Global Real Estate Mutual Funds: Managerial Skills and Diversification Benefits?

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Abstract

This paper examines the performance and the diversification benefits of U.S.-registered, active, global real estate mutual funds (GREMFs). It considers both the industry as a whole and 76 individual funds, relative to a global and to a domestic benchmark, and before and net of expenses. We estimate alpha, the conditional outperformance, and use the cross-sectional wild bootstrap method to separate funds with genuine skills from merely lucky ones. We find that the actively-managed GREMF industry, as a whole, displays no skills to beat either the global or the domestic benchmarks, even before deduction of expenses. The latter result suggests that there is no benefit from international real estate investment. We also undertake recursive estimates of alpha and conclude that, after an initial period when there were fewer than five funds, there has been no evidence of skills. At the individual fund level, against the global benchmark, we find only one skilled fund but only before expenses are deducted; and, against the domestic benchmark, we find one after the deduction of expenses. Against both benchmarks, we find a number of funds which display a significant lack of skills rather than bad luck, particularly once expenses are taken into account. We undertake a series of robustness checks, including using different benchmarks, and conclude that our results are robust. We also explore possible explanations of performance and conclude that it is linked to over-weighting portfolios in countries/regions with higher economic growth and better investor protection.

Keywords: performance, diversification, wild bootstrap, global investment

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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. 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] Accordingly, it is appropriate to investigate the performance of actively-managed mutual funds, specifically the actively-managed Global Real Estate Mutual Funds (GREMFs).

Although identifying underpriced international equities could bring return and geographical risk diversification benefits, significant efforts and costs are involved as different countries have different institutional contexts and different levels of market transparency and maturity. For their supposed skills, actively-managed mutual funds charge much higher expenses than passive funds, with 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.

In general, managers who are based in a local area may 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. For example, Coval and Moskowitz (2001) find that mutual funds that invest heavily in their local market do better. 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 the local market.

A potential counter-argument in real estate investment relates to the cost of information that, for example, for the real estate investment trust (REIT) industry is higher than for other stocks, which ensures an information advantage for REIT portfolio managers over small retail investors (Kallberg et al., 2000). Managers may also outperform as a result of information advantage from insiders. Damodaran and Liu (1993) suggest that managers specialising in the real estate sector may have superior private information, mainly due to the appraisal process. These insiders can access private information prior to its public release, which may have a material impact on REIT and real estate operating companies (REOC) pricing. And this will cause greater information asymmetry in the real estate market than other industries,

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

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

and could ensure that the better-informed active REMF managers can beat the market. To what extent these factors might apply to global funds is moot.

To assess outperformance, we employ the alpha measure, which has been widely used to examine fund performance, including in studies of domestic REMFs 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 passive real estate sector indices and asset pricing models based on the required returns of a passive portfolio.

We contribute to the empirical literature by examining the skills of U.S.-registered GREMFs that invest in securitized real estate investments outside of the U.S. We consider both gross and net performance. We use a seven risk-factor global model as the benchmark. This includes three factors, for market risk, size and book/market ratio derived from Fama and French (1993) and two, for profitability and investment, from Fama and French (2012, 2015). To these, we add a momentum factor from Carhart (1997) and a global real estate sector factor. The proposed risk factor model is empirically and theoretically driven, and variants of it are well-established in the literature of global mutual funds and REMFs. We compare the results of our seven-factor benchmark with those from the Fama-French five-factor model, the Carhart four-factor models (comprising the Fama-French three-factor model plus a momentum factor) and a real estate benchmark. We consider both global and domestic versions of each. We undertake our analysis for the GREMF sector as a whole and for individual funds. For the former, we also undertake recursive and rolling estimates of alpha to consider its time trend.

Our study also contributes to the literature by applying an appropriate methodological perspective. Recent studies show that some mutual funds may have talents (Kosowski et al., 2006; Fama and French, 2010; Berk and Van Binsbergen, 2015). However, 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, it is possible that this would be cancelled by their operating expenses. We address statistical issues that hinder the appraisal of performance, namely non-normality and heteroscedasticity, and which were not considered in studies such as Shen et al. (2012) and Ferreira et al. (2013). These are the product of fund managers' heterogeneous risk-taking behaviors and we address them by implementing a cross-sectional wild bootstrap (Flachaire, 2005; Kosowski et al., 2006; Davidson et al., 2007; Davidson and Flachaire, 2008), which enables us to separate skills from luck.

Finally, to investigate the factors affecting a fund superior performance, we estimate a panel regression and include, as explanatory variables, characteristics of the global markets within which a fund invests, with various fund's attributes, such as size, age, expenses, loads and management structure as control variables.

This paper is organized as follows. Section 2 considers the literature on the

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performance of actively managed GREMFs. Section 3 explains the data used in this study. Section 4 then outlines the methodology, specifically the benchmark models for global markets. 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 and show no evidence of outperformance after expenses have been taken into account.

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, find that a minority of funds possess genuine skills to produce outperformance when operating expenses are taken into account. Similar results are found by Fama and French (2010) and Barras et al. (2010). Fama and French (2010) examine the net returns of active diversified equity funds from 1984 to 2006 and find that only the top three percentiles funds can add enough value to cover the expenses imposed, and this is attributed to their stock-picking talents. Barras et al. (2010), in a study of net fund performance from 1975 to 2006, find that 10-15% of the 2076 funds are skilled during different periods before 1996 but none thereafter. They attribute 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.

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). Nonetheless, Khorana and Nelling (1997) suggest that the overall risk levels of sector funds are indistinguishable from small-cap or aggressive-growth funds. Studies which have considered sector funds (Dellva et al., 2001; Tiwari and Vijh, 2001; Eakins and Stansell, 2007; Kaushik et al., 2010) find that some sectors, such as technology, health care and utilities, can outperform but only during specific periods. However, superior performance may come from luck rather than genuine managerial skills. 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 most studies (Dellva et al., 2001; Tiwari and Vijh, 2001; Eakins and Stansell, 2007; Kaushik et al., 2010).

As the largest sector among all mutual fund sectors, domestic real estate is the most extensively studied. Earlier studies by Kallberg et al. (2000) and Gallo et al. (2000) find outperformance when real estate market returns are poor, which is attributed to real estate market inefficiency. However, more recent studies (O'Neal

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and Page, 2000; Lin and Yung, 2004; Rodriguez, 2007; Chiang et al., 2008)) find little or no evidence to support significant outperformance attributable to REMF managers' superior skills, regardless of the benchmarks used for the market or the real estate sector.

The performance of international property companies has been 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) considered GREMFs and found that the performance of international REMFs is time-dependent. They evaluate the performance of 59 U.S.-based GREMFs during 1998-2008 and conclude that, before 2007, GREMFs outperformed domestic REMFs but this advantage disappears thereafter.

Finally, the issue of non-normality in fund returns has not been addressed by any study of global mutual fund performance. Ample empirical evidence has been found to show the violation of the normality assumption (Kosowski et al., 2006; Fama and French, 2010; Cuthbertson et al., 2008) because of small samples and heteroskedasticity. To control for this in our study, a cross-sectional wild bootstrap has been employed.

3 Data

3.1 Mutual Fund Data

We consider the monthly performance of GREMFs from January 1992 to December 2016. The data for GREMFs come from the survivor-bias free US 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, total net asset values, operating expenses, turnover ratios, and front and rear load charges. From December 2002 onward, the database also provides details on the security holdings in fund portfolios.[3]

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 Lipper[4] as U.S.-based equity funds investing more than 25% of their assets in foreign real estate securities. However, after 2008, the CRSP definition was

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

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

changed and two new classifications of GREMFs[5] were introduced to take account of differing degrees of international investment, but these have missing histories. To deal with this, we define global funds as both the IRE and GRE categories and create historical data for the full period. We use the Lipper classification currently used by CRSP and identify GREMFs during 2002-2016 based on portfolio holdings. As the portfolio holding data in CRSP only starts from December 2002, before this we assume that funds have no significant investment policy changes with regard to their geographical investment focus.[6]

Mutual funds tend to offer different share classes to investors, where the classes differ regarding their contribution to annual operating expenses including management expenses, brokerage commissions, distribution fees (12b-1 fees) and other general expenses. In addition, the share classes also differ with respect to additional share-class-specific charges, such as front-end loads, back-end loads or deferred sales charges, which accommodate investors' heterogeneous investment horizons and tax requirements. The CRSP mutual fund database reports monthly net returns for each share class. We aggregated the net returns of the different share classes by using a weighted average, with the total net assets (TNAs) of the share classes as weights.[7] This fund net return is the return that the average investor receives after operating expenses. Next, we calculated the fund gross monthly return. For each share class, we added 1/12th of its yearly expense ratio to its net return to obtain its gross return, and then aggregate same-portfolio share class gross returns to obtain the fund gross return.[8] As we want to examine the performance of all active GREMFs, we ignore all passively-managed GREMFs.[9]

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 ($\text{TNA}_t = \sum \text{TNA}_{i,t}$),

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[5]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.

[6]According to SEC and Investment Company Act 1940, any strategic change to fund policy needs to be notified to SEC and disclosed in the prospectus.

[7]The data directly reported from CRSP are at the share class level, and have to be aggregated to generate the data for the fund family. We split the 'fund_name' by semicolon into the fund family name and share class. We also additionally adopted the approach in Gil-Bazo and Ruiz-Verdu (2009), by using the management company as the identifier for the share classes in the same fund family.

