A Comprehensive Investigation of Fund Performance: a New Technique

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We explore the ability of U.S. fund managers to forecast their respective style benchmarks by regressing the associated excess style index return of each fund on lagged values of the realized beta time series with lags of the predetermined publicly available information variables included to control for publicly available information. A significantly positive value of the coefficient on the lagged realized beta of the funds indicates an appropriate rebalancing of the fund portfolio. In the stock selection context the 'realized" beta series is fed into a market model to obtain a residual alpha time series. The time varying "realized" alpha series is then regressed on the demeaned lagged publicly available predetermined information variables and a significantly positive regression intercept indicates superior stock selection ability. We find no timing ability at monthly frequencies but at quarterly frequencies we find a significant proportion of large capitalization funds time their respective style benchmarks. Using monthly data we find a significantly negative abnormal return in the first month of the quarter and a significantly positive abnormal return in the third month of the quarter for a significant portion of small capitalization funds. At quarterly frequencies, a large portion of small capitalization funds exhibit stock picking abilities.

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1. Introduction

The funds management industry plays an important role in the management of shareholder savings and investment, especially now with the baby boomers nearing retirement. In fact a survey by the Investment Company Institute claims that approximately half of all US households hold shares in mutual funds. The importance of the role played by the mutual fund industry is further indicated by the plethora of research on the value of active fund management as indicated by the academic literature devoted to an examination of fund performance (e.g., Henriksson and Merton (1981), Elton, Gruber, Das and Hlavka (1993), Ferson and Schadt (1996), Carhart (1997), Daniel et al. (1997), Chen, Jagadeesh and Wermers (2000), Chance and Helmer (2001) and Bollen and Busse (2004)).

Most U.S. studies find little evidence that fund managers possess market timing or stock selection abilities (e.g., Treynor and Mazuy (1966), Henriksson and Merton (1984) Grahm and Harvey (1997), Ferson and Schadt (1996), Lee and Rahman (1990), Bollen and Busse (2001), Chance and Helmer (2001) and Farnsworth et al. (2002)). Recently, however, Bollen and Busse (2004) found some evidence of market timing ability using daily data. These studies and most others used the unconditional Henriksson and Merton (1981) or the Treynor and Mazuay (1966) models in their investigations. Ferson and Warther (1996) and Sawicki and Ong (2000) on the other hand apply a conditional capital asset pricing model to assess the performance of investment funds. They argue that a conditional model is superior since it allows β to vary over time, as a function of publicly available information variables. Christopherson et al. (1999) provide three reasons as to why the β of a fund may change: (a) "passive" changes in the betas of the underlying stocks; (b) major fund flows into and out of the portfolio that, at least temporarily, impact the relative balance of cash versus equities; (c) "active" rebalancing of the fund by the fund manager. Clearly, when evaluating fund performance one must isolate the third of these while controlling for the other two to avoid misattribution of the fund performance outcome.

In the words of Ferson and Schadt (1996), if market return and portfolio β change over time and are correlated, then the measure of abnormal performance and market timing ability, as estimated using an unconditional asset pricing model, may not be a true reflection of the manager's ability. Such a model, by assuming β remains constant, includes performance that may simply be attributable to known publicly available information. Thus, they used conditional models incorporating a set of public information variables. Ferson and Warther (1996) and Sawicki and Ong (2000) find that an unconditional model results in a significantly greater number of negative α's relative to the conditional model.

Another factor that may bias the findings is investor fund flows. A large sudden inflow of cash to a portfolio will result in a reduction of the overall portfolio risk. It will take some time for the manager to place the surge in cash into investments. Also, a large sudden outflow of cash may force managers to liquidate assets to accommodate the redemptions. Warther (1995) and Ferson and Schadt (1996) investigated the cash flow effects on performance. Ferson and Schadt (1996) hypothesis a negative correlation between cash and β. A regression of beta on new money flows along with the lagged dividend yield and lagged one-month T-bills show that cash flows into the fund increase when public expectations of market returns increase and, hence, β's decrease.

Until recently most studies examined performance against an aggregate market benchmark. More recent studies take account of the fact that a fund should be evaluated against its corresponding passive style index as benchmark. A passive style index benchmark should be used since the fund is somewhat constrained to select securities in accordance with the style stated in the fund prospectus.

Most prior research has used monthly data to investigate fund performance even though it is common knowledge that funds trade more frequently. Bollen and Busse (2004) demonstrate that when market timing strategies are executed daily or weekly, but fund returns are observed at monthly frequencies, standard models will not be able to detect market timing ability. Using daily data they find that approximately one third of the funds in their sample demonstrate timing ability.

Regular monthly rebalancing frequencies are difficult to justify with evidence given that a funds' actual portfolio holdings information on any given month can only be inferred from the holdings revealed on public disclosure dates which generally occur at the end of each calendar quarter. The use of quarterly intervals to assess the performance of fund managers, on the other hand, can be justified by the fact that in addition to the rebalancing that occurs more than once per month throughout each calendar quarter there is reason to believe that some systematic rebalancing activities take place at the ends of the calendar quarters. The U.S. Securities Exchange Commission (SEC) requires funds to report their portfolio holdings to shareholders at least semi-annually while most funds voluntarily disclose their portfolio holdings every calendar quarter. Therefore, in addition to intermittent rebalancing throughout the quarter, to arrive at favourable outcomes at the end of financial disclosure periods, some rebalancing of the portfolio is likely to be motivated by the window dressing and portfolio pumping phenomena.

