The new assessment of US mutual fund returns through a multiscaling approach

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Abstract

This paper applies the multiscaling approach to evaluate the performance of US mutual funds, namely Institutional, Active and Index funds. Based on this novel analysis, empirical results show that our results show that Institutional funds are clearly dominant over all time scales. Since risk and value (performance) are timescale-dependent concepts, any attempt to measure performance, such as a popular performance measure the Sharpe ratio or Jensen's alpha, must take into account the investment horizon effect.

Keywords: Mutual Fund Performance; Multiscaling; Sharpe ratio

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Abstract

This paper applies the multiscaling approach to evaluate the performance of US mutual funds, namely Institutional, Active and Index funds. Based on this novel analysis, empirical results show that our results show that Institutional funds are clearly dominant over all time scales. Since risk and value (performance) are timescale-dependent concepts, any attempt to measure performance, such as a popular performance measure the Sharpe ratio or Jensen's alpha, must take into account the investment horizon effect.

Keywords: Performance Measure; Mutual Fund; Multiscaling; Sharpe ratio.

1. Introduction

The holding period is an important factor that has a considerable bearing on the assessment of fund performance. It is notable then, that holding period has been largely overlooked in the literature, both in traditional studies and in the more recent analyses. Accordingly, the primary aim of the current study is to help redress this weakness in the literature by, for the very first time, applying multiscaling techniques to the Jensen alpha assessment of US mutual fund performance.

The holding period that is relevant for portfolio allocation is the length of time investors hold any stocks or bonds (Siegel, 1998, p. 29). In other words, the investment horizon sensitivity is very important in evaluating the performance of one or more portfolios. A private (relatively uninformed) investor might not be interested in short-term performance of portfolios at all. Institutional investors like pension funds have a very long-term investment horizons. In contrast, other investors influenced by feedback trading notions (for example) may be much more attuned to short-term performance. As such, it is of considerable interest to examine the long-term performance of the investments when the investment horizon increases.

The examination of multi-horizon performance measures are important at least two-fold. First, in terms of the performance evaluation of fund manager, the multi-horizon measures are useful. For example, consider an investment company with a large number of investors and money managers. Clearly, the investors and the money managers make decisions over different time scales. Suppose, for simplicity, that the investment horizon of an investor is one year and that the investment company reviews the performance of the money manager every quarter. The money manager will therefore focus on the three-month performance of a portfolio, while the investor will concentrate on the one-year performance. Thus, for this investor, the money manager may not provide the best service. Second, in the investor's point of view, the investors need to have sufficient information about the performance of mutual funds over a long period before selecting mutual funds. Therefore, ignoring the time-scale effect might cause a biased performance measure.

Our paper aims to contribute to the literature on the study of the performance measures of mutual fund returns using the multiscaling approach: wavelet analysis and to the best of our knowledge, no previous study has conducted such an investigation. A big advantage of adopting wavelet analysis is that it does not require any assumption on the distribution of returns, due to its nonparametric nature.

To evaluate the performance of mutual funds, the Sharpe ratio[1] has been adopted. The motivation for using the Sharpe ratio is from the studies of Pfingsten et al. (2004) and Pedersen and Rudholm-Alfvin (2003), who find that different performance measures result in a largely identical ranking. In addition, recent study of Kim and In (2005) propose the multiscale Sharpe ratio to evaluate the performance of a portfolio, based on the wavelet multiscaling decomposition. In addition, we adopt the nonparametric bootstrap method for more concrete statistical inference. The bootstrap method has been applied recently by Kosowski et al. (2006) in relation to mutual funds.

The main advantage of wavelet analysis is the ability to decompose the data into several time scales. Consider the large number of investors who trade in security markets and make decisions over different time scales. In fact, due to the different

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[1] Similar to our study, Hodges et al. (1997) examine the multiperiod Sharpe ratio using bootstrap method. The bootstrap method in their study has been used to generate the longer term returns, while the same method has been adopted for generating the statistical inference and wavelet analysis has been adopted to generate the movements of various time scales.

decision-making time scales among investors, the true dynamic structure of the relationship between variables will *vary* over different time scales associated with those different horizons. While economists and financial analysts have long recognized the idea of multiple time periods in decision making, they have traditionally been effectively forced to adopt a simplistic dichotomous characterization of ‘short-run’ versus ‘long-run’, due to the lack of analytical tools to decompose data into more than two time scales (In and Kim, 2006).

In addition to this purpose, we also examine the correlation with market index. The examination the correlation over various investment horizons is also important in the sense that the inclusion of mutual funds in a portfolio can potentially result in better risk-return tradeoffs.

Our results show that Institutional funds are clearly dominant over all time scales. Since risk and value (performance) are timescale-dependent concepts, any attempt to measure performance, such as a popular performance measure the Sharpe ratio or Jensen’s alpha, must take into account the investment horizon effect.

