**	2.80	2.82	-0.02	10.23	7.08	3.15**	7.63	3.36	4.27***	4.95	-0.43	5.39***
2010	0.26	0.35	-0.08***	1.48	2.00	-0.52***	6.18	8.28	-2.09***	5.34	7.49	-2.16***	4.48	6.70	-2.22***
2011	-0.09	0.05	-0.15***	-0.60	0.29	-0.89***	-5.21	-0.69	-4.53***	-6.17	-1.64	-4.53***	-7.13	-2.60	-4.53***
2012	0.59	0.50	0.09***	2.25	2.23	0.02	11.14	8.13	3.00***	10.75	7.84	2.91***	10.36	7.54	2.82***
2013	0.05	0.10	-0.05	0.16	0.63	-0.47	0.14	0.69	-0.55	-0.30	0.28	-0.59	-0.76	-0.13	-0.62
2014	0.34	0.52	-0.19***	1.08	2.24	-1.15***	4.85	8.03	-3.19***	4.61	7.77	-3.16***	4.36	7.50	-3.13***
2015	-0.01	0.04	-0.05***	-0.01	0.53	-0.54*	-0.64	0.17	-0.81***	-0.91	-0.22	-0.69***	-1.18	-0.61	-0.57**
2016	0.06	0.13	-0.07***	0.28	0.77	-0.49***	0.49	1.74	-1.25***	0.07	1.29	-1.22***	-0.33	0.85	-1.18***
1996-2016	0.08	0.11	-0.04**	0.42	1.02	-0.60***	0.25	1.04	-0.80**	-0.74	-0.06	-0.68*	-1.79	-1.25	-0.54*

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 7: Asset Pricing Tests of Global Funds: Panel A shows the Wald joint test (jointly equals zero) on alphas estimated from the panel of equally-weighted decile portfolios of all passively-managed global funds. The robust covariance matrix (Kiefer and Vogelsang, 2002) estimator is implemented during GMM estimation. Panel B shows the Wald joint test (jointly equal zero) on pricing errors estimated from the panel regression of pricing errors of all passively-managed global funds. The robust covariance matrix (Driscoll and Kraay, 1998) estimator is implemented during panel estimation. The time-series of pricing error are estimated from the equally-weighted portfolios of all passively-managed global funds, based on the Fama and MacBeth two-stage approach. In the first stage, for every three years, all passively-managed funds existed are sorted according to fund size, and formed as ten equal-weighted decile portfolios. The time-series of each portfolio excess return is regressed against the risk-factor models using 36-month rolling windows with a one-month step, to get the risk factor loadings for each portfolio. In the second stage, at each month, the cross-sectional regression of each passive global fund returns is run against the decile portfolio risk-factor loadings obtained from the first stage, to get the time-series of risk premia. All asset pricing models have been tested three times: the original; the one augmented with domestic real estate factor; the one augmented with both domestic and orthogonalized global real estate factors.

	Panel A: GMM Regression Wald Test of Pricing Errors																
	RE		CAPM			FF3			Carhart			FF5			FF5+MOM		
Test-Stat	19.232	16.886	5.103	7.593	8.329	14.609	15.138	14.565	17.920	18.452	17.642	36.750	36.580	33.835	38.004	37.779	35.048
P-value	0.04	0.08	0.88	0.67	0.60	0.15	0.13	0.15	0.06	0.05	0.06	0.00	0.00	0.00	0.00	0.00	0.00
	Panel B: Panel Regression (Driscoll and Kraay, 1998) Wald Test of Pricing Errors																
	RE		CAPM			FF3			Carhart			FF5			FF5+MOM		
Test-Stat	12.660	12.200	5.520	5.230	4.970	14.290	14.460	13.080	16.100	16.290	15.530	22.190	22.660	21.340	24.890	25.290	23.220
P-value	0.24	0.27	0.85	0.88	0.89	0.16	0.15	0.22	0.10	0.09	0.11	0.01	0.01	0.02	0.01	0.00	0.01

Table 8: Performance of Equally-weighted and Value-weighted Portfolios of U.S.-registered Active GREMFs Relative to Global Market: This table presents the estimated alpha (annualized) and its t-statistic for different models for the period 1992-2016. The t-statistics are computed using the heteroscedasticity consistent standard errors (Kiefer and Vogelsang, 2002). The parametric p-value comes from a standard normal distribution, the bootstrapped p-value comes from the estimated empirical distribution of the t-statistic under the null.