[8]Net Return as reported in CRSP = Gross Return (Return before Operating Expenses) - Operating Expenses. If a fund's expense ratio is missing for certain years, we assume it is the same as other actively managed funds with similar assets under management (AUM). Then the fund share classes can be aggregated to get the gross returns at the fund level (Fama and French, 2010).

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

and the concentration in the GREMFs sector as measured by the Herfindahl Index.

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

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]

3.2 Real Estate Benchmark Data

The choice of a real estate benchmark to measure the performance of GREMFs requires an understanding of the risk exposure of their portfolios. As GREMFs hold predominantly global REITs and REOCs, we employ the FTSE EPRA/NAREIT global developed index as the passive global real estate sector benchmark. This index 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,[10] thus it has been used in the literature as a global benchmark (Shen et al., 2012). For the domestic real estate benchmark, we use the Wilshire U.S. Real Estate Securities Index.[11]

Table 3 gives summary statistics for the value-weighted[12] 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]

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[10]https://www.ftse.com/products/indices/epra-nareit

[11]The Wilshire U.S. Real Estate Securities Index measures US publicly-traded real estate securities. It is designed to offer a market-based index that is of the public real estate market and comprises publicly-traded real estate equity securities. It has been widely used in the REMF literature.

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

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On average, U.S. domestic REMFs 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 domestic REMF industry, as indicated by its smaller standard deviation. This calls for a risk-adjusted measure for the performance of GREMFs.

4 Methodology

4.1 Asset Pricing Models

In return-based performance studies, the observed returns are regressed on risk factors that mimic a passive benchmark with a similar exposure to market risk. The regression includes an intercept term, alpha, which should be zero if the observed returns just compensate for the risk taken. The global funds literature suggests this benchmark can be chosen from either domestic asset pricing models (Shen et al., 2012) or domestic mutual funds (Engstrom, 2003). We test four variants of asset pricing models in this study. For each, we use a global version and a domestic version. The general specification is

$$\mathbf{r}_i = \alpha_i \boldsymbol{\iota}_i + \mathbf{X}\boldsymbol{\beta}_i + \epsilon_i \ . \tag{2}$$

where:

$\mathbf{r}_i$ is the $(T_i \times 1)$ vector of fund i monthly excess return rate or the excess return rate of an equal-weighted/value-weighted portfolio of funds;

$\boldsymbol{\iota}_i$ is a $(T_i \times 1)$ vector of ones;

$\mathbf{X}$ is $(T_i \times K)$ matrix[13] consisting of:

(RE_t) for the real estate sector model;

$(MKT_t, SMB_t, HML_t, MOM_t)'$ for the Carhart model;

$(MKT_t, SMB_t, HML_t, CMA_t, RMW_t)'$ for the Fama and French five-factor model;

$(MKT_t, SMB_t, HML_t, MOM_t, CMA_t, RMW_t, RE_t)'$ for the seven-factor model.

RE_t is the real estate excess return rate, at month t;[14]

MKT_t is the return of the value-weighted aggregate market portfolio of traded stocks, in excess of U.S. one month T-bill rate;[15]

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[13]K is the number of risk factors.

[14]For the global analysis, we use the FTSE EPRA/NAREIT global developed index; and for the domestic analysis we use the Wilshire U.S. real estate securities index.

[15]For the global market, the traded stocks are from 23 developed markets from four regions: North America, which includes the U.S. and Canada; Japan; Asia-Pacific, which includes Australia, New Zealand, Hong Kong and Singapore; and Europe, which includes Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the U.K. (Fama and French, 2015).

SMB_t is the size risk factor; HML is the value/growth risk factor; RMW is the profitability risk factor; and CMA is the investment risk factor (Fama and French, 2015);[16]

MOM_t is the momentum risk factor, is attributed to the past return momentum (Carhart, 1997).[17]

We use the global factor model to investigate performance, and the domestic factor model to consider diversification benefits, based on the review of studies on global funds performance.[18]

The appropriateness of the above four types of models as benchmarks for GREMFs is tested using value-weighted portfolios of all global passive funds. If an asset pricing model explains the expected returns of an asset, the intercept is indistinguishable from zero in the time series regression of any asset's excess returns on the model's factors (Fama and French, 2015, 2018). The approach to the estimation of the risk factor loads by the generalized method of moments (GMM) has been popularized in the finance literature, as it can accommodate potential autocorrelation and heteroscedasticity. We run GMM regressions on the global passive portfolios and the four benchmark models factor models (a real estate index factor; the Carhart four-factor model; the Fama French five-factor model; and the seven-factor model), with the coefficient t-statistic estimates adjusted using heteroscedasticity and autocorrelation robust standard errors (Kiefer and Vogelsang, 2002).

According to the result from the test using the GRS robust statistic (Gibbons et al., 1989), we find that all alphas for 16 global passive mutual fund portfolios are statistically jointly indifferent from zero for three of the benchmarks, implying that the global Carhart model, Fama and French five-factor model, and seven-factor model are appropriate to assess risks and performance for GREMFs. The exception is the real estate index factor model, both domestic and global, so we do not use it. In this study, we report the results of performance evaluation from the seven-factor benchmark model.[19]

4.2   The Bootstrap Procedure

In Eq. 2, if the manager of fund i has skills relative to the benchmark, then $\alpha_i > 0$. However, because this alpha is not observed and has to be estimated, inference has to

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[16]These are constructed from either the U.S. domestic stock market portfolios for domestic benchmark, or the global stock market portfolios for global benchmark. The latter two factors are motivated by dividend discount valuation theory and market anomalies associated with profitability and investment.

[17]All five factors are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[18]This is due to the unsettled argument between international pricing models and home country pricing models (Cumby and Glen, 1990; Redman et al., 2000; Griffin, 2002).

[19]The detailed results using the Carhart four-factor model and the Fama-French five-factor are not materially different.

be conducted correctly. An unskilled fund manager could have a positive estimated alpha simply by good luck. If we assume that the idiosyncratic return components, $\epsilon_{i,t}$, are independently, identically and normally distributed, then we could test the null of $\alpha_i = 0$ using the standard t-test, where this statistic should be asymptotically normally-distributed under the null. However, given the short history of many GREMFs, this asymptotic result might be of no relevance for the true distribution of the test statistic under the null. Nor could we assume that the idiosyncratic return component is independently, identically and normally-distributed because, according to Kosowski et al. (2006), the presence of idiosyncratic risk-taking among funds makes this assumption unrealistic.[20] Further, there is ample empirical evidence that returns of stocks follow non-normal distributions, so portfolios consisting of such stocks can exhibit similar non-normal characteristics.

Instead of relying on an asymptotic parametric distribution for inference, we adopt the basic approach of Kosowski et al. (2006), and incorporate the wild cross-sectional bootstrap to simulate the cross-sectional distribution of estimated alpha t-statistics under the null that fund managers have no skills. This approach allows us to separate luck from skills in the non-normally distributed cross-section of ranked GREMFs (by the t-statistics of the estimated alphas).

We use the cross-sectional bootstrap approach and incorporate a wild bootstrap procedure, which has been shown to perform well for the simulation of null distributions when the data generating process is characterized by heteroscedasticity of unknown form (Flachaire, 2005; Davidson et al., 2007; Davidson and Flachaire, 2008). We present the steps of implementation as follows:

In step one, for each of the I funds[21], we estimate the regression (in Eq. 2) to get the actual performance $\hat{\alpha}_i$ and associated $\hat{t}_i$. In step two, we re-estimate the regression under the restriction of an unskilled manager, that is without the constant ($\alpha_i = 0$). We keep the estimated vector of factor loadings, $\tilde{\boldsymbol{\beta}}_i$, and the vector of re-centered residuals, $\tilde{\boldsymbol{\epsilon}}_i$. In step three, we generate pseudo return rate histories of each fund $\mathbf{r}_i^b = 0 + \mathbf{X}\tilde{\boldsymbol{\beta}}_i + \boldsymbol{\Upsilon}_i^b \tilde{\boldsymbol{\epsilon}}_i$, where $\boldsymbol{\Upsilon}_i^b$ has realizations of the Rademacher distribution on the diagonal and zeros otherwise.[22]

Consider now the first bootstrap replication ($b=1$), which gives us $\{\mathbf{r}_i^b\}_{b=1}$, the first set of pseudo return rate histories under the restriction that the manager of fund i has no skill. In step four, we fit the regression (in Eq. 2) for each of the I funds to get $\hat{\alpha}_i^b$, from the first bootstrap replication, $b = 1$. To construct alpha t-statistics, we estimate the standard error of $\hat{\alpha}_i^b$ with the heteroscedasticity-consistent covariance

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[20]The non-normality is exacerbated when a fund invests heavily in a few stocks or industries, or is involved in dynamic trading strategies.

[21]We use all 76 funds that have at least 36 return observations during 1992-2016 to minimize estimation error. We follow Kosowski et al. (2006) when dealing with funds that have non-consecutive returns.