The remainder of the paper is organized as follows. Section 2 discusses the performance measure models. Section 3 describes the econometric methodology for the wavelet analysis. The data and the empirical results are discussed in Section 4. Section 5 presents the summary and concluding remarks.

2. Empirical Method

Currently, most performance studies of multi-index asst pricing models use Jensen’ (1968) alpha. Its interpretation as the risk-adjusted abnormal return of a portfolio makes it flexible enough to be used in most asset pricing specifications. Kothari and Warner

(2001) consider only this measure for multi-index asset pricing models in their empirical comparison of mutual fund performance measures. However, in this study the Sharpe ratio has been adopted following the studies of Pfingsten et al. (2004) and Pedersen and Rudholm-Alfvin (2003) In this section, we briefly explain how to derive the Sharpe ratio in multiscaling context.

Wavelet analysis is a natural tool available to investigate the dis-aggregation of performance into various time scales, as it enables us to decompose the data on a scale-by-scale basis. In this section, we summarize the discrete wavelet transform (DWT). The discrete wavelet transform (DWT) is a kind of discretization of the continuous wavelet transform. Basic wavelets are characterized into father and mother wavelets, $\phi(t)$ and $\psi(t)$, respectively. These wavelets are functions of time only. A father wavelet (scaling function) represents the smooth baseline trend, while mother wavelets (wavelet function) are used to describe all deviations from trends. Consider a time series, $f(t)$, which we want to decompose into various wavelet scales. Given the father wavelet ϕ such that its dilates and translates constitute orthonormal bases for all the V_j subspaces that are scaled versions of the subspace V_0 to which ϕ belongs, we can form a Multiresolution Analysis (MRA) for a given time series (see Burrus et al., 1998 for details).

With DWT, we are basically constructing a map from the signal domain to the wavelet coefficients domain. In other words, we apply the transform $w = Wf$. The important features of time series can better be captured by defining a slightly different set of functions $\psi(t)$, mother wavelets, which span the differences between two adjacent spaces. Combining the orthogonality property, we can describe L^2 as follows:

$$L^2 = V_0 \oplus W_1 \oplus W_2 \oplus W_3 \oplus \cdots \tag{1}$$

where $\oplus$ denotes the orthogonal sum. In equation (1), the relationship of V_0 to the wavelet spaces can be described as $V_0 = W_{-\infty} \oplus \cdots \oplus W_{-1}$. This relationship shows that the key idea of MRA consists of studying a time series by examining its increasingly coarser approximations as more and more details are canceled from the data (Abry et al., 1998). Based on this relationship, the mother wavelet $\psi(t)$ has the following form:[2]

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}} \psi(2^{-j} t - k) = 2^{-j/2} \psi\left(\frac{t - 2^j k}{2^j}\right) \tag{2}$$

According to equation (2), any time series $f(t) \in L^2$ could be written as a series expansion in terms of the scaling function and wavelets.

$$f(t) = \sum_{k=-\infty}^{\infty} s_k \phi_k(t) + \sum_{j=0}^{\infty} \sum_{k=-\infty}^{\infty} d_{j,k} \psi_{j,k}(t) \tag{3}$$

As can be seen in equation (3), the DWT algorithm has an ability to produce the wavelet coefficients for fine (coarse) scales, thus capturing high (low) frequency information. Therefore, a series of smoothed data, captured by s_k, and a series of

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[2] Intuitively, a small *j* or a low resolution level can capture smooth components of the signal, while a large *j* or a high resolution level can capture variable components of the signal (Lee and Hong, 2001).

details ($d_{j,k}$) not previously accounted for, which give information at finer resolution levels, are obtained.

Our analysis adopts the MODWT instead of DWT. It provides basically all functions of the DWT, such as MRA decomposition[3] and analysis of variance. Given the wavelet coefficients obtained from the MODWT, the wavelet variance, covariance and correlation are estimated using the coefficients for scale $\lambda_j \equiv 2^{j-1}$ under the assumption that the dependence structure of our returns is independent of time[4] through:

$$\sigma_l^2(\lambda_j) \equiv \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} [d_{j,t}^l]^2 \text{ , } l = X, Y \tag{4}$$

$$Cov_{XY}(\lambda_j) \equiv \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} d_{j,t}^X d_{j,t}^Y \tag{5}$$

$$\tilde{\rho}_{XY}(\lambda_j) \equiv \frac{Cov_{XY}(\lambda_j)}{\sigma_X(\lambda_j)\sigma_Y(\lambda_j)} \tag{6}$$

where $d_{j,t}^l$ is the wavelet coefficient of variables l at scale λ_j. $\tilde{N}_j = N - L_j + 1$ is the number of coefficients unaffected by the boundary, and $L_j = (2^j - 1)(L - 1) + 1$ is the length of the scale λ_j wavelet filter.

Given the three models (equations (1) to (3)) and these wavelet coefficients at each scale, the Sharpe ratio at various time scales can be estimated as follows:

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[3] Note that this version of MRA provides an important feature, which is not available to the original DWT. For more detail, see Percival and Walden (2000) and In and Kim (2006).