	Equal-Weighted						Value-Weighted					
	CAPM			FF3			CAPM			FF3		
		RE(D)	RE(D&G)		RE(D)	RE(D&G)		RE(D)	RE(D&G)		RE(D)	RE(D&G)
Global All												
Gross Returns												
$\hat{\alpha}$	0.36	0.09	0.11	0.10	0.02	0.06	0.30	-0.01	0.01	0.03	-0.07	-0.03
Annual $\hat{\alpha}$	4.30	1.02	1.27	1.25	0.21	0.66	3.57	-0.07	0.17	0.33	-0.83	-0.39
$t_{\hat{\alpha}}$	1.47	0.64	0.89	0.52	0.15	0.50	1.17	-0.05	0.12	0.13	-0.57	-0.28
P-value Parametric	0.14	0.52	0.37	0.60	0.88	0.62	0.24	0.96	0.91	0.90	0.57	0.78
P-value Bootstrapped	0.15	0.52	0.36	0.60	0.85	0.62	0.22	0.95	0.90	0.89	0.56	0.80
Net Returns												
$\hat{\alpha}$	0.23	-0.04	-0.02	-0.02	-0.11	-0.07	0.18	-0.12	-0.10	-0.09	-0.18	-0.15
Annual $\hat{\alpha}$	2.81	-0.52	-0.27	-0.25	-1.30	-0.86	2.21	-1.47	-1.23	-1.03	-2.21	-1.78
$t_{\hat{\alpha}}$	0.96	-0.33	-0.20	-0.10	-0.93	-0.66	0.72	-0.94	-0.87	-0.40	-1.53	-1.30
P-value Parametric	0.34	0.74	0.84	0.92	0.35	0.51	0.47	0.35	0.39	0.69	0.13	0.19
P-value Bootstrapped	0.33	0.72	0.84	0.91	0.36	0.53	0.48	0.34	0.40	0.71	0.14	0.19
Global Institutional												
Gross Returns												
$\hat{\alpha}$	0.38	0.13	0.14	0.11	0.03	0.08	0.27	0.02	0.04	0.03	-0.05	0.01
Annual $\hat{\alpha}$	4.51	1.50	1.74	1.31	0.40	1.01	3.24	0.18	0.45	0.35	-0.60	0.11
$t_{\hat{\alpha}}$	1.58	0.80	1.06	0.56	0.24	0.66	1.07	0.09	0.25	0.14	-0.32	0.06
P-value Parametric	0.12	0.42	0.29	0.57	0.81	0.51	0.28	0.93	0.81	0.89	0.75	0.95
P-value Bootstrapped	0.16	0.51	0.27	0.54	0.86	0.53	0.23	0.90	0.80	0.86	0.74	0.98
Net Returns												
$\hat{\alpha}$	0.29	0.02	0.04	0.01	-0.07	-0.02	0.18	-0.09	-0.06	-0.07	-0.15	-0.09
Annual $\hat{\alpha}$	3.43	0.18	0.42	0.16	-0.84	-0.22	2.13	-1.02	-0.77	-0.79	-1.78	-1.08
$t_{\hat{\alpha}}$	1.20	0.13	0.28	0.07	-0.54	-0.15	0.71	-0.51	-0.44	-0.31	-0.98	-0.64
P-value Parametric	0.23	0.90	0.78	0.95	0.59	0.88	0.48	0.61	0.66	0.76	0.33	0.52
P-value Bootstrapped	0.22	0.87	0.79	0.94	0.60	0.90	0.52	0.64	0.69	0.71	0.36	0.55
Global Retail												
Gross Returns												
$\hat{\alpha}$	0.41	0.12	0.14	0.14	0.05	0.10	0.38	0.11	0.14	0.10	0.03	0.06
Annual $\hat{\alpha}$	4.96	1.40	1.73	1.65	0.65	1.19	4.57	1.36	1.65	1.23	0.34	0.77
$t_{\hat{\alpha}}$	1.54	0.89	1.25	0.61	0.44	0.89	1.45	0.79	1.06	0.48	0.23	0.54
P-value Parametric	0.13	0.38	0.21	0.54	0.66	0.38	0.15	0.43	0.29	0.63	0.82	0.59
P-value Bootstrapped	0.16	0.35	0.19	0.54	0.67	0.35	0.16	0.42	0.25	0.67	0.78	0.58
Net Returns												
$\hat{\alpha}$	0.29	0.00	0.03	0.01	-0.07	-0.02	0.25	-0.04	-0.01	-0.03	-0.11	-0.07
Annual $\hat{\alpha}$	3.44	0.01	0.39	0.11	-0.89	-0.29	3.00	-0.42	-0.12	-0.31	-1.30	-0.86
$t_{\hat{\alpha}}$	1.10	0.01	0.30	0.04	-0.66	-0.24	0.93	-0.26	-0.08	-0.11	-0.91	-0.64
P-value Parametric	0.27	0.99	0.76	0.97	0.51	0.81	0.35	0.79	0.93	0.91	0.37	0.52
P-value Bootstrapped	0.23	0.97	0.76	0.98	0.52	0.83	0.36	0.80	0.94	0.94	0.37	0.50

Table 9: Performance of Individual U.S.-registered Active GREMFs Relative to Global Combined Market: This table presents the estimated alphas (annualized) and their t-statistics for the period 1992-2016. The combined benchmark, specified as the Fama and French global three-factor, the single domestic real estate factor, and the orthogonalized global real estate factor, is used. The t-statistics are computed using robust standard errors. The parametric p-value comes from a standard normal distribution, the bootstrapped p-value comes from the estimated empirical distribution of the t-statistic under the null based on Kosowski et al. (2006) cross-sectional bootstrap approach, which is robust to auto-correlation, heteroskedasticity and cross-fund dependency.