[22]Realizations of the distribution are $\upsilon \in \{-1, 1\}$ with $P(\upsilon = -1) = P(\upsilon = 1) = 0.5$. It has been shown in simulations to outperform other distributions in Davidson and Flachaire (2008).

matrix estimator (HCCME)

$$\hat{\sigma}_i^b = \left(\mathbf{e}_1'(\mathbf{Z}_i'\mathbf{Z}_i)^{-1}\mathbf{Z}_i'\hat{\mathbf{\Omega}}_i^b\mathbf{Z}_i(\mathbf{Z}_i'\mathbf{Z}_i)^{-1}\mathbf{e}_1 \right)^{1/2} \tag{3}$$

with $\mathbf{Z}_i = (\boldsymbol{\iota}_i, \mathbf{X}_i)$. The column vector $\mathbf{e}_1$ has the same length as the coefficient vector, with a one as the first element and zeros elsewhere. The covariance matrix $\hat{\mathbf{\Omega}}_i^b$ has elements

$$\hat{\omega}_{i,tt}^b = \frac{(\hat{\varepsilon}_{i,t}^b)^2}{(1 - z_{i,tt})^2} \tag{4}$$

on the diagonal and zeros elsewhere. In Eq. 4, $\hat{\varepsilon}_{i,t}^b$ is the residual from the full regression for the actual return rates of each fund, saved from step one. $z_{i,tt}$ is the t'th diagonal element of the hat matrix $\mathbf{Z}_i(\mathbf{Z}_i'\mathbf{Z}_i)^{-1}\mathbf{Z}_i'$. So, the t-statistic of alpha for fund i after bootstrapping once is computed as $\{\hat{t}_i^b\}_{b=1} = \hat{t}_i^b = \hat{\alpha}_i^b/\hat{\sigma}_i^b$. The actual fund alpha t-statistic is computed in the same way.

In step five, after completing one draw of the bootstrapped alpha t-statistics, we sort the cross-section of funds by the t-statistics $\{\hat{t}_i^b\}_{b=1}$.

In step six, we repeat the steps above for a further 999 bootstrap iterations $b = 2\ldots, B$, where $B = 1000$. We now have the cross-sectional distribution of funds, sorted by rank, for each of 1000 iterations, under the null that the true alpha equals zero. Thus, for example, the distribution of the top ranked GREMF is generated from the largest alpha t-statistics from all bootstrap iterations under assumption of null.[23] When we find that the actual alpha t-statistic is larger than all pseudo values generated from bootstrap, we can conclude that sampling variation is not the only cause for this performance, and that this fund has skill. We can estimate the marginal significance level or bootstrapped p-value of each fund by comparing $\hat{t}_i$ with its associated cross-sectional bootstrapped t-statistics with the same rank, which can help us to draw inferences on the existence of an individual fund manager's genuine skill among the cross-section of funds.

To assess if the GREMF industry, as a whole, has skilled managers or, on average, has diversification advantages, we compute for each month the returns of a portfolio that invests in all individual active GREMFs available. The returns of the GREMF industry portfolio are calculated as both the equal-weighted and the value-weighted averages of all existing active GREMFs. This implies that this GREMF industry portfolio is re-balanced monthly. We then fit the benchmark models from Eq. 2 to the returns of this active GREMFs portfolio. This produces an estimate of the actual alpha and its t-statistic. To assess if the portfolio alpha is statistically different from zero, we need to construct the simulated distribution of alpha estimates under the null hypothesis that managers on average have no talent. To do so, we estimate the bootstrapped alpha and the t-statistic for each of the 1000 notional returns

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[23]And these bootstrapped largest alpha t-statistics may come from different funds at each iteration.

data, generated under the null with the bootstrap. We use the same benchmark model in these regressions as was used in the regression for the actual returns. Effectively, we fit Equation 2. For each regression, we obtain the estimated alpha and its t-statistic, which is computed using heteroscedasticity consistent covariance estimator in Equation 3.[24] As we have 1000 bootstrapped observations for each fund, we can use their bootstrapped distributions to assess if the actual alpha of a portfolio is really significant and, accordingly, draw inferences on whether managers, on average, have skills.[25]

4.3 Fund Performance and Regional Investments

We study the potential linkage between GREMF performance and fund portfolio holdings in global markets, to see how country characteristics, such as economic conditions (GDP *per capita*), financial market development and law enforcement protection, are related to fund risk-adjusted performance. A set of fund characteristics has been employed as the control variables, including fund size, age, expenses and fees, fund flows and management structure.

The existing literature provides no conclusive findings on the effect of fund size on fund performance. Large funds may have advantages over smaller ones owing to economies of scale from allocating costs over a larger asset base but, on the other hand, they may also face potential dis-economies of scale. Chen et al. (2004) find that fund returns decrease with the lagged fund size, owing to the organizational dis-economies. They suggest that liquidity may be an important reason explaining why size erodes performance. According to their findings, the relationship is most pronounced for funds investing in small-cap, illiquid equities.

Similarly, the relationship between fund age and performance also remains unclear. A younger fund is more at risk of failure owing to lack of experience but may also be more likely to outperform by taking large risks. Ferreira et al. (2013) find no significant relation between age and funds invested inside the U.S. but a negative relationship between age and fund performance for funds invested outside of the U.S., with younger funds performing better.

The impact of fees and expenses on fund performance is typically considered as negative, since they are regarded as the price paid by investors to fund managers.

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[24]This procedure is essentially the same as for the individual funds except that there is no ranking to be undertaken as there is only one portfolio. We use the Davidson-MacKinnon (HC3) heteroscedasticity consistent covariance estimator.

[25]We also implemented the block bootstrap, which re-samples a subset of consecutive values of residuals, instead of each individual residual, to cope with autocorrelation among residuals. The block length of residuals is set as optimal to reflect the significant autocorrelation among fund's returns accurately, as $T^{1/3}$ (Hall et al., 1995), without imposing independence assumption on the residuals. We adopted the bootstrap with block length as 7 ($T^{1/3}$) but also used 3, 5 and 10 monthly returns. Since the results from the bootstrap with different block lengths have no qualitative differences from the wild bootstrap results, we do not present the analysis here.

Some studies find evidence supporting negative relationships between expenses and performance before or net of expenses (Carhart, 1997; Gil-Bazo and Ruiz-Verdu, 2009). But a study by Chen et al. (2004) finds no statistically significant relationship between expenses and performance.

Funds also charge investors front- and back-end loads to discourage the redemption of shares, and 12b-1 fees at the fund level for promotion or marketing purposes. The relationship between loads and performance has been found either negative (Carhart, 1997) or insignificant (Chen et al., 2004) in the literature.

According to the 'smart money' hypothesis proposed by Gruber (1996), fund flow is positively related with future performance since investors can detect and reward the skilled managers by investing in them. Empirical evidence has been found by Gruber (1996) to support this hypothesis. Ferreira et al. (2013) find that the smart money effect is more evident in the global market, suggesting that investors are better at detecting skilled managers outside of the U.S.

Whether a fund is team- or individually-managed is also a factor to consider when forecasting future performance. Funds managed by a team may perform better than those managed by individual managers, as a result of being relatively free of constraints of resources and networks. However, team-management structure is considered to be less efficient in terms of the coordination of personnel and organisation. Massa et al. (2010) and Ferreira et al. (2013) find that team-managed funds performed worse than those managed individually.

The level of economic development may also be a factor. On the one hand, a country with high economic development is associated with a better educated workforce, which is likely to increase the possibility of skilled managers. On the other, it is likely to imply a more transparent real estate market, which might reduce information asymmetry and decrease the probability of outperformance. Ferreira et al. (2013) find a negative relationship between per capita GDP and fund performance.

The characteristics of the stock market of a country may also play an important role in fund performance. A better-developed financial infrastructure could enable higher liquidity and lower trading costs for investors. The law enforcement system of a country may also affect fund performance. Ferreira et al. (2013) find that a common law system, compared with a civil law system, has a positive impact on fund performance.

For active global funds, we analyze the relationship between fund performance and the characteristics of the countries in which the funds invest, and we use fund characteristics as control variables. As a result of missing data before 2001, we focus on the period 2002-16 and run the OLS regression on the cross-section of individual funds.[26] The dependent variable is the net alpha. The explanatory variables include

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[26]As there is a possible problem with endogeneity, the estimated regression coefficients only indicate a relationship, not causality. Future work is required to find appropriate instrumental variables or other exogenous variation that would make it possible to identify causal effects.

fund control variables, and weighted country characteristics. The list of explanatory variables is as follows:

TNA_i is fund i's size in millions of U.S. dollars;

Age_i is the number of years since a fund's launch date;

ER_i is fund i's annual expense ratio;

$Load_i$ is the sum of fund i's front- and back-end loads fees;

$Flow_i$ is the growth rate of TNA as $Flow_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1+r_{i,t})]/TNA_{i,t-1}$, where $r_{i,t}$ is the cumulative return between fund's inception and present date (Berk and Green, 2004; Gil-Bazo and Ruiz-Verdu, 2009);

$Team_i$ is the bivariate variable to indicate whether fund i is managed by more than one person or team-managed;

$w_{i,j}$ is the weight of fund i's investment in each country j, computed by the percentage of market value of fund i's holding securities from the same market divided by fund i's total market value. We weight the following three country characteristics for each fund;

GDP_j is GDP per capita in U.S. dollars for each country j invested by fund i, quoted from World Development Indicators (WDI);[27]

Liq_j, is a measure of stock market liquidity, the turnover ratio - the ratio of total value of stocks traded to market capitalization for country j from WDI (Ferreira et al., 2013).

$D_{Law,j}$ is a dummy variable with value one for a common law system of country j and zero otherwise.