A fund that is guilty of window dressing will sell stocks with large losses and purchase good performing stocks near the end of the quarter in order to make their quarterly reports more appealing to their clients. See Wermers (2000), Chen et al. (2000) and Gibson et al. (2000) for papers that suggest that mutual fund managers engage in such activities. If fund managers engage in this sort of activity the effect on performance should be minimal given the fact that the fund only holds the "winners" after their appreciation and sells the "losers" just after absorbing the loss. Since this is a cosmetic exercise designed to fool the public it is not likely to increase/decrease market exposure when the market is up/down, nor is it likely to lead to positive risk adjusted abnormal returns. Musto (2004) reports that for equity managers disclosing a portfolio different from the one they usually hold amounts to transaction costs around two times the average bid/ask spread. Therefore window dressing activities for equity fund managers such as the ones selected for this study may in fact destroy value.

Portfolio pumping, on the other hand, is the act of buying securities already held by the fund, just before public disclosure in order to cause a surge in the value of the securities held, with the intent of increasing the value of their holdings at the ends of the calendar quarters. Carhart et al (2006) find that the returns of U.S. equity funds at calendar quarter end dates are consistent with portfolio pumping activities. Thus, portfolio pumping can provide a partial explanation for a finding that betas measured at quarterly intervals are positively correlated with the ensuing quarterly excess index returns. Although this activity is not carried out in order to time their exposure to the market it may contribute to that effect. This may happen since an aggregation of large purchase orders will cause the market to go up on the day just before disclosure. On the other hand, an aggregation of large sales orders will cause the market to go down the day just after disclosure. Each portfolio pumping fund will therefore experience an increasing NAV when the market goes up, thereby increasing the funds up-market exposure to the market, while sales of these securities just after disclosure will decrease their exposure when the market is subsequently down. Furthermore, some non-portfolio pumping fund managers will also experience these benefits. If funds "herd" to certain equities, and a few fund managers mark up some of these securities, then other funds will benefit from the effect of the portfolio pumpers.

Using a new technique, this article examines the market timing and stock selectivity skills of mutual fund managers. The proposed nonparametric method represents a significant improvement over standard classical market model based testing methods, such as the Treynor and Mazuay (1966) and Hendrickson and Merton (1986) models. The conditional classical models, used in prior studies, such as that of Ferson and Schadt (1996), attempt to remove the bias in the market timing and stock selectivity skills coefficients using a time varying beta specfication that is linear in the lagged public information variables. However, if the functional forms for the crucial α and β parameters of the conditional classical models are misspecified the estimated market timing and selectivity testing coefficients will be biased and the results of the tests will remain misleading. As a solution to this problem, we derive a "realized" beta series as inputs to our models. Under certain regularity conditions, the betas are continuous record consistent estimates of the true unobservable betas. These unrestricted data driven realized betas should therefore better represent the total variation in beta that is an aggregate of passive variation and variation due to active portfolio rebalancing activities. The beta series is then used as inputs to the market timing and stock selectivity models discussed in Section 2.

In the market timing context, we explore the ability of U.S. fund managers to forecast their respective style benchmarks by regressing the associated excess style index return of each fund on lagged values of the realized beta time series. We include lags of the predetermined publicly available information variables, which have been found to be useful in forecasting stock returns, in the regressions to control for publicly available information. We also include net cash flows of the funds as a regressor since this variable is expected to impact on the funds systematic risk. We investigate the ability of fund managers to forecast their respective style benchmark returns by examining the estimated coefficient on the lagged realized beta of the funds. Successful market timing is indicated by a significantly positive estimate of this parameter since it suggests that the beta of the fund is positively correlated with the ensuing excess style index return.

In the stock selection ability context the 'realized" beta series is fed into a market model to obtain a residual alpha time series. The time varying "realized" alpha (risk adjusted abnormal returns) series is then regressed on the demeaned lagged publicly available predetermined information variables and the lagged demeaned cash flow variable and a significantly positive regression intercept indicates superior stock selection ability.

Using the four corners of the Morningstar Principia style boxes we sort our sample of funds into large growth, large value, small growth and small value funds. We find that a significant proportion of large capitalization fund managers in our sample are able to time their respective style benchmarks at quarterly frequencies. We also find, at quarterly frequencies, that a significant proportion of small capitalization fund managers exhibit stock selection ability.

Next, following Ferson and Qian (2003) we examine the extent to which conditional excess index return forecasting performance can be predicted using characteristics such as turnover in cross-sectional regressions. We find that turnover and expense ratios can explain the ability to forecast the excess index return. Interestingly, we find that there is a positive relationship between turnover ratios and market timing coefficients for large capitalization funds while for small capitalization funds the relationship is negative.

Since window dressing and portfolio pumping are confined to the ends of the calendar quarters, are not intended to have a market timing effect and do not involve a search for undervalued stocks, the market timing and stock selectivity test results suggest that some fund managers may be performing their major rebalancing activities throughout the quarter with the intention of looking good at the ends of financial disclosure periods.

Our data is subject to survivorship bias. However, we believe this does not affect the conclusion that some large capitalization fund managers are able to forecast their respective benchmarks or that some small capitalization funds exhibit superior stock picking abilities, since the strength of our results go well beyond what can be expected due to survivorship and selectivity bias alone. This argument will be elaborated at the end of Section 4.2 and Section 5.2.