	Ordered Cross Section of Fund Alphas and t-Statistics																		
	Bottom	2.	3.	4.	5.	10%	20%	30%	40%	Median	40%	30%	20%	10%	5.	4.	3.	2.	Top
	Global All																		
	Gross Returns																		
$\hat{\alpha}$	-0.32	-0.40	-0.43	-0.27	-0.20	-0.21	-0.23	-0.29	-0.12	-0.21	-0.09	-0.02	0.01	0.09	0.08	0.08	0.08	0.17	0.24
Annualized $\hat{\alpha}$	-3.81	-4.75	-5.14	-3.27	-2.43	-2.58	-2.81	-3.54	-1.48	-2.47	-1.03	-0.27	0.13	1.06	0.91	0.92	1.00	2.00	2.83
$t_{\hat{\alpha}}$	-2.60	-2.35	-1.89	-1.86	-1.82	-1.77	-1.40	-1.08	-0.89	-0.63	-0.33	-0.16	0.08	0.42	0.70	0.75	0.98	1.36	1.49
P-value Parametric	0.01	0.02	0.07	0.07	0.07	0.08	0.16	0.29	0.38	0.54	0.74	0.87	0.93	0.68	0.49	0.46	0.33	0.17	0.14
P-value Bootstrapped	0.45	0.31	0.55	0.35	0.22	0.07	0.06	0.11	0.20	0.26	0.49	0.66	0.55	0.97	0.96	0.99	0.94	0.99	1.00
	Net Returns																		
$\hat{\alpha}$	-0.33	-0.27	-0.57	-0.30	-0.30	-0.32	-0.25	-0.21	-0.18	-0.19	-0.27	-0.18	-0.06	-0.06	-0.01	0.03	0.11	0.06	0.13
Annualized $\hat{\alpha}$	-3.97	-3.30	-6.80	-3.62	-3.59	-3.86	-3.01	-2.58	-2.21	-2.34	-3.28	-2.17	-0.70	-0.73	-0.13	0.39	1.30	0.75	1.50
$\hat{t}_{\hat{\alpha}}$	-3.21	-2.56	-2.48	-2.41	-2.32	-2.24	-1.77	-1.55	-1.37	-1.15	-0.89	-0.80	-0.54	-0.32	-0.05	0.14	0.29	0.52	0.80
P-value Parametric	0.00	0.01	0.02	0.02	0.02	0.03	0.08	0.13	0.17	0.25	0.38	0.42	0.59	0.75	0.96	0.89	0.78	0.60	0.43
P-value Bootstrapped	0.13	0.12	0.04	0.01	0.01	0.02	0.05	0.02	0.07	0.13	0.34	0.22	0.14	0.17	0.28	0.98	0.99	0.94	1.00
	Global Institutional																		
	Gross Returns																		
$\hat{\alpha}$	-0.24	-0.43	-0.20	-0.34	-0.19	-0.24	-0.30	-0.15	-0.05	-0.07	-0.02	-0.01	0.03	0.04	0.06	0.04	0.07	0.17	0.08
Annualized $\hat{\alpha}$	-2.83	-5.19	-2.35	-4.14	-2.25	-2.87	-3.54	-1.86	-0.64	-0.80	-0.27	-0.08	0.36	0.53	0.73	0.46	0.90	2.01	0.94
$\hat{t}_{\hat{\alpha}}$	-1.91	-1.91	-1.86	-1.53	-1.45	-1.43	-1.08	-0.91	-0.54	-0.37	-0.14	-0.05	0.19	0.38	0.43	0.59	0.69	0.73	0.76
P-value Parametric	0.06	0.06	0.07	0.13	0.15	0.15	0.28	0.36	0.59	0.71	0.89	0.96	0.85	0.71	0.67	0.56	0.49	0.47	0.45
P-value Bootstrapped	0.84	0.54	0.33	0.52	0.45	0.28	0.24	0.13	0.16	0.21	0.27	0.91	0.90	0.99	0.99	1.00	1.00	1.00	1.00
	Net Returns																		
$\hat{\alpha}$	-0.30	-0.31	-0.54	-0.33	-0.28	-0.47	-0.23	-0.24	-0.25	-0.10	-0.09	-0.11	-0.04	-0.02	-0.17	-0.02	-0.02	-0.01	0.05
Annualized $\hat{\alpha}$	-3.55	-3.75	-6.44	-3.92	-3.34	-5.67	-2.78	-2.82	-2.98	-1.19	-1.03	-1.36	-0.49	-0.28	-2.09	-0.21	-0.21	-0.13	0.61
$\hat{t}_{\hat{\alpha}}$	-2.82	-2.53	-2.36	-2.28	-2.15	-2.10	-1.58	-1.39	-1.23	-0.95	-0.80	-0.65	-0.32	-0.22	-0.20	-0.17	-0.12	-0.05	0.22
P-value Parametric	0.01	0.01	0.02	0.03	0.03	0.04	0.12	0.17	0.22	0.35	0.42	0.52	0.75	0.83	0.84	0.86	0.90	0.96	0.82
P-value Bootstrapped	0.55	0.57	0.59	0.63	0.55	0.41	0.24	0.02	0.07	0.21	0.28	0.43	0.89	0.23	0.99	0.90	0.96	0.99	1.00
	Global Retail																		
	Gross Returns																		
$\hat{\alpha}$	-0.76	-0.43	-0.18	-0.19	-0.23	-0.19	-0.13	-0.09	-0.08	-0.04	-0.01	-0.01	0.03	0.23	0.07	0.08	0.08	0.17	0.24
Annualized $\hat{\alpha}$	-9.12	-5.14	-2.11	-2.23	-2.73	-2.29	-1.57	-1.07	-0.92	-0.45	-0.17	-0.07	0.36	2.80	0.84	0.92	1.01	2.00	2.83
$\hat{t}_{\hat{\alpha}}$	-2.30	-1.88	-1.64	-1.44	-1.36	-1.33	-1.07	-0.74	-0.45	-0.32	-0.14	-0.08	0.23	0.62	0.63	0.75	0.99	1.36	1.49
P-value Parametric	0.03	0.07	0.10	0.15	0.18	0.19	0.29	0.46	0.65	0.75	0.89	0.94	0.82	0.54	0.53	0.46	0.32	0.17	0.14
P-value Bootstrapped	0.20	0.08	0.04	0.02	0.07	0.02	0.02	0.00	0.01	0.43	0.76	0.99	0.98	1.00	1.00	1.00	1.00	0.96	0.98
	Net Returns																		
$\hat{\alpha}$	-0.33	-0.30	-0.90	-0.58	-0.31	-0.30	-0.23	-0.34	-0.40	-0.16	-0.17	-0.27	-0.11	-0.09	-0.13	-0.18	0.10	0.06	0.13
Annualized $\hat{\alpha}$	-3.97	-3.65	-10.79	-6.97	-3.76	-3.59	-2.77	-4.03	-4.81	-1.90	-2.03	-3.28	-1.31	-1.04	-1.54	-2.12	1.17	0.75	1.50
$\hat{t}_{\hat{\alpha}}$	-3.21	-2.86	-2.72	-2.56	-2.43	-2.27	-1.88	-1.69	-1.51	-1.36	-1.03	-0.89	-0.67	-0.43	-0.22	-0.20	0.26	0.52	0.80
P-value Parametric	0.00	0.01	0.01	0.01	0.02	0.03	0.06	0.09	0.14	0.18	0.31	0.38	0.50	0.67	0.83	0.84	0.80	0.60	0.43
P-value Bootstrapped	0.11	0.04	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.03	0.25	0.53	0.89	0.99	0.91	0.90	1.00	1.00	1.00