5   Empirical Results

We use global and domestic versions of a seven-factor benchmark to assess the performance of the GREMF industry, and of individual funds. This benchmark contains the Fama-French five factors plus the Carhart momentum factor and a real estate index. We consider returns both before and net of operating expenses. The domestic benchmark enables us to consider the possible benefits of global diversification by GREMFs.[28]

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[27]http://datatopics.worldbank.org/world-development-indicators/

[28]We also undertook the analyses using the Carhart four-factor model and the Fama-French five-factor model but, as the results are very similar, we do not generally report them.

5.1 Performance of the GREMF Industry

The performance and associated statistical significance of the GREMFs industry, relative to three global benchmarks, are presented in Table 4.

[Table 4 about here]

Compared with the benchmarks, both equal- and value-weighed portfolios of GREMFs show no significant outperformance at the gross returns level. The gross alphas are either insignificantly positive or, in the case of the value-weighted Fama-French five-factor model, insignificantly negative. This result holds for both the assumption of normality and when the empirical bootstrapped distribution is used. Net of expenses, the estimated alpha is insignificantly negative for all but the equal-weighted Carhart model, for which it is insignificantly positive.

In summary, there is no evidence that GREMF fund managers, as a whole, can demonstrate skills even before expenses are taken into account. This is consistent with earlier findings in the literature on GREMFs (Shen et al., 2012).

5.1.1 Industry Performance from Recursive and Rolling Estimation of Alpha

Particularly after the 1990s, the REITs market, which is the main investment vehicle for REMFs, has matured through growth and the availability to investors of more reliable information. REIT prices can better reflect the performance of their underlying assets, which improves market efficiency and transparency and reduces the degree of information asymmetry. Arguably, it has become more difficult for REIT and REMF managers to outperform. Thus, the assumption of constant alpha and betas in the model may be inappropriate. We now consider time variation in these factors, first using recursive estimates and then rolling estimates.

Recursive estimates[29] are a popular method (Mamaysky et al., 2007; Cuthbertson et al., 2008) to consider variations in the conditional performance. We use recursive regressions, anchored on January 1992 and adding a month for each re-estimation. In this way, we are able to examine the time patterns of the estimates of alpha and the betas (the risk factor loadings). In Figure 1, we present the recursive estimates of alphas from the value-weighted portfolio of active GREMFs, net of costs, relative to the seven-factor benchmark.[30] It is moot whether the initial fluctuations are artefacts of the recursive estimation method or are real economic phenomena.

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[29]The recursive estimates implemented in this study are based on OLS with robust standard errors.

[30]Only a value-weighted portfolio of funds is considered here because the results on the equal-weighted portfolio are similar as those on value-weighted. Similarly, we only present the findings against the seven-factor model global model since there are no material differences across the models.

The recursive estimates of net alpha of the value-weighted portfolio of GREMFs relative to the global market begin positive and significant in 1993[31] but become insignificantly different from zero towards the end of 1994 and are then remarkably stable around zero. There were only two funds in 1992, only three until 1995 and fewer than 10 until 1998. The pattern of returns is consistent with the proposition of market maturity and competition within the general mutual fund market. Similarly, the real estate market has become more transparent, which makes it more challenging for fund managers to pick mis-priced real estate securities. And the increasing number of funds may also compete away any abnormal performance.

The market beta starts above one but steadily falls to around 0.20, then rises again and settles at around 0.30. The other beta coefficients, except RE, fluctuate at the start of the estimation period but soon stabilize. SMB settles at around 0.15 but is only marginally significant at the end of the period; HML is around 0.3 and significant much of the time; and the MOM, CMA and RMW factors are not significant. In contrast to the others, the RE coefficient has been growing steadily over the period, from 0.28 in 1995 to 0.62 in 2016, perhaps reflecting a growing awareness of the risks and lack of returns from global real estate investment.

Another perspective is provided by the three-year rolling window regressions of the factors as shown in Figure 2. Alpha is always insignificantly different from zero. Market beta is almost always below one and almost always insignificantly different from zero until 2008, after which it rises and falls again. With the exception of RE, the other factors fluctuate around zero and are rarely significant. The RE factor is almost always positive and significant but has risen and fallen in cycles but these are not obviously linked to general real estate cycles.

5.2 The Diversification Benefits of the GREMF Industry

We evaluate the overall benefits from globalisation of REMFs, both before and net of operating expenses, by regressing excess returns of active GREMFs portfolio against the domestic seven-factor, Carhart four-factor and Fama-French five-factor benchmarks. The results are presented in Table 5. If there were diversification benefits, we would expect the results against the domestic benchmark to be poorer than against the global benchmark. In fact, we find no significant result, irrespective of the benchmarks used. The gross alphas are positive but insignificant (or negative and insignificant in the cases of the value-weighted portfolio against the Fama-French

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[31]Degrees of freedom restrictions mean that the first possible estimate is for September 1992. In the figure, we present the results from January 1993.

five-factor and seven-factor benchmarks). The inferences based on non-parametric p-value confirm the conclusions from parametric p-value on both gross and net alphas.

[Table 5 about here]

5.2.1 Industry Diversification Benefit Recursive Estimates

Next, we repeat the analysis using recursive regressions, anchored on January 1992 and adding a month for each re-estimation.[32] The results are shown in Figure 3.

[Figure 3 about here]

As with the previous recursive analysis against the global benchmark, after the initial estimations, the recursive coefficients are remarkably stable. The recursive estimates of alpha are not significantly different from zero throughout. The result is clear - there are no risk-adjusted performance benefits from international diversification within GREMFs.

The market beta is around 0.25 and always significant after the initial few years. SMB is similar is magnitude and also always significant after the initial few years. HML, MOM and RMW are never significant; and CMA is consistently around 0.13 and on the margins of significance. Finally, after the initial period, RE is always significant, on average around 0.70. The rolling widow estimations show some greater volatility in the factors after the global financial crisis. Of note is the rise in the RE factor from 2013, and the subsequent levelling off, which is also evident in the analysis relative to the global benchmark. This was a period when rents in the U.S. domestic real estate market were rising.

[Figure 4 about here]

5.3 Individual GREMF Managers

Before assessing the performance of individual GREMFs, we first report on model fitness and on tests for independence, homoscedasticity and normality among GREMFs returns from the selected risk-factor models.[33] Comparison of the Schwarz Information Criteria (SIC) across different models suggests that, for 77% of funds, the global seven-factor model should be preferred. This empirical evidence further confirms our choice of seven-factor model based on asset pricing model test.

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[32]Similarly to the global benchmarks, as the domestic findings are robust to the benchmark used, we only present the recursive net alphas relative to the seven-factor model

[33]We use the Schwarz information criterion, Lagrange Multiplier test with lags 1 and 6, the White heteroscedasticity test, and the Sharpiro-Wilk W test.

We use the Lagrange Multiplier test (LM test) with lags 1 and 6[34] to detect whether there is serial correlation of individual GREMFs of benchmark models. Of all funds, 69% (lag 1) and 59% (lag 6) using the seven-factor model, are shown to exhibit serial correlation. In terms of heteroscedasticity, the White test shows that 31% of all funds exhibit significant heteroscedasticity using the seven-factor model. The tests for independence of the residuals indicate the adequacy of the risk-factor models, while the tests on homoscedasticity of the residuals suggest that the implementation of the heteroscedasticity-consistent covariance matrix estimator (Eq. 4) is required.

Thus, to minimize the associated heteroscedasticity biases from the regression, we use the heteroscedasticity-consistent covariance matrix estimator, and impose a minimum of 36 observations requirement on the sample of funds that are used. Over half of all active GREMF returns show non-normality in their returns, based on p-values from the Sharpiro-Wilk W test that are smaller than the 10% significance level. This finding proves that the asymptotic normal distribution is not an appropriate approximation for the conventional t-test, so we rely on the true distribution of funds, and derive associated bootstrapped p-values for the estimated alpha t-statistics.

We now examine the performance of individual GREMF managers using the same procedure as for the market as a whole, and the same global and national benchmarks, before and net of expenses. We are now interested in determining whether individual fund managers have skills. We evaluate the significance of a fund's performance (whether fund manager is truly skilled) by deriving the bootstrapped p-value on alpha t-statistic, based on its associated bootstrapped cross-sectional distribution. The associated cross-sectional bootstrapped distribution varies for each ranked fund, generated under the null hypothesis of zero-alpha from the residual bootstrap procedure. We sort all active GREMFs based on their ex-post t-statistic for alpha, and report the associated parametric p-value, and non-parametric p-value for selected percentile points in the funds' cross-section.

5.3.1   Performance of Individual Managers

Table 6 shows the results for the sorted performance (by the t-statistics for the alphas) of individual active GREMFs, relative to the seven-factor global benchmark, both before and net of expenses. The first row in the table reports the ex-post t-statistic for alpha in percentiles of the performance distribution of all funds, sorted from the bottom to the top ranked fund. The second and third rows presents the associated alpha and its annualized value for the presented t-statistics. The fourth and fifth rows exhibit the parametric p-value, and the bootstrapped p-value for the associated t-statistic after 1000 residual re-sampling iterations.

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[34]The LM test with lags 1 and 6 is also used in Cuthbertson et al. (2008).