The remainder of this paper is organized as follows. In Section 2 we discuss the method used to construct the monthly and the quarterly realized beta series that are inputs to our models. In this section we also discuss the models used to investigate the performance of fund managers. In Section 3 we discuss the data. In Sections 4 and 5 we discuss the results and in Section 6 we give concluding remarks.

2. The Models and Construction of Realized Betas

2.1. Construction of Realized Betas

We construct a beta series for each fund using the method of Anderson et al (2004). Each series is then used as the dependent variable in Model (1), as a regressor in Model (2) and as an input to Model (4) in sub-sections 2.2, 2.3 and 2.5 respectively. The monthly/quarterly realized beta series, constructed from the daily continuous return series of the funds and of the style benchmark indexes, are constructed for each fund as follows:

1) Calculate the N monthly/quarterly market/style index volatilities as $\sigma^2_{iM} = \sum_{t=1}^{n_i} r^2_{M,i,t}$, $i = 1, 2, \cdots, N$ where $r_{M,i,t}$ is the return on the style index for the t^{th} day of the i^{th} month/quarter, n_i is the number of actual trading days in month/quarter i and N is the number of months/quarters.
2) Calculate the N monthly/quarterly covariances of the fund and style index returns as $Cov_{M,j,i} = \sum_{t=1}^{n_i} r_{M,i,t} \cdot r_{j,i,t}$, $i = 1, 2, \cdots, N$ where $r_{M,i,t}$ and $r_{j,i,t}$ are the return on the style index for the t^{th} day of the i^{th} month/quarter for the style index and the j^{th} fund, respectively, n_i is the number of actual trading days in month/quarter i and N is the number of months/quarters.
3) Calculate the N betas β_i, $i = 1, 2, \cdots, N$ as the ratio $\dfrac{Cov_{M,j,i}}{\sigma^2_{i,M}}$.

Assume joint asset prices follow a multivariate diffusion process $dp_t = \mu_t dt + \Omega_t dW_t$ with p_t, μ_t, dt, Ω_t, and W_t representing the price, mean of the process, time interval, stationary diffusion matrix and $N-$ dimensional Brownian motion process respectively all at time t. Then if the continuously compounded $h-$ period return is $r_{t+h,h} = p_{t+h} - p_t$, by the theory of quadratic variation, we have under weak regularity conditions $\sum_{j=1}^{[h/\Delta]} r_{t+j\Delta,\Delta} \cdot r_{t+j\Delta,\Delta} \rightarrow \int_0^h \Omega_{t+\tau} d\tau$ almost surely for all t as the sampling frequency increases or as $\Delta \rightarrow 0$. In other words the realized covariances/variance and therefore betas are continuous record consistent.[1]

2.2. Conditional Beta Model

We begin by examining which of the lagged predetermined publicly available information variables used in Ferson and Schadt (1996) are significant in explaining variation of the fund betas. For this purpose we estimate Model (1) below for each of the funds. Note that the realized betas, β_t, of Models (1) and (2) below are calculated using the appropriate style index I as benchmark. Using the predetermined variables of Ferson and Schadt (1996) beta is modeled as:

$$\beta_t = \alpha_0 + \alpha_1 (TB)_{t-1} + \alpha_2 (D/P)_{t-1} + \alpha_3 (YS)_{t-1} + \alpha_4 (QS)_{t-1} + \alpha_5 Jan_t + \delta (Cash)_{t-1} + \varepsilon_t \quad (1)$$

The predetermined variables $TB, D/P, YS, QS$ and Jan are the one month Treasury bill rate, dividend yield, yield spread, quality spread and a dummy for the month of January. These variables as well as the cash flow variable $Cash_t$ will be described in Sections 3.3 and 3.4. We run these regressions for each fund simply to determine the variables that should be controlled for in tests of the market timing ability of fund managers.

2.3. Conditional Market Timing Model

Next, in order to examine the market timing ability of fund managers, we estimate Model (2) below and conduct an upper-tail t-test of the significance of $\hat{\gamma}$. Again the betas are based on the appropriate index fund portfolio benchmarks. We examine the market timing ability of each fund using the appropriate style index portfolio as the dependent variable in model (2).

$$(R_I - R_f)_t = \theta_0 + \theta_1 (TB)_{t-2} + \theta_2 (D/P)_{t-2} + \theta_3 (YS)_{t-2} + \theta_4 (QS)_{t-2} + \theta_5 Jan_{t-1} + \eta (Cash)_{t-1} + \gamma \beta_{t-1} + \varepsilon_t \quad (2)$$

Significantly positive values of $\hat{\gamma}$ are suggestive of market timing ability in the sense that on average the fund manager has rebalanced the fund so that the beta is positively correlated with the ensuing value of the excess index return.

2.4. Cross-Sectional Model: Market Timing Ability and Fund Characteristics

Next, we expand our analysis of market timing ability by examining the fund characteristics that may explain market timing ability. We use the following cross sectional regression model to determine if market timing ability can be explained by fund characteristics such as size, expense ratio, turnover, age of fund, load fees etc. We conduct this analysis using the following cross sectional regressions.

$$\gamma_i = \varphi_0 + \varphi_1^{'} x_i + \omega_i , \qquad i = 1, \cdots, N \quad (3)$$

where N is the number of funds in the sample, γ_i is the estimated timing coefficient of fund i from Model (2) and x_i is a vector of fund $i's$ characteristics. We will conduct the cross-sectional analysis within fund style groups, so that the coefficients describe individual fund performance relative to funds with the same style.