[4] This assumption basically says that the statistical properties of original time series at scale λ_j are invariant over time, which is true for a stationary time series, and hence can be usefully summarized by the time-independent wavelet variance (sufficient conditions for this statement can be found in Percival and Walden (2000, pp.304 – 306)).

$$SR_p^w(\lambda_j) = \frac{\overline{R}_p(\lambda_j) - \overline{R}_f(\lambda_j)}{\sqrt{\sigma^2(\lambda_j)}} \tag{7}$$

where $\overline{R}_p(\lambda_j)$ and $\overline{R}_f(\lambda_j)$ are the mean values of hedge fund returns and the risk-free rate at scale λ_j. These mean values are calculated using the scaling coefficients, following Gençay et al. (2003). In this specification, SR_p^w indicates the wavelet multiscale Sharpe ratio of hedge fund returns, which can be varying depending on the wavelet scales (i.e., investment horizons).

3. Data and empirical results

We use monthly nominal mutual fund returns (index fund, institutional, and active funds) for the US over the period January 1991 to December 2005. Data were collected from CRSP. To construct the returns of each fund group, the value weighted returns are calculated using the total net asset under management. More specially, for the index fund category there are 12 sampled funds and their returns weighted averaged using the their net asset values. Similarly, the institutional fund and the active fund group returns are calculated from 35 institutional funds and 346 active funds, respectively. For the market return proxy, we use the CRSP value-weighted market index return, for the risk free return we use one-month Treasury bills.

Institutional funds are defined as mutual funds that target pension funds, endowments, and other high net worth entities and individuals. Institutional funds usually have lower operating costs and higher minimum investments than retail funds.

The main objective of institutional funds is to reduce risk by investing in hundreds of different securities. The objective of active funds is to outperform the market average by actively seeking out stocks that will provide superior total return. In contrast, index funds are a form of passive investment. Index funds are mutual funds whose portfolio aims to match holdings (with some degree of tolerance on tracking error) of a market index such as the S&P 500 Index. Therefore, their performance mirrors the market as a whole.

Table 1 presents several summary statistics for the monthly data of our three groupings of mutual fund (Institutional, Active and Index funds) returns and market returns, indicated as MKT. As shown in Table 1, all sample means range from 0.985 (Index) to 1.080 (Institutional). Comparing the three fund categories, all have very similar mean return and standard deviation with slight low standard deviation in Institutional funds. Table 1 also reveals that across the four reported variables, first-order autocorrelation of monthly data ranges from –0.060 (Index) to 0.050 (Institutional), implying that the Institutional funds are more persistent than the two mutual fund categories and the market portfolio. The Ljung-Box statistics indicate the persistence of linear dependency of each set of data and the Ljung-Box statistics for the squared data show strong evidence of non-linear dependency in all data except Institutional fund. The measures for skewness and kurtosis are also reported to check whether monthly data are normally distributed. These statistics indicate that all data are not normally distributed.

3.1. Estimation results for the three aggregate groups.

The purpose of this paper is to examine the performance of the mutual funds multihorizontally. To do so, we use a multihorizon version of the Sharpe ratio, using the wavelet multiscaling approach. Considering the balance between the sample size and the length of the wavelet filter, we settle with the Daubechies extremal phase wavelet filter of length 4 (D(4)), while we decompose our data up to scale 5. Since we use monthly data, scale 1 represents 1-2 month period dynamics. Equivalently, scale 2, 3, 4, and 5 correspond to 2-4, 4-8, 8-16, and 16-32 month period dynamics, respectively.

First, we examine the variances of the three groups of mutual returns against various time scales. The examination of the variance at each time scale is important in our study because the variance at each scale shows how much risk investors possess at each time scale in the context of the Sharpe ratio. An important characteristic of the wavelet transform is its ability to decompose (analyze) the variance of the stochastic process. Figure 1 illustrates the wavelet variance of three series against the wavelet scales. The return variances of the three mutual fund categories decrease as the wavelet scale increases. Note that the variance-versus-wavelet scale curves show a broad peak at the lowest scale (scale 1) in all mutual funds groups. This result implies that an investor with a short investment horizon has to respond to every fluctuation in the realized returns, while for an investor with a much longer horizon, the long-run risk is significantly less (Kim and In, 2005).

Table 2 presents the multiscale correlation with market portfolios. Investigating the correlation with market returns is important in terms of the construction of a portfolio of investors because inclusion of mutual fund with low correlation in a portfolio can provide the better risk-return tradeoffs. Note that the mean and the upper and lower bounds at 5% significance level are calculated using the nonparametric bootstrap method[5] by generating 3000 replications. As can be seen in Table 2, the average across replications is very similar to the original estimates, which means that no correction for small-sample bias is needed. Most correlations regardless of time scales show very high correlation with market returns, while Institutional funds at scale 5 shows a little lower correlation with market returns, implying that including an additional mutual fund in a portfolio is not a good strategy for all investors with various investment horizons.