First, we consider outperformance, which is to the right hand side of Table 6. Based on a significance level of 10% for the bootstrapped p-values, only the top-ranked fund can outperform the seven-factor benchmark before expenses are taken into account. This fund can generate sufficiently large alpha t-statistic to reject the hypothesis that the top-ranked fund manager only achieved this performance by luck alone. So, only this single fund exhibits skills rather than luck but the outperformance is lost once expenses are taken into account. For the middle-ranked funds in the ex post cross-section distribution of the alpha t-statistics, such as between the lower 40th percentile and the upper 40th percentile, their rankings are mostly influenced by their expense ratios. Turning now to underperformance, and again based on a significance level of 10% for the bootstrapped p-values, before deductions of expenses, the bottom four managers lack skills, and this rises to the bottom five once expenses are taken into account.[35]

In summary, the general findings on the performance of individual active GREMF managers are clear and are robust and consistent, and are not dependent on the choice of the global benchmark. During the period, only one manager showed skills before expenses were deducted but not after, and five showed lack of skills once expenses were deducted.

[Table 6 about here]

5.3.2 Diversification Benefits of Individual Managers

We next evaluate the performance of individual active GREMF managers against domestic benchmarks to assess whether these funds have been able to benefit from global diversification. Table 7 presents the performance and associated statistical significance for individual active GREMF funds, relative to the domestic seven-factor benchmark.

[Table 7 about here]

Before deduction of expenses, we can only reject the null of no skills for the top-ranked fund, as indicated by the p-value of 2% from the asymptotic distribution. After deduction of expenses, this top-ranked fund still displays skills rather than luck. In contrast, we find lack of skills, both before and after deduction of expenses, among the lower 10% percentile of funds, according to both parametric and bootstrapped p-values.[36]

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[35]The results are essentially the same when the other two benchmarks are employed.

[36]We also implemented a series of robustness tests to examine whether the conclusions on active GREMF performance are sensitive to: the existence of serial correlation in fund returns (using a block bootstrap); and the change of funds samples (including incubation bias (Evans, 2010) controlled, observation requirement as 60-month). Overall, the inferences on results have no qualitative changes.

5.3.3 Individual Fund Performance and Regional Investment Allocations

Finally, we investigate the relationship between fund performance, as measured by fund net alpha, and the fund investment allocations within global regions. We use cross-sectional OLS regression on 76 funds during 2002-2016. The coefficient estimates of the performance regression of the seven-factor alphas against fund and country characteristics are presented in Table 8.

[Table 8 about here]

Only three of the explanatory variables are found statistically significant at 10% significance level: the fund flow, the per capita GDP and the legal system weighted by the portfolio allocations in countries. We find a positive and significant relationship between fund performance and flow, which is consistent with the smart money hypothesis proposed by Gruber (1996). The funds with higher inflows perform significantly better than funds experiencing outflows. This implies that GREMF investors are able to detect the skilled funds. We take the weighted GDP per capita, $log[\sum w_{i,j} GDP_j]$, as a proxy for economic development for each fund's portfolio. The weight is calculated as the percentage of fund investment by country. We find that the weighted GDP per capita makes a significant and positive contribution to fund performance. A country with higher economic development can provide a better educated workforce for the investment industry, leading to superior manager performance. We confirm that there is a positive link between the weighted GDP per capital and fund performance. We also computed the weighted score for the dummy of law systems, $\sum w_{i,j} D_{law,j}$, as a proxy for investor protection. Fund investments in a common law legal system normally have better investor protection than in a civil legal system. This may be due to better enforcement of contract. We find a significantly positive relationship between legal system and fund performance.

Other fund control variables are insignificant statistically. The relationship between fund size and performance is mixed in the fund literature. We find that there is no significant relationship between fund performance and fund size among GREMFs. Age - $log[Age_i]$ is found to have a positive but insignificant impact on fund performance. This can be interpreted as the cost efficiencies and increased intellectual capital within funds as they grow older. Younger funds typically face higher operational costs and are subject to insufficient experience during early years. As a fund grows older, the accumulated intellectual capital of fund managers will lead to a higher future performance. We find the relationship between the expenses ratio and 12b-1 fees with fund performance insignificant. This is consistent with Chen et al. (2004), who also find no relationship between expenses and performance. We also find loads to make no significant contribution to better fund performance, which is also consistent with the literature (Chen et al., 2004; Ferreira et al., 2013). Funds can be managed either by individual or team. Funds managed by individuals have

more flexibility but fewer resources compared with team managed funds. We find no significant relationship between management structure and performance. According to column two to six, the statistical significance of the relationships remains robust for different model specifications.

6   Conclusion

This paper has considered 76 active GREMFs between 1992-2016 to examine if, both as a sector and individually, they have genuine skills and can produce benefits from global diversification, or if their performance is the result of luck. To do so,we implemented a wild cross-section bootstrap which has not been used in the existing literature. We considered both gross and net returns.

First, we examined performance relative to global benchmarks, specifically a seven-factor benchmark derived from the global stock market and global real estate market. Second, we used the domestic equivalents of the global benchmarks to investigate the benefits from investing internationally. Third, to consider time variation and market maturity, we calculated recursive estimates of alpha and the beta weights in the benchmarks. Last, we used a probit model to examine the roles of the characteristics of funds and the global regions within which they invest, in explaining performance relative to the benchmark, as measured by net alpha. We also implemented a series of robustness tests on both funds industry and individual fund.

Our key results are as follows. First, the actively-managed GREMF industry, as a whole, fails to beat any of the benchmarks. Second, the active GREMF industry, as a whole, cannot beat U.S. domestic benchmarks, implying no significant benefit from internationalization.

Third, at the individual GREMF level, and against the global benchmark, we find only one manager with genuine skills but the outperformace is insufficient to cover the management expenses, and we find four at the gross level and five at the net level who display significant underperformance. Fourth, at the individual GREMF level, and against the domestic benchmark, we find only one manager with genuine skills and these persist at the net level, and we find all of the lower 10% of managers display significant underperformance at both gross and net levels.

Fifth, we considered recursive estimates of alpha and showed that after an initial period, alpha is consistently not significantly different from zero, the beta risk loads are constant, although some are not significantly different from zero. Against the global benchmark, the real estate coefficient is increasing, which we attribute to an increased awareness of the risk of international real estate investment; whereas against the domestic benchmark is fell between 2002-8 and then stabilized, which we attribute to increased market maturity.

These findings are further confirmed after a series of robustness checks are implemented, including the block bootstrap (with block length as 3, 7, and 10 months) to control for autocorrelation of each fund, the wild bootstrap with increased iterations of 5000, the replication using the Carhart model and the Fama-French five-factor model, and the subperiod study.

Finally, we considered which characteristics are associated with fund performance. Three factors were significant, all positively: fund flow; and per capita GDP and the legal systems of the countries within which a fund invests. The last two of these may suggest better opportunities in more developed economies and with better legal protection.

Overall, therefore, all but the very best funds exhibit no significant skills and several exhibit a value-destroying lack of skills. These are strong findings against several benchmarks, using appropriate methods and subject to a number of robustness checks. And they are consistent for over 25 years. While these funds may be a convenient vehicle for international real estate investment, evidence of their performance and wider evidence on the performance of mutual funds, particularly when costs are taken into account, does not suggest that they offer any financial benefits to an investor.

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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.

Year	Number	TNA	Concentration
1992	2	8.31	100.00
1993	3	146.17	100.00
1994	3	106.62	85.38
1995	3	70.76	75.61
1996	4	106.45	40.78
1997	7	634.40	48.81
1998	10	635.60	34.97
1999	10	962.70	43.08
2000	10	1057.00	48.00
2001	11	1216.10	33.95
2002	11	1671.20	23.63
2003	12	3038.00	20.25
2004	15	5681.90	21.19
2005	19	8110.40	18.88
2006	34	17176.40	9.31
2007	52	23357.60	7.12
2008	69	15497.70	4.18
2009	71	19908.50	4.35
2010	65	24047.20	4.69
2011	68	24212.90	4.67
2012	66	33683.10	4.56
2013	70	38997.00	4.52
2014	77	45030.10	5.13
2015	82	44390.40	4.92
2016	82	40664.30	5.19

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 in the table is the simple average presented in percentage.

			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: Summary statistics for monthly excess return rates of the value- and equal-weighted portfolio of active GREMFs, active domestic REMFs, the global real estate index (FTSE/NAREIT global countries index), and the domestic real estate index (U.S. Wilshire real estate securities index), from January 1992 to December 2016.