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[1] We realize the limitations of obtaining realized monthly betas from around 21 daily observations per month. The sampling frequency in this case is low relative to the monthly horizon of interest. However, the realized quarterly betas were obtained from around 63 daily observations per quarter. In this case the sampling frequency is fairly high relative to the quarterly horizon of interest. Note also that we calculated the betas with an adjustment of the variance/covariances calculated each month. The adjustment entailed multiplying each monthly beta by 21/ n_i in order to compensate for the variation in the number of observations per month. We made a similar adjustment in the calculation of the quarterly betas.

2.5. Conditional Stock Selection Models

Finally, in order to examine the stock picking abilities of fund managers, we construct a realized α series by superimposing the realized betas into the market model, Model (4). Then Model (5) is estimated using the series generated from Model (4) as the dependent variable. Since the public information and cash flow variables, on the right side of the equation, have been demeaned, the estimated intercept, δ_0, represents the average abnormal return. Significantly positive estimates of this coefficient indicate stock selection skill.

$$\hat{\alpha}_{it} + \varepsilon_{it} = (R_i - R_f)_t - \hat{\beta}_{it}(R_m - R_f)_t \tag{4}$$

$$\begin{aligned} a_{it} = {} & d_0 + d_1(TB - \overline{TB})_{t-1} + d_2\left(\frac{D}{P} - \overline{\frac{D}{P}}\right)_{t-1} + d_3(YS - \overline{YS})_{t-1} + \\ & d_4(QS - \overline{QS})_{t-1} + d_5(cash - \overline{cash}) + e_{pt} \end{aligned} \tag{5}$$

3. The Data

3.1. The Fund Returns

The funds included in our sample were identified using the January 1997 Morningstar Principia database. We used the four corners of the Morningstar style boxes for active US equity funds in conjunction with several other criteria. In particular we selected all large growth, large value, small growth and small value funds with at least 85% of their holdings in stocks, at least 85% of their holdings in US or Canadian securities and for which the inception date of the funds dates back to 1994 or earlier and for which the management tenure on January 1997 was at least three years. This provided us with a short list of 346 funds. We then obtained daily-adjusted closing price data, adjusted for dividends and splits, for each of the funds from Commodity Systems, Inc. (CSI). The returns include the reinvestment of all distributions and are net of trading commissions but not of management fees. All analysis is performed using returns net of the 3-month Treasury bill. The Treasury bill data were obtained from Datastream. We ended up with only 217 funds since some of the 346 funds were not available in the CSI database. Our final sample of 217 funds breaks down as 65 large growth, 95 large value, 9 small growth and 48 small value funds. Investment style is determined on January 1997 and applied to the historical data for each fund. We feel confident about holding the style constant over the entire period of analysis since Chan, Chen and Lakonishok (1998) found that the mutual funds in their sample generally had consistent styles over time and because our requirement that management tenure be at least 3 years at the intermediate date of January 1997 should minimize variation in style for each fund.

All Small Growth funds were open ended while all but seven, two and four of the Small Value, Large Growth and Large Value funds were open-ended respectively.

The fund data we use is subject to survivorship and selectivity bias. Data on funds that have deceased by January 1997 were not identified on the Morningstar Principia database. The dropout rate due to poor performance biases the results upwards. However, there will also be a counter-veiling downward bias due to the drop out of exceptional performers who leave the sample to manage larger accounts. The net effect on the bias of our results is therefore difficult to determine. However, since data for only 217 of the 346 funds that were identified on 1997 were available on December 2005 a dropout rate as much as 37% may be indicated.

Given that our unique approach requires daily returns data we were not able to avoid the survivorship bias problem. The only survivorship bias free data available at daily frequencies is offered by CRSP starting in 2003. Unfortunately the length of this time period does not permit a reasonable application of our models. However, we feel that the strength of our results go well beyond what can be explained by survivorship or selectivity bias alone. We elaborate on this at the end of Section 4.2 and Section 5.2.

3.2. The Benchmark Index Returns

The passive benchmarks for the four investment styles of the funds in our sample are the Large Growth Russell 2000, Large Value Russell 2000, Small Growth Russell 1000 and Small Value Russell 1000 index series[2]. The Large/Small Growth/Value Russell indexes are value-weighted indexes of large/small capitalization and growth/value oriented stocks listed on the NYSE and AMEX. This data, provided by Russell Data Services, was downloaded from the Russell web site. The historical data on these Russell style indexes only go back to 1995.

Our final sample of 217 funds provides daily-adjusted closing price time series that start on December 31, 1995 and end on December 31, 2005. The raw daily price indexes data was used to construct monthly and quarterly realized betas using the method illustrated in Anderson, Bollerslev, Diebold and Wu (2004), and discussed in Subsection 2.1 above. We began by constructing daily continuously compounded percentage return series, as the difference of the log of the prices, for each of the 217 funds and for the composite benchmark indexes.