In Table 3, we report the estimated Sharpe ratio, the average Sharpe ratio, and the corresponding standard errors, calculated from the nonparametric bootstrap method. In this table, we present the Sharpe ratio of the market portfolio for comparison reason with other mutual funds. From this table, three things are worth noting. First, overall the Sharpe ratio at scale 4 shows the highest value in all portfolios, indicating that investors have the highest compensation for a unit of risk at 8-16 month period, i.e., approximately 1-year period. Second, while the Sharpe ratio at raw data of Index fund is lower than that of the market portfolio, the Sharpe ratio of Index fund is consistently higher than the market portfolio, indicating that the performance of Index funds is better than the market portfolio. Finally, Institutional (Active) funds have the highest (lowest) Sharpe ratio at all time scales, indicating that Institutional (Active) funds are a best (worst) performer among mutual funds. The final result indicates that the winner (loser) at short scale consistently outperforms (underperforms).

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[5] Kosowski et al. (in press) argue the three reasons for the bootstrap method. First, the bootstrap frees the researcher from having to make a prior assumption about the shape of the distribution. Second, this method allows us to avoid having to estimate the entire covariance matrix characterizing the joint distribution of individual funds. Finally, refinement of the bootstrap provide a general approach for dealing with unknown time-series dependencies that are due to heteroskedasticity or serial correlation in the residuals from performance regressions. See Kosowski et al. (in press) for more detail.

In sum, our results show that Institutional funds tend to outperform the Index and Active funds at all time scales, suggesting that the persistence of the performance exists at the time scales.

3.2. Estimation results for the individual mutual funds.

To examine the performance of individual funds, we select the 5 bottom funds and 5 top funds for each group. The 5 bottom and 5 top funds are selected in terms of their average net asset values during 2005. More specifically, bottom1 (top1) in each fund group indicates the fund, which has the lowest (highest) average net asset value during 2005. The estimated Sharpe ratios, the average Sharpe ratios and the corresponding standard errors in index fund group are reported in Table 4. Note that as in Table 3, the average Sharpe ratio (reported in parentheses) and the standard errors (reported in brackets) are calculated using the nonparametric bootstrap method by generating 3000 replications

Overall, the Sharpe ratio at scale 4 shows the highest value in all portfolios, indicating that investors have the highest compensation for a unit of risk at 8-16 month period, as found in Table 3. Comparing the Sharpe ratios at each time scale shows that the size of funds does not play an important role in the performance of funds. For example, Top5 (Bottom1) always has the highest (lowest) Sharpe ratio at all time scales, indicating that the winner (loser) at short scale consistently outperforms (underperforms). However, the estimated Sharpe ratios are statistically different from each other, because the 95% confidence interval of Bottom1's Sharpe ratio includes all estimated Sharpe ratio.

Next, we examine the individual funds among the institutional fund group, illustrated in Table 5. Overall, the estimated Sharpe ratios with the lower net asset values are lower than those with the higher net asset values at all time scales. That is, the performances of funds with the higher net asset values are consistently better than those with the lower net asset values, implying that the size of funds matters. Note that from the bootstrapped results, the estimated Sharpe ratios between the Bottom funds and Top funds are statistically different using the 95% confidence interval. In addition, it is found that the estimated Sharpe ratios with the lower net asset values are increasing up to scale 4, while those with the higher net asset values increasing with time scales. This indicates that institutional funds with the lower net asset values provide the highest compensations bearing a unit of risk at one-year period, while institutional funds with higher net asset values give the increasing compensations with time scales. Therefore, the pension funds, whose investment horizon is longer than one-year, can be better off to invest the institutional funds with higher net asset values. Furthermore, overall ranking, calculated by the estimated Sharpe ratios, has not been changed over the time scales, indicating that without calculating the Sharpe ratio for their specific investment horizon, investors decide their investment using the Sharpe ratio at the short investment horizon.

Turning to active funds, the estimated Sharpe ratios are reported in Table 6. Overall results are similar to those of institutional funds. As indicated above, the purpose of active funds is to outperform the market average by actively seeking out stocks that will provide superior total return. Comparing the estimated Sharpe ratio of market returns, shown in Table 3, individual active funds with higher (lower) net asset values consistently performs better (worse) than market return. This result suggests that investors seeking superior returns can be better off by investing active funds with the higher net asset values.

4. Summary and Concluding Remarks

In the literature, despite its importance in modern financial analysis, the evaluation of mutual fund performance have not been accompanied by examination of the impact of investment horizon, an important factor for investments. This paper uses the Sharpe ratio at various time scales to evaluate the performance of three groups of US mutual funds (Institutional, Active and Index funds). The wavelet multiscaling approach has the advantage of being able to decompose the time series over the various time scales. This advantage allows us to investigate the behavior of our data over multiple horizons.