Table 10: Fund Performance vs. Fund Characteristics: This table presents Fama and MacBeth (1973) estimates of GREMF monthly gross benchmark-adjusted returns regressed against fund lagged characteristics and regional investments 2009-2016. The fund monthly gross benchmark-adjusted returns are calculated as the fund's gross returns minus the product of the observed risk factors and associated loadings from the benchmark models. *Outsource* is a dummy variable that equals one if the fund is outsourced. *Team* is a dummy variable that equals one if the fund is team-managed. $log(Size)$ is the logarithm of TNA of fund. $log(FaFd)$ is the logarithm of the number of funds in fund family. $log(FaSiz)$ is the logarithm of one plus the TNA of the family that the fund belongs to, excluding its own TNA. *Expense* is the annual expense ratio over the fund's assets under management. *Age* is the number of years since the inception of the fund. *Flow* is the percentage of new fund flow into the fund over the previous 12 months. *CumRet* is the cumulative gross return over the previous 12 months. The sample period is from January 2009 to December 2016 (96 months). The coefficients estimates are the time-series average of cross-section estimates from each month. The N range shows the number of funds included in the cross-section regression. The t-statistics are adjusted using robust Newey-West standard errors from lag 3. R^2 is the time-series average of monthly R^2 estimates. A similar approach was used in Chen et al. (2013).

	Bench-Adj Gross monthly r_t											
	CAPM		CAPM+RE(D)		CAPM+RE(D&G)		FF3		FF3+RE(D)		FF3+RE(D&G)	
$Outsource_{t-1}$	0.136	0.125	0.146	0.133	0.146	0.134	0.137	0.127	0.152	0.139	0.153	0.141
t-Stat	1.99	1.92	2.19	2.04	2.20	2.05	2.01	1.95	2.28	2.12	2.31	2.16
$Team_{t-1}$	0.056	0.088	0.057	0.089	0.061	0.092	0.053	0.083	0.045	0.078	0.049	0.081
t-Stat	1.13	1.73	1.13	1.78	1.22	1.81	1.06	1.62	0.90	1.52	0.97	1.59
$Expense_{t-1}$	-0.009	-0.006	-0.018	-0.005	-0.022	-0.009	-0.002	-0.007	-0.013	-0.002	-0.018	-0.007
t-Stat	-0.17	-0.12	-0.34	-0.09	-0.44	-0.18	-0.04	-0.14	-0.26	-0.04	-0.36	-0.14
$log(FaFd)_{t-1}$		-0.086		-0.083		-0.083		-0.075		-0.083		-0.082
t-Stat		-0.09		-1.11		-1.11		-1.00		-1.11		-1.09
$Log(Size)_{t-1}$	-0.012	-0.007	-0.025	-0.018	-0.027	-0.021	-0.007	-0.001	-0.010	-0.003	-0.013	-0.006
t-Stat	-0.85	-0.41	-1.70	-1.09	-1.85	-1.25	-0.45	-0.05	-0.72	-0.17	-0.89	-0.38
$log(FaSiz)_{t-1}$		-0.012		-0.014		-0.013		-0.012		-0.015		-0.014
t-Stat		-0.74		-0.86		-0.80		-0.77		-0.97		-0.87
Age_{t-1}	0.002	0.005	0.001	0.003	-0.001	0.003	0.003	0.005	0.002	0.005	0.002	0.005
t-Stat	0.13	0.36	0.04	0.23	-0.01	0.21	0.19	0.40	0.15	0.38	0.14	0.36
$CumRet_{t-1}$	-0.464	-0.542	-0.632	-0.704	-0.665	-0.741	-0.402	-0.452	-0.465	-0.546	-0.481	-0.563
t-Stat	-0.28	-0.52	-0.42	-0.52	-0.42	-0.51	-0.27	-0.30	-0.31	-0.37	-0.32	-0.38
$Flow_{t-1}$	0.001	0.003	0.002	0.002	0.002	0.002	0.002	0.001	-0.002	-0.001	0.002	-0.004
t-Stat	0.03	0.01	0.10	0.08	0.11	0.09	0.08	0.07	-0.12	-0.05	0.07	-0.18
N range	32-61	32-61	32-61	32-61	32-61	32-61	32-61	32-61	32-61	32-61	32-61	32-61
R^2	21.62%	23.13%	21.79%	23.30%	21.82%	23.31%	21.56%	23.05%	21.63%	23.15%	21.63%	23.13%