3.3. The Predetermined Information Variables

The conditional beta model (1), the conditional market timing model (2) and the conditional stock selectivity Model (5) include the lagged information variables used in Ferson and Schadt (1996). The publicly available information variables are lags of the short-term interest rate (TB) the dividend yield (D / P) the yield spread (YS) the quality spread (QS) and a dummy for the month of January. For the short-term interest rate we used the three-month T-bill. The dividend yield was constructed as the previous twelve months of dividend payments, proxied by the S&P500 Composite Dividend Yield, divided by the price level, at the end of the previous month, of the S&P500 Market Index. These series were obtained from Datastream. The ten-year Treasury bond and the three-month Treasury bill, obtained from the US Federal Reserve website, were used to construct the yield spread. The Moody AAA and BAA bond rates, obtained from the St. Louis Federal Reserve Bank web site, were used to construct the quality spread. The yield spread was calculated as the difference between the 10-year bond and 3-month bill rates. The quality spread was obtained as the difference between Moody's BAA-rated corporate bond and AAA-rated corporate bond yields.

3.4. The New Cash Flow Variable

The conditional beta model (1), the conditional market timing model (2) and the conditional stock selectivity Model (4) include cash flow as one of the regressors. We construct mutual fund flows using the CRSP U.S. Mutual Fund database. Since flows cannot be observed directly, following Zheng (1999) and Ferson and Qian (2003), we infer flows from fund returns and total net assets obtained from CRSP. Letting TNA_t^i represent the total net assets of fund i at time t and R_t^i represent the return for fund i between period $t-1$ and period t the calculation is $Cash\ Flow_t^i = (TNA_t^i - (1+R_t^i)\cdot TNA_{t-1}^i) / TNA_{t-1}^i$.

4. Market Timing Results

4.1. Market Timing Results: Monthly Frequency Assessments

Assuming a monthly frequency we began our study by constructing monthly realized betas which were used in the estimation of models (1) and (2) of Section 2. Using Model (1) with the style index benchmark based betas as dependent variable we found that all publicly available predetermined information variables except the January dummy (D/P, TB, QS, YS) discussed in Ferson and Schadt (1996) were significant in predicting fund betas with higher relative frequencies

[2] Russell definitions of market capitalizations breakpoints are as follows: The largest 200 stocks are large-cap, the next 800 are mad-cap and the next 2000 are small-cap (the Russell 2000). Value-growth delineation is based on price-to-book ratio and concensus I/B/E/S earnings growth forecasts. The indexes are reconstituted every May 1.

than expected if the null of no influence is true at the 10% level. We present the results in Table 1, for the full model excluding the January dummy, where the numbers in each row are the percentages of funds in the fund style class, indicated by the row designation, for which the independent variable, indicated by the column heading, is significant at the 10% level. In this table we present a breakdown based on models estimated without the January dummy since this variable was significant for less than 10% of the funds in all four classes.

Table 1
Monthly Frequencies and Index as Benchmark

$$\beta_t = \alpha_0 + \alpha_1(TB)_{t-1} + \alpha_2(D/P)_{t-1} + \alpha_3(YS)_{t-1} + \alpha_4(QS)_{t-1} + \delta(Cash)_{t-1} + \varepsilon_t$$

	α_1	α_2	α_3	α_4	δ
SV	85%	44%	23%	61%	17%
SG	89%	33%	11%	89%	11%
LV	90%	87%	17%	83%	35%
LG	71%	72%	39%	85%	34%

Notes: SV, SG, LV and LG are small growth, small value, large value and large growth respectively. TB, D/P, YS, QS and Cash are T-bill, dividend yield, yield spread, quality spread and cash flow respectively. The numbers in each row are the percentage of funds in the fund class, indicated by the row designation, for which the independent variable, indicated by the column heading, is significant at the 10% level. We used White's (1980) heteroscedasticity consistent standard errors in our determinations.

In Table 2 we estimated a composite model using the index based betas. For each of the four fund classes a single composite return series was obtained as the simple arithmetic average of the returns in that class for each period. The four composite series were then used to estimate Model (1). Table 2 indicates that the lagged 3-month T-bill and the lagged Moody quality spread variables are significant at the 1% level for all four style categories and that the lagged Dividend Yield is significant at the 1% level for all but the Small Growth category. The Cash Flow variable was found to be significant at the 10% level for the Large and Small Value funds while the lagged Yield Spread variable was significant at the 5% level for only the Small Value fund.

Table 2
Composite Funds - Monthly Frequencies and Index as Benchmark

$$\beta_t = \alpha_0 + \alpha_1(TB)_{t-1} + \alpha_2(D/P)_{t-1} + \alpha_3(YS)_{t-1} + \alpha_4(QS)_{t-1} + \delta(Cash)_{t-1} + \varepsilon_t$$

	α_0	α_1	α_2	α_3	α_4	δ
SV	2.221***	-2.205***	-0.157***	-0.093**	-0.475***	0.023*
SG	1.703***	-0.919***	-0.060	-0.005	-0.445***	0.002
LV	-0.044	1.179***	0.164***	0.029	0.362***	0.050**
LG	0.085	0.822***	0.128***	0.036	0.337***	0.015

Notes: For each of the fund classes, small value, small growth, large value and large growth, a single composite return series was obtained as the simple arithmetic average of the returns in that class in each period. The four composite series were then used to estimate model (1). The entries in the table are estimates of the parameters. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. White's (1980) heteroscedasticitiy consistent standard errors were used in the determination of significance.