In terms of the performance measures of the three mutual fund groups, our empirical results indicate that Institutional funds are clearly dominant over all time scales. Since risk and value (performance) are timescale-dependent concepts, any attempt to measure performance, such as a popular performance measure the Sharpe ratio or Jensen’s alpha, must take into account the investment horizon effect.

From examining individual funds, it is found that while choosing index fund, the size of funds does not matter in terms of their performance, while in institutional and active funds, funds with the higher net asset values consistently perform better than those with the lower net asset values, implying that investors seeking superior returns can be better off by investing funds with the higher net asset values.

References

Abry, P. A., D. Veitch, and P. Flandrin, (1998) “Long range dependence: Revisiting aggregation with wavelets.” *Journal of Time Series Analysis* 19, 253-266.

Burrus, C. S., R. A. Gopinath, and H. Guo, (1998) *Introduction to wavelets and wavelet transforms*. Prentice-Hall, New Jersey.

Gençay, R., F. Selçuk, and B. Whitcher, (2003) “Systematic risk and time scales.” *Quantitative Finance* 3, 108–116.

Hodges, C. W., W. R. Taylor, and J. A. Yoder, (1997) “Stocks, bonds, the Sharpe ratio, and the investment horizon.” *Financial Analysts Journal* 53, 74–80.

In, F., and S. Kim, (2006) “The hedge ratio and the empirical relationship between the stock and futures markets: A new approach using wavelet analysis.” *Journal of Business* 79, 799-820.

Jensen, M. J., (1968) “The Performance of Mutual Funds in the Period 1945-1964.” *Journal of Finance* 23, 389-416.

Kosowski, R., A. Timmermann, R. Wermers, and H. White (2006) “Can mutual fund “stars” really pick stocks? New evidence from a bootstrap analysis.” *Journal of Finance* 61, 2551-2596.

Kosowski, R., N. Y. Naik, and T. Melvyn (in press) “Do hedge funds deliver alpha? A Baysian and bootstrap analysis.” *Journal of Financial Economics*.

Kim, S., and F. In, (2005) “Multihorizon Sharpe ratio.” *Journal of Portfolio Management* 31, 105-101

Kothari, S.P. and Jerold B. Warner (2001) “Evaluating mutual fund performance.” *Journal of Finance* 56, 1985-2010.

Lee, J., and Y. Hong, (2001), “Testing for serial correlation of unknown form using wavelet methods.” *Econometric Theory* 17, 386-423.

Pedersen, C. S., and T. Rudholm-Alfvin (2003) “Selecting a risk-adjusted shareholder performance measure.” *Journal of Asset Management* 4, 152-172.

Percival, D. B., and A. T. Walden (2000) *Wavelet methods for time series analysis*. Cambridge University Press, Cambridge, UK.

Pfingsten, A., P. Wagner, and C. Wolferink, (2004). “An empirical investigation of rank correlation between different risk measures.” *Journal of Risk* 6, 55-74.

Siegel, J. J. (1998) “Stocks for the long run.” New York, McGraw-Hill.

Table 1. Descriptive statistics

	Market	Index	Institutional	Active
mean	1.0200	0.9850	1.0800	0.9999
std.dev	4.1500	4.0500	3.5100	4.0200
skewness	-0.6870	-0.4951	-0.8406	-0.6086
kurtosis	1.1292	0.9026	2.2494	1.1020
LB(5)	1.1987	3.7449	3.1053	0.9449
	(0.5492)	(0.1537)	(0.2117)	(0.6235)
LB(10)	6.5884	8.6028	5.6759	5.2442
	(0.4730)	(0.2824)	(0.5781)	(0.6302)
$LB^2(5)$	10.5675*	12.7537*	1.7071	7.1816*
	(0.0051)	(0.0017)	(0.4259)	(0.0276)
$LB^2(10)$	23.5555*	22.0862*	9.4895	16.9636*
	(0.0014)	(0.0025)	(0.2194)	(0.0176)
ρ(t,t-1)	0.0032	-0.0604	0.0499	-0.0103

Note: Institutional funds are a mutual funds which target pension funds, endowments, and other high net worth entities and individuals. The objective of active funds is to outperform the market average by actively seeking out stocks that will provide superior total return. Index funds are a mutual fund whose portfolio matches that of a market index such as the S&P 500 Index. Market is the CRSP value weighted returns. * indicates significance at 5% level. LB(*k*) and $LB^2(k)$ denotes the Ljung-Box test of significance of autocorrelations of k lags for returns and squared returns, respectively. rho(t,t-1) is the first order autocorrelation coefficient. Skewness and kurtosis are defined as $E[(R_t - \mu)]^3$ and $E[(R_t - \mu)]^4$, respectively, where μ is the sample mean.

Table 2. Estimated correlation.