	VW Global	EW Global	VW Domestic	EW Domestic	Global Index	Domestic Index
Mean	0.61	0.68	0.73	0.69	0.85	1.04
Median	0.74	0.97	1.02	1.02	1.16	1.31
Maximum	19.84	18.75	26.17	24.92	16.33	31.02
Minimum	-26.05	-25.91	-28.88	-28.44	-33.53	-31.67
Std. Dev.	4.87	4.84	4.96	4.83	5.19	5.46
Skewness	-0.69	-0.76	-0.78	-0.88	-1.07	-0.77
Kurtosis	6.64	6.66	10.06	10.15	9.49	11.41

Table 4: Performance of Equal-weighted and Value-weighted Portfolio of U.S.-registered Active GREMFs Relative to Global Market: Presents the estimated alpha (annualized) and its t-statistic for different models for the period 1992-2016. The t-statistics are computed using the Davidson-MacKinnon (HC3) heteroscedasticity consistent standard errors (Davison and MacKinnon, 2004; Davidson and Flachaire, 2008). P-values are for the t-statistic that $\alpha = 0$. 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		
	Gl Carhart	Gl FF5	Gl 7-Factor	Gl Carhart	Gl FF5	Gl 7-Factor
	Gross Returns					
$\hat{\alpha}$	0.17	0.02	0.11	0.10	-0.08	0.03
Annual $\hat{\alpha}$	1.99	0.21	1.34	1.15	-0.91	0.36
$t_{\hat{\alpha}}$	0.88	0.09	0.76	0.46	-0.37	0.19
P-value Parametric	0.38	0.93	0.45	0.64	0.72	0.85
P-value Bootstrapped	0.36	0.90	0.48	0.60	0.80	0.86
	Net Returns					
$\hat{\alpha}$	0.04	-0.11	-0.02	-0.02	-0.19	-0.09
Annual $\hat{\alpha}$	0.46	-1.35	-0.22	-0.27	-2.32	-1.07
$t_{\hat{\alpha}}$	0.20	-0.59	-0.12	-0.11	-0.93	-0.56
P-value Parametric	0.84	0.56	0.90	0.91	0.35	0.57
P-value Bootstrapped	0.86	0.58	0.90	0.96	0.42	0.60

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Table 5: Performance of Equal-weighted and Value-weighted Portfolio of U.S.-registered Active GREMFs Relative to Domestic Market: Present estimated alpha (annualized) and its t-statistic for different benchmark models for the period 1992-2016. The t-statistics are computed using the Davidson-MacKinnon (HC3) heteroscedasticity consistent standard errors (Davison and MacKinnon, 2004; Davidson and Flachaire, 2008). P-values are for the t-statistic that $\alpha = 0$. 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		
	Carhart	FF5	7-Factor	Carhart	FF5	7-Factor
	Gross Returns					
$\hat{\alpha}$	0.14	0.00	0.03	0.08	-0.09	-0.05
Annual $\hat{\alpha}$	1.74	-0.05	0.37	0.96	-1.06	-0.61
$t_{\hat{\alpha}}$	0.70	-0.02	0.22	0.36	-0.40	-0.35
P-value Parametric	0.48	0.98	0.83	0.72	0.69	0.73
P-value Bootstrapped	0.50	0.98	0.84	0.70	0.72	0.76
	Net Returns					
$\hat{\alpha}$	0.02	-0.13	-0.10	-0.04	-0.21	-0.17
Annual $\hat{\alpha}$	0.18	-1.61	-1.20	-0.47	-2.48	-2.04
$t_{\hat{\alpha}}$	0.07	-0.65	-0.72	-0.18	-0.94	-1.19
P-value Parametric	0.94	0.52	0.47	0.86	0.35	0.23
P-value Bootstrapped	0.92	0.50	0.52	0.82	0.38	0.28

Table 6: Performance of Individual U.S.-registered Active GREMFs Relative to Global Combined Market: Presents estimated alpha (annualized) and its t-statistic for the period 1992-2016. The combined benchmark, specified as Fama and French global five factors, global momentum factor, and single real estate factor, is used. The t-statistics are computed using heteroscedasticity robust (Davidson and Flachaire, 2008) standard errors. P-values are for the t-statistic that $\alpha = 0$. The parametric p-value comes from a standard normal distribution. the bootstrapped p-value comes from estimated empirical distribution of the t-statistic under the null.

	Bottom	2.	3.	4.	5.	10%	20%	30%	40%	Median	40%	30%	20%	10%	5.	4.	3.	2.	Top
										Ordered Cross Section of Fund Alphas and t-Statistics									
										Relative to Global Market of Global 7-Factor Model									
										Gross Returns									
$\hat{t}_{\hat\alpha}$	-2.25	-2.13	-1.98	-1.93	-1.82	-1.81	-1.28	-0.99	-0.74	-0.56	-0.30	-0.19	0.22	0.42	0.69	0.72	0.73	0.92	1.40
$\hat\alpha$	-0.48	-0.59	-0.43	-0.43	-0.32	-0.38	-0.43	-0.25	-0.15	-0.10	-0.28	-0.04	0.04	0.09	0.17	0.18	0.14	0.21	0.22
Annualized $\hat\alpha$	-5.82	-7.04	-5.18	-5.10	-3.89	-4.62	-5.18	-2.96	-1.85	-1.20	-3.37	-0.42	0.52	1.14	1.99	2.12	1.68	2.50	2.63
P-value Parametric	0.03	0.04	0.05	0.06	0.07	0.07	0.20	0.33	0.46	0.58	0.76	0.85	0.83	0.68	0.49	0.47	0.47	0.36	0.16
P-value Bootstrapped	0.10	0.05	0.03	0.09	0.11	0.15	0.22	0.32	0.50	0.64	0.82	0.86	0.86	0.74	0.46	0.50	0.48	0.40	0.08
										Net Returns									
$\hat{t}_{\hat\alpha}$	-2.54	-2.41	-2.34	-2.01	-1.98	-1.88	-1.56	-1.34	-1.10	-0.86	-0.73	-0.66	-0.31	-0.01	0.19	0.22	0.30	0.30	0.74
$\hat\alpha$	-0.45	-0.52	-0.50	-0.43	-0.55	-0.42	-0.36	-0.34	-0.19	-0.20	-0.18	-0.14	-0.06	0.00	0.10	0.05	0.06	0.08	0.12
Annualized $\hat\alpha$	-5.42	-6.21	-5.97	-5.16	-6.56	-5.06	-4.27	-4.05	-2.30	-2.35	-2.14	-1.69	-0.69	-0.04	1.15	0.62	0.70	0.96	1.39
P-value Parametric	0.01	0.02	0.02	0.05	0.05	0.06	0.12	0.18	0.27	0.39	0.47	0.51	0.76	0.99	0.85	0.83	0.76	0.76	0.46
P-value Bootstrapped	0.02	0.02	0.04	0.06	0.10	0.12	0.15	0.24	0.30	0.44	0.44	0.52	0.70	0.98	0.86	0.78	0.74	0.82	0.50

Table 7: Performance of Individual U.S.-registered Active GREMFs Relative to Domestic Market and Domestic REMFs: Presents estimated alpha (annualized) and its t-statistic for the period 1992-2016. The combined benchmark, specified as Fama and French domestic five factors, momentum factor, and single real estate factor, is used. The t-statistics are computed using heteroscedasticity robust (Davidson and Flachaire, 2008) standard errors. P-values are for the t-statistic that $\alpha = 0$. The parametric p-value comes from a standard normal distribution, the bootstrapped p-value comes from estimated empirical distribution of the t-statistic under the null.

	Bottom	2.	3.	4.	5.	10%	20%	30%	40%	Median	40%	30%	20%	10%	5.	4.	3.	2.	Top
	Ordered Cross Section of Fund Alphas and t-Statistics																		
	Relative to Domestic Market of Global 7-Factor Model																		
	Gross Returns																		
$\hat{t}_{\hat{\alpha}}$	-2.36	-2.22	-2.09	-2.05	-1.96	-1.87	-1.62	-1.32	-1.07	-0.82	-0.64	-0.29	-0.04	0.17	0.51	0.51	0.64	1.31	2.11
$\hat{\alpha}$	-0.48	-0.32	-0.38	-0.47	-0.31	-0.36	-0.33	-0.39	-0.23	-0.23	-0.11	-0.05	-0.01	0.07	0.09	0.10	0.10	0.19	0.54
Annualized $\hat{\alpha}$	-5.77	-3.89	-4.55	-5.59	-3.66	-4.31	-3.93	-4.67	-2.71	-2.76	-1.36	-0.64	-0.10	0.85	1.14	1.14	1.19	2.33	6.46
P-value Parametric	0.02	0.03	0.04	0.05	0.05	0.07	0.11	0.19	0.29	0.41	0.53	0.77	0.97	0.87	0.61	0.61	0.52	0.19	0.04
P-value Bootstrapped	0.02	0.04	0.06	0.06	0.06	0.08	0.14	0.32	0.34	0.46	0.66	0.80	0.94	0.98	0.60	0.64	0.54	0.18	0.02
	Net Returns																		
$\hat{t}_{\hat{\alpha}}$	-3.32	-2.69	-2.52	-2.50	-2.45	-2.25	-1.80	-1.63	-1.49	-1.28	-1.07	-0.92	-0.53	-0.29	-0.12	0.07	0.09	0.62	1.67
$\hat{\alpha}$	-0.36	-0.42	-0.50	-0.57	-0.47	-0.41	-0.39	-0.50	-0.33	-0.26	-0.21	-0.19	-0.08	-0.26	-0.02	0.01	0.03	0.09	0.43
Annualized $\hat{\alpha}$	-4.34	-5.01	-5.98	-6.81	-5.60	-4.86	-4.65	-5.96	-3.97	-3.06	-2.49	-2.23	-0.96	-3.14	-0.22	0.15	0.34	1.10	5.11
P-value Parametric	0.00	0.01	0.01	0.02	0.02	0.03	0.08	0.10	0.14	0.20	0.29	0.36	0.60	0.77	0.91	0.95	0.93	0.54	0.10
P-value Bootstrapped	0.00	0.02	0.02	0.05	0.04	0.06	0.12	0.15	0.15	0.22	0.29	0.56	0.76	0.78	0.86	0.92	0.90	0.52	0.06

Table 8: Fund Performance vs. Regional Investment Characteristics: We use cross-sectional OLS regression model to find the relationship between each fund performance and the fund attributes and regional investment characteristics. The dependent variable is the net alpha estimates of each fund alpha of global 7-factor model, and the explanatory variables include fund size, age, expenses, fees, flow, team management, GDP per capita, liquidity and law system. The coefficient t-statistics are presented in parentheses.