Table 11: Fund Performance vs. Fund Characteristics: This table presents the robust panel regression estimates of GREMF monthly gross benchmark-adjusted returns regressed against fund lagged characteristics and regional investments during 2009-2016. The fund monthly gross benchmark-adjusted returns are calculated as the fund's gross returns minus the product of the observed risk factors and associated loadings from the benchmark models. $Outsource$ is a dummy variable that equals one if the fund is outsourced. $Team$ is a dummy variable that equals one if the fund is team-managed. $log(Size)$ is the logarithm of TNA of fund. $log(FaFd)$ is the logarithm of the number of funds in fund family. $log(FaSiz)$ is the logarithm of one plus the TNA of the family that the fund belongs to, excluding its own TNA. $Expense$ is the annual expense ratio over the fund's assets under management. Age is the number of years since the inception of the fund. $Flow$ is the percentage of new fund flow into the fund over the previous 12 months. $CumRet$ is the cumulative gross return over the previous 12 months. The sample period is from January 2009 to December 2016. The t-statistics are adjusted using robust standard errors (Driscoll and Kraay, 1998).

	Bench-Adj Gross monthly r_t											
	CAPM		CAPM+RE(D)		CAPM+RE(D&G)		FF3		FF3+RE(D)		FF3+RE(D&G)	
$Outsource_{t-1}$	0.139	0.142	0.144	0.149	0.145	0.149	0.142	0.146	0.154	0.156	0.155	0.158
t-Stat	1.93	1.75	1.69	1.66	1.69	1.65	1.56	1.60	1.69	1.71	1.82	1.65
$Team_{t-1}$	0.072	0.079	0.075	0.077	0.071	0.079	0.076	0.072	0.076	0.076	0.074	0.076
t-Stat	0.98	1.11	0.93	1.13	0.63	1.10	0.90	1.13	1.20	1.22	1.16	1.18
$Expense_{t-1}$	-0.013	-0.014	-0.013	-0.014	-0.014	-0.014	-0.013	-0.013	-0.014	-0.014	-0.014	-0.014
t-Stat	-0.97	-0.98	-0.21	-0.19	-0.21	-0.20	-0.20	-0.19	-0.21	-0.20	-0.22	-0.20
$log(FaFd)_{t-1}$		-0.072		-0.071		-0.069		-0.074		-0.073		-0.072
t-Stat		-1.13		-1.08		-1.08		-1.15		-1.12		-1.03
$Log(Size)_{t-1}$	-0.013	-0.016	-0.015	-0.014	-0.026	-0.027	-0.020	-0.015	-0.016	-0.013	-0.013	-0.012
t-Stat	-1.52	-1.59	-1.62	-1.69	-1.82	-1.32	-1.91	-1.68	-1.72	-1.58	-1.59	-1.42
$log(FaSiz)_{t-1}$		-0.008		-0.006		-0.007		-0.008		-0.005		-0.006
t-Stat		-0.32		-0.25		-0.28		-0.29		-0.18		-0.23
Age_{t-1}	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
t-Stat	0.94	1.29	1.44	1.33	1.44	1.35	1.36	1.28	1.37	1.28	1.37	1.26
$CumRet_{t-1}$	-0.292	-0.297	-0.297	-0.297	-0.297	-0.297	-0.297	-0.297	-0.297	-0.297	-0.297	-0.297
t-Stat	-1.01	-1.41	-1.41	-1.32	-1.41	-1.41	-1.41	-1.41	-1.41	-1.41	-1.41	-1.33
$Flow_{t-1}$	0.018	0.018	0.017	0.017	0.017	0.017	0.018	0.018	0.018	0.018	0.018	0.018
t-Stat	0.62	0.67	0.61	0.60	0.60	0.61	0.67	0.68	0.64	0.64	0.63	0.62
$Recession_{t-1}$	-0.074	-0.084	-0.083	-0.085	-0.083	-0.086	-0.079	-0.081	-0.078	-0.079	-0.079	-0.081
t-Stat	-0.04	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.04
Constant	0.156	0.156	-0.013	-0.017	0.026	0.022	0.326	0.324	0.021	0.019	0.035	0.034
t-Stat	0.34	0.36	-0.03	-0.04	0.06	0.05	0.71	0.74	0.04	0.04	0.08	0.07
N	4683	4683	4683	4683	4683	4683	4683	4683	4683	4683	4683	4683

Table 12: Fund Performance vs. Fund Characteristics: This table presents Fama and MacBeth (1973) estimates of all global fund monthly gross benchmark-adjusted returns regressed against fund lagged characteristics during 2009-2016. The fund monthly gross benchmark-adjusted returns are calculated as the fund's gross returns minus the product of the observed risk factors and associated loadings from the benchmark models. $Outsource$ is a dummy variable that equals one if the fund is outsourced. $Team$ is a dummy variable that equals one if the fund is team-managed. $log(Size)$ is the logarithm of TNA of fund. $log(FaFd)$ is the logarithm of the number of funds in fund family. $log(FaSiz)$ is the logarithm of one plus the TNA of the family that the fund belongs to, excluding its own TNA. $Expense$ is the annual expense ratio over the fund's assets under management. Age is the number of years since the inception of the fund. $Flow$ is the percentage of new fund flow into the fund over the previous 12 months. $CumRet$ is the cumulative gross return over the previous 12 months. The sample period is from January 2009 to December 2016 (96 months). The coefficients estimates are the time-series average of cross-section estimates from each month. The N range shows the number of funds included in the cross-section regression. The t-statistics are adjusted using robust Newey-West standard errors from lag 3. R^2 is the time-series average of monthly R^2 estimates. A similar approach was used in Chen et al. (2013).