	Panel A. estimated correlation			Panel B. average correlation		
	Index	Institutional	Active	Index	Institutional	Active
Raw	0.969	0.956	0.988	0.945	0.918	0.963
scale 1	0.977	0.971	0.995	0.977	0.971	0.995
scale 2	0.969	0.965	0.994	0.969	0.965	0.994
scale 3	0.973	0.955	0.992	0.972	0.955	0.992
scale 4	0.975	0.922	0.989	0.975	0.920	0.989
scale 5	0.980	0.795	0.990	0.980	0.796	0.990
	Panel C. lower bound			Panel D. upper bound		
	Index	Institutional	Active	Index	Institutional	Active
Raw	0.906	0.868	0.925	0.985	0.967	1.000
scale 1	0.964	0.959	0.993	0.990	0.982	0.997
scale 2	0.951	0.951	0.991	0.987	0.978	0.996
scale 3	0.958	0.937	0.988	0.987	0.972	0.995
scale 4	0.964	0.887	0.985	0.985	0.954	0.993
scale 5	0.972	0.739	0.986	0.987	0.853	0.993

Note: To calculate the correaltion at scale λ_j, we decompose each time series up to level 5, using the Daubechies extremal phase wavelet filter of length 4 (D(4)). Scale 1, 2, 3, 4, and 5 represent 1-2, 2-4, 4-8, 8-16, and 16-32 month period dynamics, respectively. The upper and lower bounds indicate the 95% confidence interval. The average correlation, lower and upper bounds are calculated using bootstrap method, by generating 3,000 replications.

Table 3. Estimated Sharpe ratios for aggregate funds.

	Market	Index	Institutional	Active
Raw	0.170	0.165	0.217	0.170
	(0.243)	(0.228)	(0.322)	(0.242)
	[0.109]	[0.106]	[0.112]	[0.109]
scale 1	0.220	0.208	0.293	0.216
	(0.221)	(0.208)	(0.294)	(0.216)
	[0.076]	[0.071]	[0.083]	[0.075]
scale 2	0.298	0.306	0.370	0.300
	(0.300)	(0.309)	(0.372)	(0.303)
	[0.075]	[0.076]	[0.074]	[0.077]
scale 3	0.425	0.462	0.525	0.416
	(0.428)	(0.464)	(0.529)	(0.419)
	[0.084]	[0.092]	[0.081]	[0.084]
scale 4	0.661	0.742	0.774	0.618
	(0.667)	(0.749)	(0.782)	(0.624)
	[0.123]	[0.142]	[0.104]	[0.117]
scale 5	0.422	0.439	0.707	0.394
	(0.421)	(0.439)	(0.709)	(0.394)
	[0.165]	[0.201]	[0.131]	[0.157]

Note: To calculate the Sharpe ratio at scale λ_j, we decompose each time series up to level 5, using the Daubechies extremal phase wavelet filter of length 4 (D(4)). Scale 1, 2, 3, 4, and 5 represent 1-2, 2-4, 4-8, 8-16, and 16-32 month period dynamics, respectively. The mean values of the Sharpe ratio for each portfolio returns are reported in parentheses, while the standard deviations are reported in brackets. The mean values and standard errors calculated using bootstrap method, by generating 3,000 replications.

Table 4. Estimated Sharpe ratios for individual index funds.

	Bottom1	Bottom2	Bottom3	Bottom4	Bottom5	Top5	Top4	Top3	Top2	Top1
Raw	0.150	0.157	0.164	0.160	0.163	0.172	0.164	0.164	0.168	0.166
	(0.207)	(0.217)	(0.226)	(0.221)	(0.225)	(0.242)	(0.226)	(0.226)	(0.232)	(0.229)
	[0.105]	[0.106]	[0.106]	[0.106]	[0.106]	[0.108]	[0.106]	[0.106]	[0.106]	[0.106]
scale1	0.187	0.197	0.206	0.200	0.205	0.222	0.205	0.206	0.211	0.208
	(0.188)	(0.198)	(0.207)	(0.201)	(0.206)	(0.223)	(0.206)	(0.207)	(0.212)	(0.209)
	[0.070]	[0.071]	[0.071]	[0.071]	[0.071]	[0.074]	[0.071]	[0.071]	[0.071]	[0.071]
scale2	0.277	0.291	0.303	0.296	0.302	0.318	0.302	0.303	0.312	0.307
	(0.280)	(0.294)	(0.306)	(0.299)	(0.305)	(0.321)	(0.305)	(0.306)	(0.315)	(0.310)
	[0.076]	[0.077]	[0.076]	[0.076]	[0.076]	[0.078]	[0.076]	[0.076]	[0.076]	[0.076]
scale3	0.416	0.433	0.456	0.446	0.456	0.480	0.455	0.457	0.470	0.463
	(0.418)	(0.436)	(0.459)	(0.448)	(0.458)	(0.482)	(0.458)	(0.460)	(0.473)	(0.466)
	[0.091]	[0.091]	[0.092]	[0.092]	[0.093]	[0.094	[0.092]	[0.092]	[0.092]	[0.092]
scale4	0.672	0.697	0.736	0.719	0.729	0.769	0.733	0.735	0.756	0.744
	(0.678)	(0.703)	(0.743)	(0.725)	(0.736)	(0.775)	(0.740)	(0.741)	(0.762)	(0.751)
	[0.140]	[0.140]	[0.142]	[0.142]	[0.142]	[0.143]	[0.142]	[0.142]	[0.142]	[0.142]
scale5	0.357	0.384	0.428	0.396	0.418	0.484	0.430	0.428	0.457	0.443
	(0.356)	(0.384)	(0.428)	(0.396)	(0.418)	(0.483)	(0.430)	(0.427)	(0.457)	(0.443)
	[0.200]	[0.202]	[0.201]	[0.201]	[0.200]	[0.211]	[0.201]	[0.201]	[0.201]	[0.201]