Overall, Tables 1, and 2 indicate that the predetermined variables and cash flow variable have a significant influence on the betas for most of the funds. We therefore proceeded to estimate Model (2) for each of the 217 funds with all four of the predetermined information variables and the Cash Flow variable controlled for in the model. We estimated Model (2) for each fund with β_{t-1} on the right hand side of the equation and found that $\hat{\gamma}$ was not significantly positive for a large portion of funds. When we replaced β_{t-1} with β_{t-2} and re-estimated the model there was a slight overall increase in the portion of funds for which $\hat{\gamma}$ was significantly positive. However, when we estimated Model (2) with β_{t-3} in place of β_{t-1}, we found, that $\hat{\gamma}$ was significantly positive for a very large percentage of the funds. In the following subsections we discuss the results for each style in more detail.

4.1.1. Large Growth Fund Results: Monthly Frequency Assessments

Tables 3, 4 and 5 provide a summary of the estimations of Model (2) for the style benchmark based market timing models. The numbers in each row of these tables are the percentage of funds in the fund class, indicated by the row designation, for which $\hat{\gamma}$ satisfies the condition indicated by the column heading. Looking at the style benchmark based results, for the Large Growth funds Tables 3 and 4 show that β_{t-1} and β_{t-2} in Model (2) are seldom significantly positive. However, Table 5 shows that when β_{t-3} is used in place of β_{t-1}, $\hat{\gamma}$ was significantly positive at the 10% level for 92% of the 65 Large Growth Funds. Furthermore, all but one of the sixty-five $\hat{\gamma}$ was positive.

Table 3
Monthly Frequencies and Index as Benchmark

$$(R_I - R_f)_t = \theta_0 + \theta_1 (TB)_{t-2} + \theta_2 (D/P)_{t-2} + \theta_3 (YS)_{t-2} + \theta_4 (QS)_{t-2} + \eta (Cash)_{t-1} + \gamma\beta_{t-1} + \varepsilon_t$$

	$\hat{\gamma} > 0$	$\hat{\gamma}\ signif > 0$	$\hat{\gamma}\ signif < 0$
SV	42%	14%	31%
SG	89%	0%	0%
LV	29%	1%	10%
LG	69%	14%	3%

Notes: SV, SG, LV and LG are small growth, small value, large value and large growth respectively. TB, D/P, YS, QS and Cash are T-bill, dividend yield, yield spread, quality spread and cash flow respectively. The numbers in each row are the percentage of funds in the fund class, indicated by the row designation, for which $\hat{\gamma}$ satisfies the condition indicated by the column heading. $\hat{\gamma}\ signif > 0$ and $\hat{\gamma}\ signif > 0$ mean $\hat{\gamma}$ is significantly positive and negative respectively at the 10% level. We used White's (1980) heteroscedasticity consistent standard errors in our determinations.

Table 4
Monthly Frequencies and Index as Benchmark

$$(R_I - R_f)_t = \theta_0 + \theta_1 (TB)_{t-3} + \theta_2 (D/P)_{t-3} + \theta_3 (YS)_{t-3} + \theta_4 (QS)_{t-3} + \eta (Cash)_{t-2} + \gamma\beta_{t-2} + \varepsilon_t$$

	$\hat{\gamma} > 0$	$\hat{\gamma}\ signif > 0$	$\hat{\gamma}\ signif < 0$
SV	58%	25%	8%
SG	78%	11%	0%
LV	55%	1%	7%
LG	85%	15%	0%

Notes: SV, SG, LV and LG are small growth, small value, large value and large growth respectively. TB, D/P, YS, QS and Cash are T-bill, dividend yield, yield spread, quality spread and cash flow respectively. The numbers in each row are the percentage of funds in the fund class, indicated by the row designation, for which $\hat{\gamma}$ satisfies the condition indicated by the column heading. $\hat{\gamma}\ signif > 0$ and $\hat{\gamma}\ signif > 0$ mean $\hat{\gamma}$ is significantly positive and negative respectively at the 10% level. We used White's (1980) heteroscedasticity consistent standard errors in our determinations.

Table 5
Monthly Frequencies and Index as Benchmark

$$(R_I - R_f)_t = \theta_0 + \theta_1 (TB)_{t-4} + \theta_2 (D/P)_{t-4} + \theta_3 (YS)_{t-4} + \theta_4 (QS)_{t-4} + \eta (Cash)_{t-3} + \gamma\beta_{t-3} + \varepsilon_t$$

	$\hat{\gamma} > 0$	$\hat{\gamma}$ $signif > 0$	$\hat{\gamma}$ $signif < 0$
SV	48%	17%	19%
SG	11%	0%	33%
LV	100%	73%	0%
LG	99%	92%	0%

Notes: SV, SG, LV and LG are small growth, small value, large value and large growth respectively. TB, D/P, YS, QS and Cash are T-bill, dividend yield, yield spread, quality spread and cash flow respectively. The numbers in each row are the percentage of funds in the fund class, indicated by the row designation, for which $\hat{\gamma}$ satisfies the condition indicated by the column heading.

To lend support to these findings, in Tables 6, 7 and 8 we estimated a composite Model (2) for the style based models. For each of the four fund classes a single composite return series was obtained as the simple arithmetic average of the returns in that class for each period.