	Bench-Adj Gross monthly r_t											
	CAPM		CAPM+RE(D)		CAPM+RE(D&G)		FF3		FF3+RE(D)		FF3+RE(D&G)	
$Outsource_{t-1}$	-0.015	-0.024	-0.015	-0.023	-0.014	-0.022	-0.016	-0.025	-0.015	-0.024	-0.015	-0.023
t-Stat	-2.38	-2.62	-2.37	-2.61	-2.35	-2.59	-2.42	-2.66	-2.39	-2.63	-2.38	-2.62
$Team_{t-1}$	-0.007	-0.001	-0.007	-0.005	-0.007	-0.004	-0.008	-0.002	-0.008	-0.002	-0.008	-0.002
t-Stat	-0.18	-0.02	-0.17	-0.01	-0.17	-0.01	-0.20	-0.05	-0.20	-0.05	-0.20	-0.05
$Expense_{t-1}$	-0.085	-0.056	-0.085	-0.056	-0.084	-0.055	-0.081	-0.052	-0.082	-0.053	-0.081	-0.053
t-Stat	-1.78	-1.14	-1.79	-1.15	-1.76	-1.12	-1.70	-1.07	-1.72	-1.09	-1.71	-1.08
$log(FaFd)_{t-1}$		-0.025		-0.025		-0.026		-0.025		-0.025		-0.025
t-Stat		-1.12		-1.13		-1.13		-1.12		-1.11		-1.11
$Log(Size)_{t-1}$	-0.011	-0.025	-0.009	-0.023	-0.010	-0.025	-0.014	-0.029	-0.013	-0.027	-0.013	-0.028
t-Stat	-1.79	-2.66	-1.13	-2.46	-1.32	-2.61	-1.84	-3.01	-1.66	-2.86	-1.73	-2.92
$log(FaSiz)_{t-1}$		0.036		0.036		0.036		0.036		0.035		0.035
t-Stat		2.99		2.97		2.98		2.96		2.94		2.94
Age_{t-1}	0.004	0.003	0.004	0.003	0.004	0.003	0.004	0.003	0.004	0.003	0.004	0.003
t-Stat	1.21	1.09	1.20	1.08	1.20	1.08	1.23	1.12	1.23	1.11	1.22	1.11
$CumRet_{t-1}$	-0.130	-0.137	-0.130	-0.137	-0.131	-0.137	-0.130	-0.138	-0.131	-0.138	-0.130	-0.138
t-Stat	-1.29	-1.41	-1.29	-1.41	-1.30	-1.41	-1.29	-1.42	-1.30	-1.42	-1.29	-1.42
$Flow_{t-1}$	-0.004	-0.001	-0.004	-0.001	-0.004	-0.001	-0.004	-0.002	-0.004	-0.003	-0.004	-0.003
t-Stat	-0.20	-0.03	-0.22	-0.04	-0.21	-0.03	-0.18	-0.01	-0.18	-0.01	-0.18	-0.01
N	359-575	359-575	359-575	359-575	359-575	359-575	359-575	359-575	359-575	359-575	359-575	359-575
R^2	12.26%	12.41%	12.26%	12.41%	12.25%	12.41%	12.26%	12.41%	12.26%	12.41%	12.26%	12.41%

Table 13: Fund Performance vs. Fund Characteristics: This table presents the robust panel regression estimates of all global fund monthly gross benchmark-adjusted returns regressed against fund lagged characteristics during 2009-2016. The fund monthly gross benchmark-adjusted returns are calculated as the fund's gross returns minus the product of the observed risk factors and associated loadings from the benchmark models. *Outsource* is a dummy variable that equals one if the fund is outsourced. *Team* is a dummy variable that equals one if the fund is team-managed. $log(Size)$ is the logarithm of TNA of fund. $log(FaFd)$ is the logarithm of the number of funds in fund family. $log(FaSiz)$ is the logarithm of one plus the TNA of the family that the fund belongs to, excluding its own TNA. *Expense* is the annual expense ratio over the fund's assets under management. *Age* is the number of years since the inception of the fund. *Flow* is the percentage of new fund flow into the fund over the previous 12 months. *CumRet* is the cumulative gross return over the previous 12 months. The sample period is from January 2009 to December 2016. The t-statistics are adjusted using robust standard errors (Driscoll and Kraay, 1998).