Note: To calculate the Sharpe ratio at scale λ_j, we decompose each time series up to level 5, using the Daubechies extremal phase wavelet filter of length 4 (D(4)). Scale 1, 2, 3, 4, and 5 represent 1-2, 2-4, 4-8, 8-16, and 16-32 month period dynamics, respectively. The mean values of the Sharpe ratio for each portfolio returns are reported in parentheses, while the standard errors are reported in brackets. The mean values and standard deviations are calculated using bootstrap method, by generating 3,000 replications.

Table 5. Estimated Sharpe ratios for individual institutional funds.

	Bottom1	Bottom2	Bottom3	Bottom4	Bottom5	Top5	Top4	Top3	Top2	Top1
Raw	0.091	0.063	0.211	0.132	0.191	0.194	0.288	0.283	0.159	0.280
	(0.132)	(0.091)	(0.304)	(0.194)	(0.278)	(0.270)	(0.457)	(0.449)	(0.228)	(0.436)
	[0.111]	[0.110]	[0.111]	[0.113]	[0.110]	[0.105]	[0.121]	[0.121]	[0.109]	[0.119]
scale1	0.128	0.084	0.280	0.171	0.254	0.244	0.426	0.417	0.193	0.406
	(0.127)	(0.083)	(0.282)	(0.171)	(0.256)	(0.245)	(0.428)	(0.419)	(0.195)	(0.407)
	[0.078]	[0.077]	[0.078]	[0.079]	[0.081]	[0.072]	[0.097]	[0.097]	[0.075]	[0.094]
scale2	0.159	0.118	0.375	0.213	0.338	0.368	0.496	0.475	0.280	0.473
	(0.160)	(0.120)	(0.378)	(0.215)	(0.341)	(0.371)	(0.501)	(0.479)	(0.283)	(0.477)
	[0.071]	[0.090]	[0.075]	[0.074]	[0.075]	[0.077]	[0.083]	[0.080]	[0.073]	[0.080]
scale3	0.220	0.154	0.524	0.300	0.477	0.551	0.687	0.666	0.423	0.678
	(0.222)	(0.154)	(0.528)	(0.303)	(0.480)	(0.554)	(0.694)	(0.673)	(0.425)	(0.685)
	[0.081]	[0.103]	[0.080]	[0.080]	[0.082]	[0.091]	[0.089]	[0.088]	[0.086]	[0.089]
scale4	0.255	0.178	0.916	0.463	0.622	0.815	0.895	0.850	0.642	0.847
	(0.260)	(0.181)	(0.925)	(0.470)	(0.626)	(0.821)	(0.903)	(0.857)	(0.646)	(0.852)
	[0.090]	[0.131]	[0.125]	[0.106]	[0.092]	[0.118]	[0.093]	[0.091]	[0.098]	[0.084]
scale5	0.079	-0.138	0.895	0.279	0.567	0.721	1.049	0.949	0.647	0.944
	(0.079)	(-0.141)	(0.897)	(0.280)	(0.569)	(0.723)	(1.058)	(0.957)	(0.651)	(0.950)
	[0.086]	[0.149]	[0.181]	[0.087]	[0.113]	[0.193]	[0.110]	[0.097]	[0.157]	[0.097]