Table 6
Composite Funds - Monthly Frequencies and Index as Benchmark

$$(R_I - R_f)_t = \theta_0 + \theta_1 (TB)_{t-2} + \theta_2 (D/P)_{t-2} + \theta_3 (YS)_{t-2} + \theta_4 (QS)_{t-2} + \eta (Cash)_{t-1} + \gamma\beta_{t-1} + \varepsilon_t$$

	θ_0	θ_1	θ_2	θ_3	θ_4	δ	γ
SV	6.457	-12.694**	2.053**	-1.423**	-2.659	-0.066	-0.256
SG	3.820	-11.970**	2.428**	-1.220	-3.379	0.051	1.577
LV	1.181	-3.760	1.422**	-0.243	-1.088	-0.122	-0.601
LG	6.236	-17.870*	1.650	-1.702	-1.642	-0.026	1.312

Notes: For each of the fund classes, small value, small growth, large value and large growth, a single composite return series was obtained as the simple arithmetic average of the returns in that class in each period. The four composite series were then used to estimate model (2). The composite cash flow series was obtained similarly. The entries in the table are estimates of the parameters. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. White's (1980) heteroscedasticitiy consistent standard errors were used in the determination of significance. The significance in the last column is based on an upper-tail test.

Table 7
Composite Funds - Monthly Frequencies and Index as Benchmark

$$(R_I - R_f)_t = \theta_0 + \theta_1 (TB)_{t-3} + \theta_2 (D/P)_{t-3} + \theta_3 (YS)_{t-3} + \theta_4 (QS)_{t-3} + \eta (Cash)_{t-2} + \gamma\beta_{t-2} + \varepsilon_t$$

	θ_0	θ_1	θ_2	θ_3	θ_4	δ	γ
SV	0.667	-3.667	1.930**	-0.460	-1.626	-0.292	0.791
SG	-2.862	-3.845	2.678***	-0.492	-1.603	-0.032	2.872
LV	-0.846	-1.029	1.599**	0.024	-1.347	-0.705*	0.875
LG	3.417	-17.114	1.411	-1.336	0.132	0.646	2.101

Notes: For each of the fund classes, small value, small growth, large value and large growth, a single composite return series was obtained as the simple arithmetic average of the returns in that class in each period. The four composite series were then used to estimate model (2). The composite cash flow series was obtained similarly. The entries in the table are estimates of the parameters. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. White's (1980) heteroscedasticitiy consistent standard errors were used in the determination of significance. The significance in the last column is based on an upper-tail test.

The four composite series were then used to estimate Model (2). These tables indicate that for the Large Growth composite fund style based model $\hat{\gamma}$ is insignificant at lags 1 and 2 (see Tables 6 and 7) but significantly positive at lag 3 at the 10% level (see Table 8). This suggests that perhaps Large Growth fund managers do their major rebalancing of the fund on a quarterly basis.

Table 8
Composite Funds - Monthly Frequencies and Index as Benchmark

$$(R_I - R_f)_t = \theta_0 + \theta_1 (TB)_{t-4} + \theta_2 (D/P)_{t-4} + \theta_3 (YS)_{t-4} + \theta_4 (QS)_{t-4} + \eta(Cash)_{t-3} + \gamma\beta_{t-3} + \varepsilon_t$$

	θ_0	θ_1	θ_2	θ_3	θ_4	δ	γ
SV	2.270	5.980	1.540**	-0.710	-1.785	-0.181	0.872
SG	13.370**	-15.786**	2.002**	-0.941	-6.595**	-0.089	-4.194*
LV	2.592	-10.169*	0.814	-0.644	-3.391	-0.949*	4.436**
LG	7.127	-26.539**	0.028	-1.686	-6.084*	0.248	10.216**

Notes: For each of the fund classes, small value, small growth, large value and large growth, a single composite return series was obtained as the simple arithmetic average of the returns in that class in each period. The four composite series were then used to estimate model (2). The composite cash flow series was obtained similarly. The entries in the table are estimates of the parameters. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. White's (1980) heteroscedasticitiy consistent standard errors were used in the determination of significance. The significance in the last column is based on an upper-tail test.

4.1.2. Large Value Fund Results: Monthly Frequency Assessments

Looking at the style benchmark based results, for the Large Value funds Tables 3 and 4 show that β_{t-1} and β_{t-2} in Model (2) are significantly positive for only 1% of the funds. However, Table 5 shows that when β_{t-3} is used in place of β_{t-1}, $\hat{\gamma}$ was significantly positive at the 10% level for 73% of the 95 Large Value Funds. Furthermore, all of the ninety-five $\hat{\gamma}$ were positive. As was the case for Large Growth funds this suggests that perhaps Large Value fund managers do their major rebalancing of the fund on a quarterly basis with an emphasis in the last month of the quarter.

Again, the parameter estimates of the Large Value composite style based model in Tables 6, 7 and 8 indicate that $\hat{\gamma}$ is insignificant at lags 1 and 2 (see Tables 6 and 7) but significantly positive at lag 3 at the 10% level (see Table 8). This suggests that perhaps Large Value fund managers do their major rebalancing of the fund on a quarterly basis.

4.1.3. Small Growth Fund Results: Monthly Frequency Assessments

Looking at the style benchmark based results, for the Small Growth funds Table 3 shows that the coefficient on β_{t-1} $\hat{\gamma}$ is not significantly positive for any of the 9 funds but that $\hat{\gamma}$ is positive for all but one fund. Table 4 shows that the coefficient on β_{t-2} in Model (2) is significantly positive for only one of the nine funds and that all but two of the coefficients are positive. Table 5 shows that when β_{t-3} was used in place of β_{t-1}, $\hat{\gamma}$ was not significantly positive at the 10% level for any of the 9 Small Growth Funds, and that only one of the nine $\hat{\gamma}$ were positive.