	GREMF alpha				
TNA (in mil$) (log)	0.0140	0.0067	0.0152	0.0110	0.0046
	(0.73)	(0.34)	(0.78)	(0.58)	(0.22)
Age (in year) (log)	0.0150	0.0416	0.0133	0.0323	0.0470
	(0.23)	(0.63)	(0.20)	(0.51)	(0.69)
Expense Ratio	0.0280	-0.0034	0.0263	0.0494	-0.0067
	(0.35)	(-0.04)	(0.33)	(0.63)	(-0.08)
Load Fees	0.0323	0.0436	0.0303	0.0128	0.0469
	(0.56)	(0.76)	(0.52)	(0.20)	(0.80)
12b-1 Fees	-0.0495	-0.0342	-0.0546	-0.0268	-0.0278
	(-0.31)	(-0.21)	(-0.33)	(-0.78)	(-0.17)
Flow	0.0028*	0.0027*	0.0029*	0.0040**	0.0027*
	(1.79)	(1.77)	(1.81)	(2.39)	(1.69)
Team Management	0.0156	0.0065	0.0113	0.0253	0.0085
	(0.30)	(0.13)	(0.21)	(0.49)	(0.16)
$\sum w \times$GDP (log)		0.1600**			0.1841*
		(1.96)			(1.68)
$\sum w \times$Liquidity			-0.0003		-0.0002
			(-0.52)		(-0.36)
$\sum w \times D_{law}$				0.0070	0.0053
				(1.78*)	(1.70*)
Intercept	-0.3480**	-2.0126*	-0.3875**	-0.3645**	-2.2314*
	(-1.99)	(-1.86)	(-2.02)	(-2.13)	(-1.78)
Obs	76	76	76	76	76
R^2	16.07%	21.11%	16.67%	17.52%	21.38%

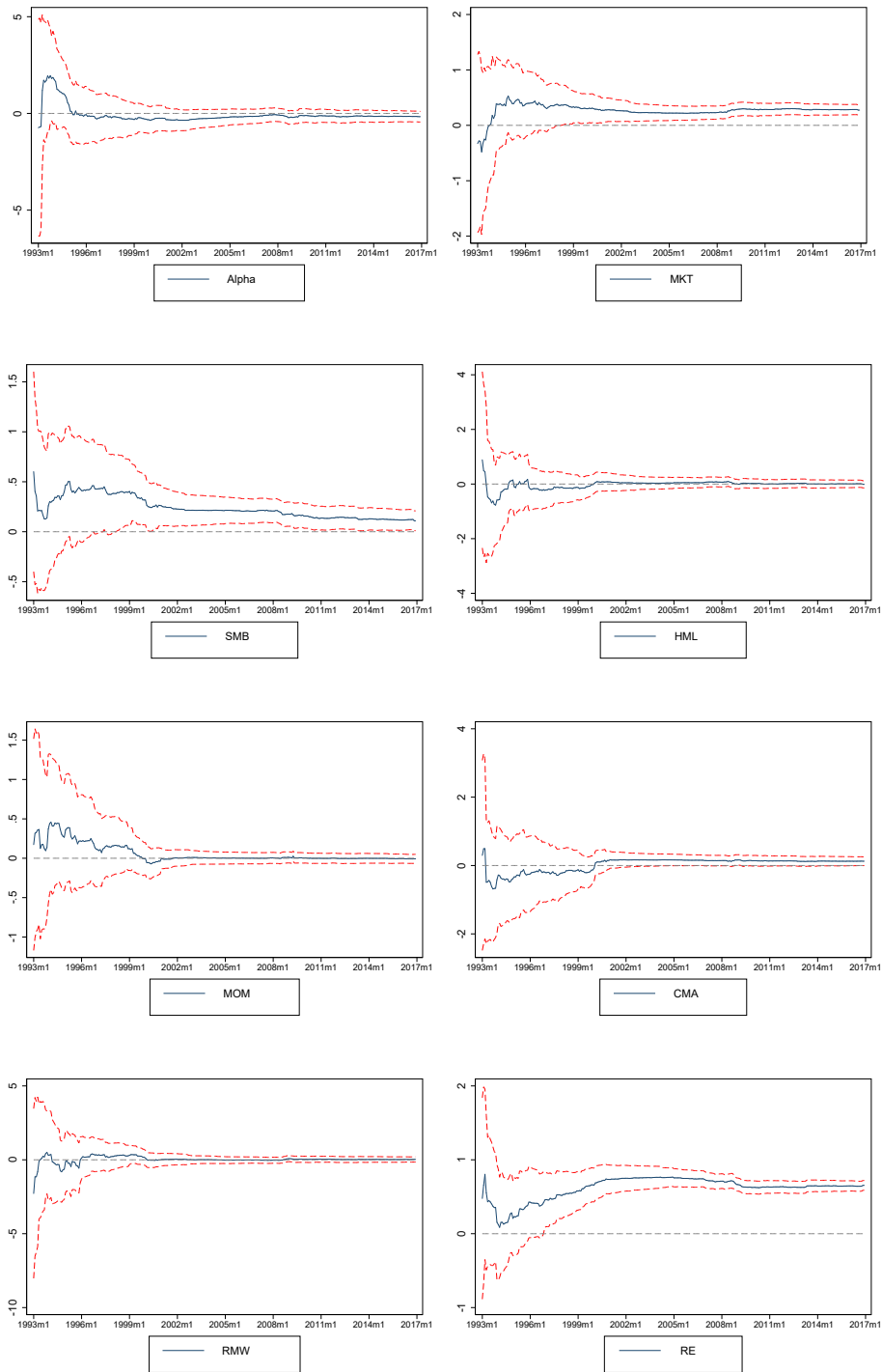*10% significance level, **5% significance level.
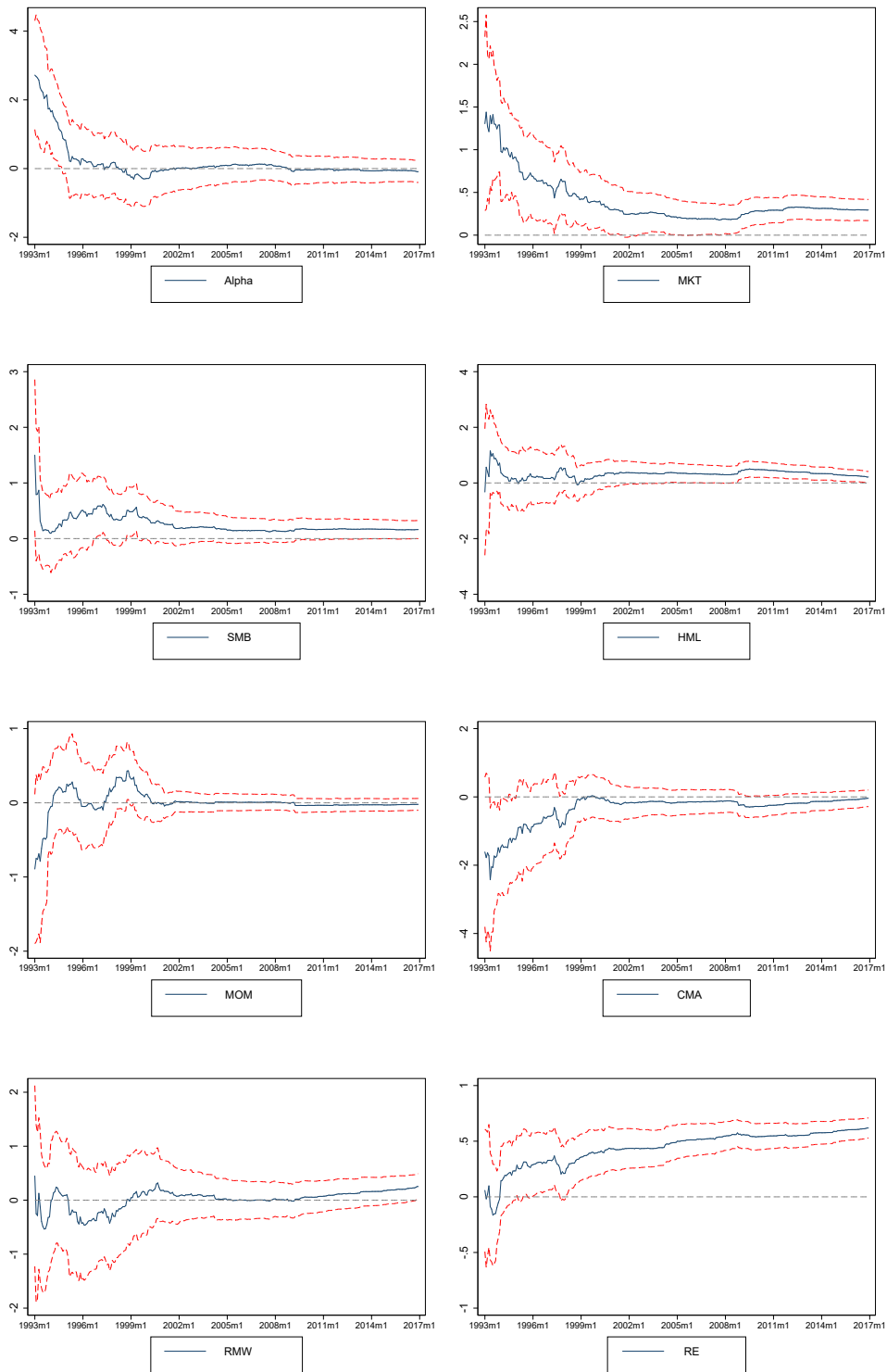
Figure 1: Recursive Alpha and Beta Estimates Relative to Global Market: Recursive coefficients of value-weighted portfolio of GREMFs, net of expenses, relative to global 7-factor model for the period 1992-2016.
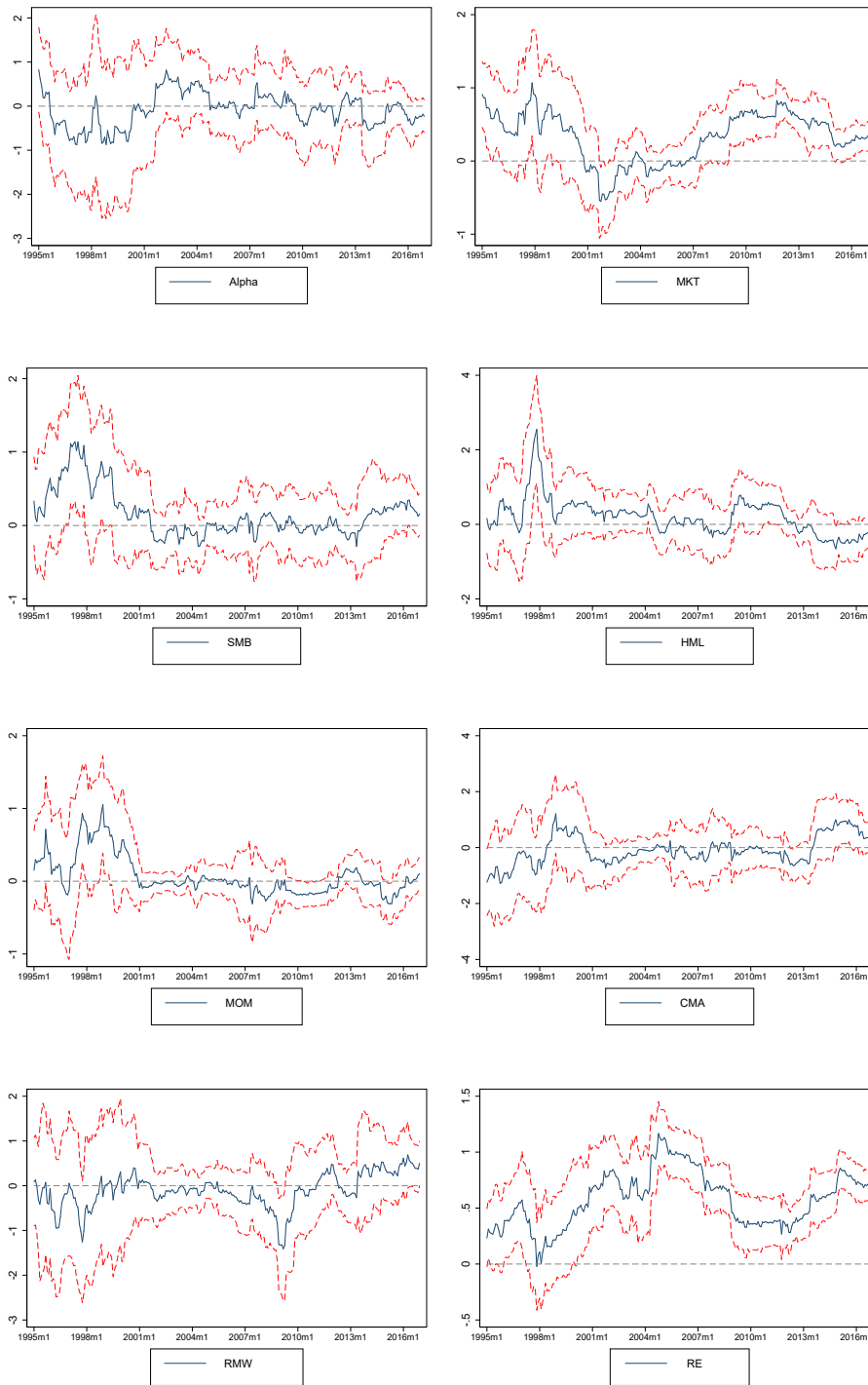
Figure 2: Three-year Rolling Window Alpha and Beta Estimates Relative to Global Market: 36-month rolling window coefficient estimates of value-weighted portfolio of GREMFs, net of expenses, relative to global 7-factor model for the period 1992-2016.