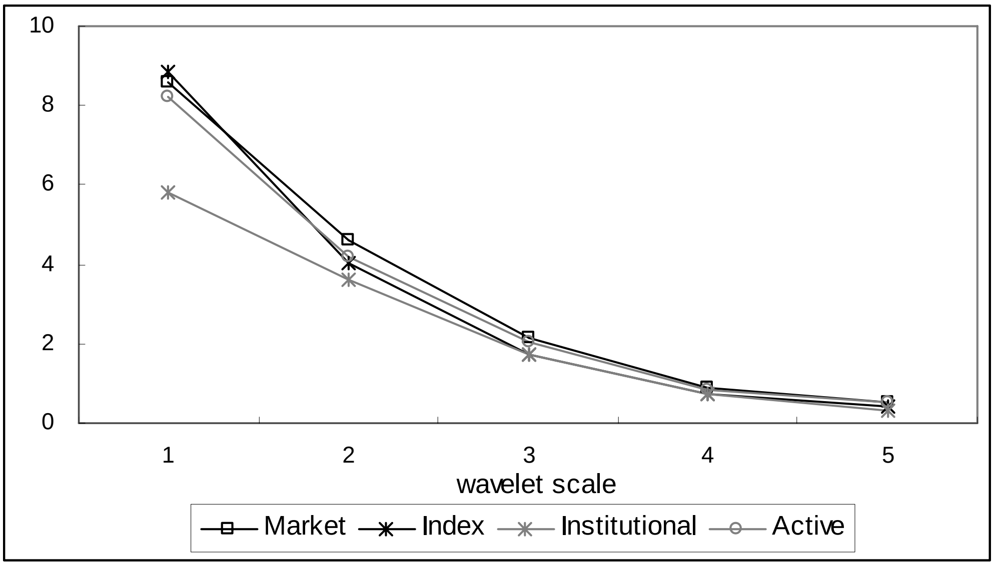
Note: To calculate the Sharpe ratio at scale λ_j, we decompose each time series up to level 5, using the Daubechies extremal phase wavelet filter of length 4 (D(4)). Scale 1, 2, 3, 4, and 5 represent 1-2, 2-4, 4-8, 8-16, and 16-32 month period dynamics, respectively. The mean values of the Sharpe ratio for each portfolio returns are reported in parentheses, while the standard errors are reported in brackets. The mean values and standard deviations are calculated using bootstrap method, by generating 3,000 replications.

Table 6. Estimated Sharpe ratios for individual active funds.

	Bottom1	Bottom2	Bottom3	Bottom4	Bottom5	Top5	Top4	Top3	Top2	Top1
Raw	-0.187	-0.032	0.110	0.057	0.127	0.252	0.260	0.201	0.206	0.197
	(-0.290)	(-0.047)	(0.176)	(0.079)	(0.188)	(0.361)	(0.380)	(0.279)	(0.283)	(0.284)
	[0.120]	[0.109]	[0.118]	[0.106]	[0.114]	[0.108]	[0.115]	[0.106]	[0.105]	[0.112]
scale1	-0.288	-0.054	0.135	0.076	0.169	0.335	0.339	0.260	0.257	0.255
	(-0.293)	(-0.056)	(0.135)	(0.076)	(0.169)	(0.337)	(0.340)	(0.262)	(0.259)	(0.256)
	[0.091]	[0.076]	[0.090]	[0.072]	[0.082]	[0.079]	[0.080]	[0.073]	[0.071]	[0.076]
scale2	-0.360	-0.073	0.164	0.109	0.220	0.455	0.476	0.372	0.391	0.359
	(-0.363)	(-0.073)	(0.165)	(0.110)	(0.222)	(0.459)	(0.480)	(0.375)	(0.395)	(0.361)
	[0.093]	[0.080]	[0.073]	[0.072]	[0.083]	[0.074]	[0.090]	[0.071]	[0.075]	[0.080]
scale3	-0.591	-0.151	0.211	0.144	0.270	0.676	0.561	0.609	0.570	0.494
	(-0.595)	(-0.152)	(0.211)	(0.144)	(0.272)	(0.680)	(0.564)	(0.612)	(0.574)	(0.496)
	[0.107]	[0.091]	[0.074]	[0.081]	[0.071]	[0.078]	[0.086]	[0.093]	[0.085]	[0.083]
scale4	-0.801	-0.284	0.288	0.272	0.406	0.965	0.777	0.805	0.946	0.762
	(-0.803)	(-0.284)	(0.290)	(0.277)	(0.408)	(0.970)	(0.781)	(0.811)	(0.955)	(0.768)
	[0.144]	[0.122]	[0.073]	[0.120]	[0.071]	[0.083]	[0.111]	[0.105]	[0.128]	[0.114]
scale5	-0.651	-0.297	0.530	0.061	0.582	1.558	0.673	0.883	1.089	0.693
	(-0.655)	(-0.300)	(0.533)	(0.061)	(0.584)	(1.568)	(0.675)	(0.888)	(1.094)	(0.696)
	[0.150]	[0.127]	[0.059]	[0.127]	[0.105]	[0.131]	[0.156]	[0.158]	[0.212]	[0.129]

Note: To calculate the Sharpe ratio at scale λ_j, we decompose each time series up to level 5, using the Daubechies extremal phase wavelet filter of length 4 (D(4)). Scale 1, 2, 3, 4, and 5 represent 1-2, 2-4, 4-8, 8-16, and 16-32 month period dynamics, respectively. The mean values of the Sharpe ratio for each portfolio returns are reported in parentheses, while the standard errors are reported in brackets. The mean values and deviations are calculated using bootstrap method, by generating 3,000 replications.

Figure 1. Estimated wavelet variances.



Note: The wavelet scales are the following: scale 1, 1 - 2 month period dynamics; scale 2, 2 – 4 month period dynamics; scale 3, 4 – 8 month period dynamics frequency; scale 4, 8 – 16 month period dynamics; scale 5, 16 – 32 month period dynamics.