	Bench-Adj Gross monthly r_t											
	CAPM		CAPM+RE(D)		CAPM+RE(D&G)		FF3		FF3+RE(D)		FF3+RE(D&G)	
$Outsource_{t-1}$	-0.024	-0.027	-0.021	-0.028	-0.026	-0.028	-0.027	-0.028	-0.027	-0.028	-0.027	-0.027
t-Stat	-2.06	-2.14	-2.07	-2.17	-2.08	-2.16	-2.04	-2.11	-2.06	-2.13	-2.06	-2.14
$Team_{t-1}$	-0.016	-0.003	-0.016	-0.003	-0.016	-0.003	-0.017	-0.002	-0.017	-0.002	-0.017	-0.002
t-Stat	-0.33	-0.06	-0.32	-0.06	-0.32	-0.07	-0.35	-0.04	-0.35	-0.04	-0.35	-0.04
$Expense_{t-1}$	-0.011	-0.022	-0.011	-0.022	-0.013	-0.023	-0.015	-0.026	-0.014	-0.025	-0.015	-0.025
t-Stat	-0.08	-0.15	-0.08	-0.15	-0.09	-0.16	-0.10	-0.17	-0.10	-0.16	0.10	-0.17
$log(FaFd)_{t-1}$		-0.075		-0.075		-0.075		-0.075		-0.075		-0.075
t-Stat		-1.33		-1.35		-1.32		-1.33		-1.33		-1.34
$Log(Size)_{t-1}$	-0.013	-0.014	-0.011	-0.012	-0.013	-0.013	-0.017	-0.017	-0.015	-0.016	-0.016	-0.016
t-Stat	-1.55	-1.71	-1.47	-1.60	-1.53	-1.68	-1.70	-1.88	-1.64	-1.80	-1.67	-1.83
$log(FaSiz)_{t-1}$		0.009		0.010		0.010		0.010		0.010		0.010
t-Stat		0.32		0.34		0.33		0.33		0.34		0.34
Age_{t-1}	0.006	0.007	0.006	0.007	0.006	0.007	0.005	0.006	0.005	0.006	0.005	0.006
t-Stat	0.80	0.94	0.81	0.94	0.81	0.94	0.79	0.92	0.79	0.93	0.80	0.93
$CumRet_{t-1}$	-0.154	-0.154	-0.154	-0.154	-0.154	-0.154	-0.154	-0.154	-0.154	-0.154	-0.154	-0.154
t-Stat	-0.93	-0.93	-0.93	-0.90	-0.93	-0.93	-0.93	-0.93	-0.93	-0.93	-0.93	-0.93
$Flow_{t-1}$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
t-Stat	-0.43	-0.40	-0.43	-0.37	-0.42	-0.39	-0.43	-0.40	-0.43	-0.40	-0.43	-0.40
$Recession_{t-1}$	0.122	0.121	0.122	0.121	0.122	0.121	0.122	0.121	0.122	0.121	0.122	0.121
t-Stat	0.77	0.77	0.78	0.75	0.77	0.77	0.77	0.77	0.77	0.77	0.77	0.77
Constant	-0.206	-0.363	-0.202	-0.357	-0.176	-0.332	-0.270	-0.426	-0.314	-0.469	-0.300	-0.455
t-Stat	-0.51	-0.86	-0.50	-0.81	-0.43	-0.79	-0.66	-1.01	-0.77	-1.11	-0.74	-1.08
N	46818	46818	46818	46818	46818	46818	46818	46818	46818	46818	46818	46818

Table 14: Regional Timing and Picking: This table presents the average and standard derivation of the regional timing and picking ability of all GREMFs. We adjust the method in Kacperczyk et al. (2014) using the regional risk exposure, to measure the regional timing and picking skills for fund i in region K, including U.S., Pacific Asia, Europe, Middle East and Africa, Latin America, and others. The regional timing and picking factors are defined in Equations 5 and 6.

	Global RE-CAPM			
Year	$\overline{Timing}$	$\sigma(Timing)$	$\overline{Picking}$	$\sigma(Picking)$
2003	1.24***	0.70	0.14	0.66
2004	0.63	2.26	-0.43***	0.72
2005	1.17***	1.90	-0.55**	1.28
2006	1.47***	1.43	-0.60**	1.66
2007	-0.38	2.33	-0.55***	1.11
2008	-1.58***	3.78	1.24**	2.05
2009	1.37***	2.49	0.15	3.47
2010	0.18***	1.30	0.35***	1.41
2011	0.00	1.02	0.02	0.63
2012	0.03	0.60	0.09**	0.71
2013	0.02	0.52	-0.04	0.74
2014	0.01	0.30	-0.01	0.51
2015	0.01	0.42	0.03	0.71
2016	0.00	0.62	-0.05	0.87
2003-2016	0.30	1.02	-0.02	0.80

Table 15: Fund Timing/Picking vs. Fund Characteristics with Fixed Effects: This table presents panel regression estimates of all GREMFs monthly regional timing and picking abilities regressed against fund lagged characteristics and regional investments, with roust standard errors (Driscoll and Kraay, 1998) clustered by fund. The fund monthly regional timing and picking abilities are calculated using Equations 5 and 6. *Recession* is a dummy variable that equals one if the month is in economic recession according to NBER. *Outsource* is a dummy variable that equals one if the fund is outsourced. *Team* is a dummy variable that equals one if the fund is team-managed. $log(Size)$ is the logarithm of TNA of fund. $log(FaFd)$ is the logarithm of the number of funds in fund family. $log(FaSiz)$ is the logarithm of one plus the TNA of the family that the fund belongs to, excluding its own TNA. *Expense* is the annual expense ratio over the fund's assets under management. *Age* is the number of years since the inception of the fund. *Flow* is the percentage of new fund flow into the fund over the previous 12 months. *CumRet* is the cumulative gross return over the previous 12 months. All characteristic variables are demeaned. The sample period is from January 2009 to December 2016.

	Timing			Picking		
$Outsource_{t-1}$		0.010	0.008		0.023	0.019
t-Stat		0.07	0.06		0.14	0.03
$Team_{t-1}$		-0.212	-0.205		0.519	0.520
t-Stat		-1.55	-1.51		2.01	1.93
$Expense_{t-1}$		0.364	0.314		-0.409	-0.376
t-Stat		0.66	0.48		-1.45	-1.04
$log(FaFd)_{t-1}$			-0.063			0.201
t-Stat			-0.20			0.82
$Log(Size)_{t-1}$		-0.029	-0.016		-0.023	-0.029
t-Stat		-0.73	-0.75		-0.38	-0.64
$log(FaSiz)_{t-1}$			-0.057			-0.018
t-Stat			-1.12			-0.43
Age_{t-1}		-0.004	-0.004		-0.014	-0.012
t-Stat		-0.80	-0.85		-1.17	-1.22
$CumRet_{t-1}$		-0.041	-0.042		-0.183	-0.187
t-Stat		-0.18	-0.13		-1.18	-1.31
$Flow_{t-1}$		0.010	0.010		0.006	0.006
t-Stat		1.87	1.93		1.41	1.08
$Recession_{t-1}$	1.428	1.294	1.290	0.041	0.037	0.041
t-Stat	2.52	2.16	2.19	0.11	0.46	0.44
Constant	0.014	0.046	0.049	0.038	0.035	0.034
t-Stat	0.74	1.68	1.63	1.20	1.06	1.01
N	2512	1850	1850	2512	1850	1850
Fund fixed effect	√	√	√	√	√	√