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Figure 3: Recursive Alpha and Beta Estimates Relative to Domestic Market: Recursive coefficients of value-weighted portfolio of GREMFs, net of expenses, relative to domestic 7-factor model for the period 1992-2016.
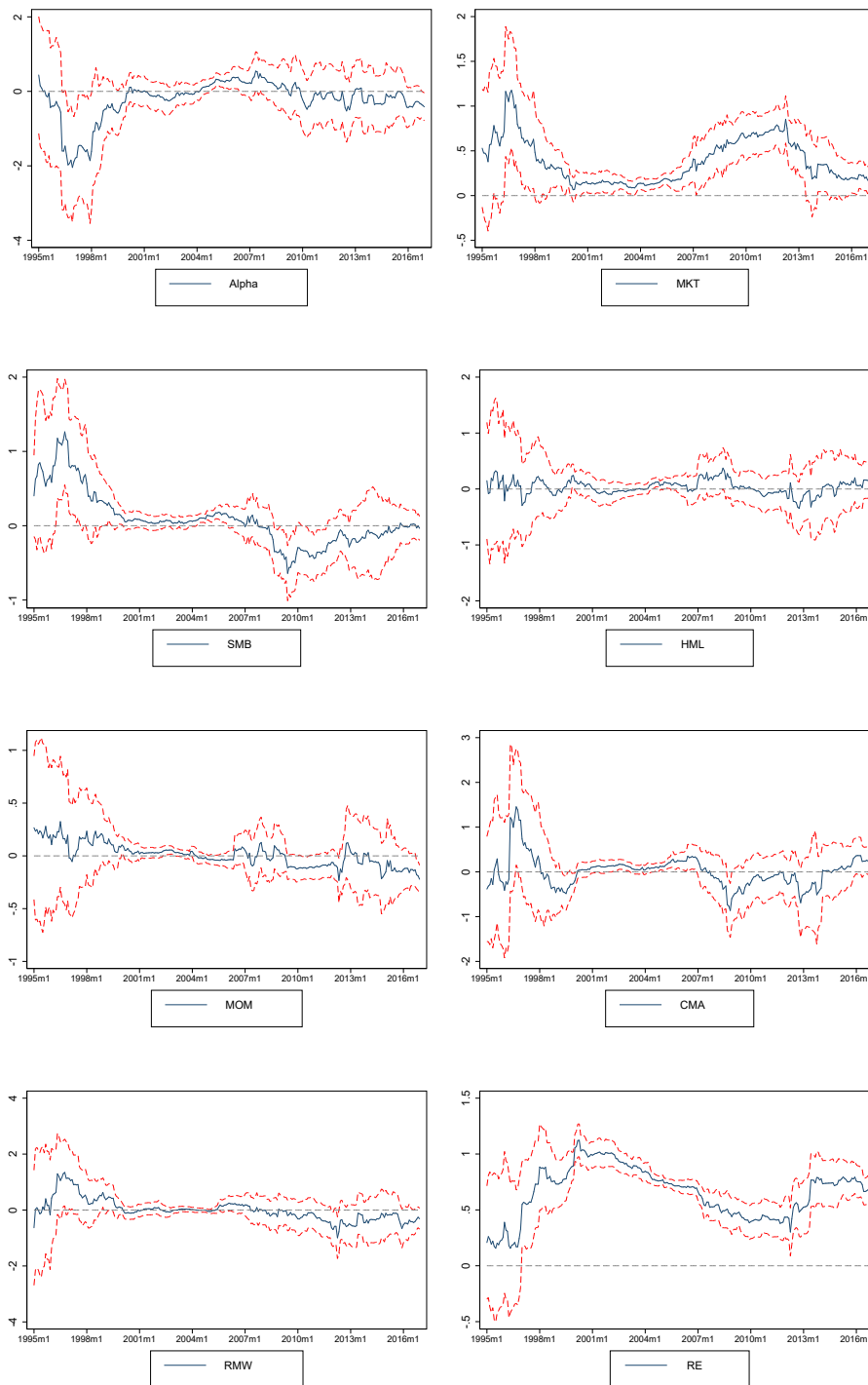
Figure 4: Three-year Rolling Window Alpha and Beta Estimates Relative to U.S. Domestic Market: 36-month rolling window coefficient estimates of value-weighted portfolio of GREMFs, net of expenses, relative to domestic 7-factor model for the period 1992-2016.

Appendix A   Appendix

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 domestic and GREMFs 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[37] on-
line 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%.

Appendix 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).

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