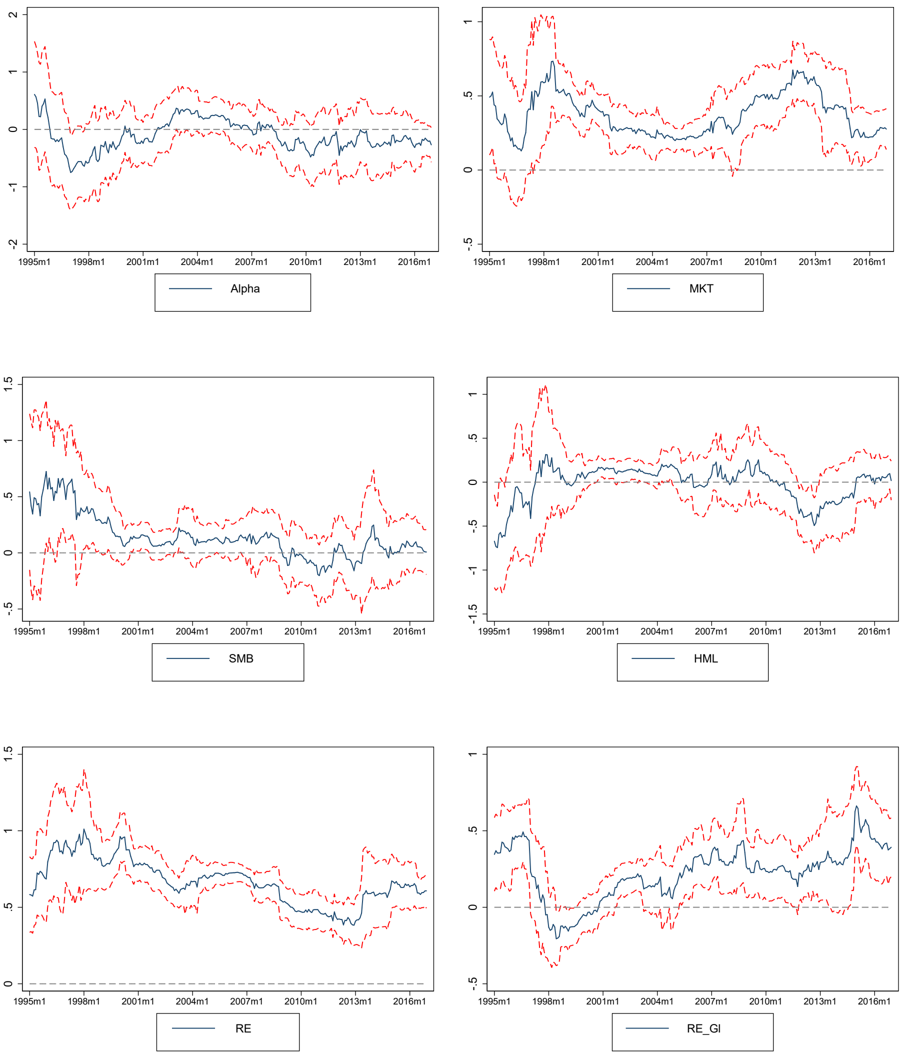

Figure 1: Three-year Rolling Window Alpha and Beta Estimates Relative to Global Market: the figure shows the 36-month rolling window coefficient estimates and associated 95% CI of equal-weighted portfolio of all GREMFs, net of expenses, relative to global FF 3-factor model augmented with domestic RE and orthogonalised global RE factors for the period 1992-2016.

A Appendix

A.1 GREMFs Portfolio Exposure

The GREMFs in CRSP, defined by Lipper investment objectives, only starts their existence from 2008, because Lipper introduced the classification on GREMFs since then. Other studies tend to trace back funds' returns history, assuming no changes on their risk exposures. However, this assumption might be problematic, because funds may convert their investment objectives from domestic to global. Thus, we reclassify GREMFs using Lipper's definition, once their portfolio holdings are identified. All securities held by DREMF and GREMF portfolios are identified manually in this study using the domiciled country and industry classification from Datastream, the CUSIP Master File, Bloomberg, and Financial Times. For those funds with portfolio information missing in CRSP, we use the N-30D or N-Q filling from EDGAR[21] online database to fill in the gaps. In addition, there are some funds that altered their investment objectives from U.S. domestic to global or international. Part of their returns will be included into sample once it meets the Lipper classification of non-U.S. stock exposure more than 25%.

A.2 Exclusion of Index Funds

To ensure our results are purely driven by fund manager active management, we also remove the passively operated index funds, by using the 'index fund flag' identifier in the CRSP database. However, strict use of this method would omit some index funds whose inception dates are prior to 2008, because this identifier only became available after June 2008. Thus, before 2008, we consider a fund as an index fund only if the fund's name contains 'Index', 'Idx', 'Ix', 'Indx', 'NASDAQ', 'Nasdaq', 'Dow', 'Mkt', 'DJ', 'S & P 500', 'BARRA'. The use of this index dummy has been proven accurate for an index fund coverage by Gil-Bazo and Ruiz-Verdu (2009).

[21]The EDGAR database is compiled by SEC from the mandatory filings along with the fund's voluntarily disclosure.