The Small Growth style based composite models in Tables 6, 7 and 8 indicate that $\hat{\gamma}$ is insignificant at lags 1 and 2 (see Tables 6 and 7) while significantly negative at lag 3 at the 10% level (see Table 8). We cannot draw firm conclusions from these results since the sample size limits the ability to infer these results to the population of all Small Growth Funds.

4.1.4. Small Value Fund Results: Monthly Frequency Assessments

Looking at the style benchmark based results, for the Small Value funds Tables 3, 4 and 5 show that the coefficients on β_{t-1}, β_{t-2} and β_{t-3} in Model (3) are seldom significantly positive. The Small

Value style based composite models in Tables 6, 7 and 8 indicate that $\hat{\gamma}$ is insignificant at lags 1, 2 and 3.

The results based on the monthly frequency assessments, at least for the Large Funds, are suggestive of the possibility that fund managers perform their major rebalancing activities on a quarterly basis. Therefore in the next section we investigate this possibility by aggregating our data up to the quarterly level and re-estimating Models (1) and (2).

Since we found that large capitalization fund managers were forecasting their excess style returns 3-months in advance, although not reported, we estimated Model (1) for each of the four composite style based return series with end of quarter month dummy and beginning of quarter month dummy variables in addition to the predetermined and cash flow variables. Both dummy variables were not significant for any of the four composite funds therefore it does not seem to be the case that fund managers are simply systematically increasing or decreasing their risks at the beginning or end of the calendar quarters. As mentioned earlier the January dummy was insignificant in Model (1) for the vast majority of the funds. Now we have added to that by finding no systematic March, June, September, December or April, July and October effects as well.

4.2. Market Timing Results: Quarterly Frequency Assessments

The fact that β_{t-3} in place of β_{t-1} in Model (2) was so frequently found to be significantly positive for Large Growth and Large Value funds while all other lags were seldom significant hints of the possibility that fund managers do their major rebalancing on a quarterly basis. This prompted us to recalculate the realized betas aggregating up to the quarterly level. After aggregating up to the quarterly level we go from having 117 monthly observations to 39 quarterly observations. When we estimated Model (1) using quarterly data again we found that all of the predetermined information variables were frequently significant in predicting the fund betas. See Table 9 for the style benchmark based results.

Table 9
Quarterly Frequencies and Index as Benchmark

$$\beta_t = \alpha_0 + \alpha_1(TB)_{t-1} + \alpha_2(D/P)_{t-1} + \alpha_3(YS)_{t-1} + \alpha_4(QS)_{t-1} + \delta(Cash)_{t-1} + \varepsilon_t$$

	α_1	α_2	α_3	α_4	δ
SV	92%	83%	6%	90%	25%
SG	78%	56%	11%	100%	11%
LV	67%	70%	2%	77%	46%
LG	49%	51%	17%	89%	35%

Notes: SV, SG, LV and LG are small growth, small value, large value and large growth respectively. TB, D/P, YS, QS and Cash are T-bill, dividend yield, yield spread, quality spread and cash flow respectively. The numbers in each row are the percentage of funds in the fund class, indicated by the row designation, for which the independent variable, indicated by the column heading, is significant at the 10% level. We used White's (1980) heteroscedasticity consistent standard errors in our determinations.

Again we estimated a composite Model (1) and the results are in Tables 10. The results in Table 10 show that the lagged T-bill is significant at the 5% level for all four composite funds. The lagged Dividend Yield is significant at the 5% level for all but the Large Growth fund. The lagged Yield Spread was insignificant for all four of the composite funds. The Moody Quality Spread was significant at the 1% level for all four composite funds. Finally, the Cash Flow variable was positive and found to be significant at the 5% level for all but the Large Growth fund.

Given the strength of the results in Tables 9 and 10 for the style based model again we proceeded to estimate Model (2) with all five of these variables as well as β_{t-1} on the right hand side of this model. Now, as the results in the following subsection indicate, we find strong evidence of forecasting ability of fund managers.

Table 10
Composite Funds - Quarterly Frequencies and Index as Benchmark

	α_1	α_2	α_3	α_4	δ
SV	2.296***	-0.736***	-0.058***	-0.088	-0.163***
SG	2.037***	-0.418***	-0.037**	-0.014	-0.176***
LV	-0.044	1.179***	0.164***	0.029	0.362***
LG	0.121	0.238**	0.030*	0.011	0.123***

Notes: For each of the fund classes, small value, small growth, large value and large growth, a single composite return series was obtained as the simple arithmetic average of the returns in that class in each period. The four composite series were then used to estimate model (1). The entries in the table are estimates of the parameters. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.. White's (1980) heteroscedasticitiy consistent standard errors were used in the determination of significance.

4.2.1. Large Growth Fund Results: Quarterly Frequency Assessments

Interestingly, using the style based model for the Large Growth Funds we found that 65% of the $\hat{\gamma}$'s were significantly positive at the 10% level of significance and that all but four of the sixty-five $\hat{\gamma}$ were positive. See Table 11 below for a summary of the results based on the style benchmark model. This provides strong evidence that Large Growth Fund managers are able to forecast their style benchmark at quarterly frequencies. The composite model estimates in Table 12 confirm this since $\hat{\gamma}$ is significantly positive at the 5% level.

4.2.2. Large Value Fund Results: Quarterly Frequency Assessments

Interestingly, using the style based model for the Large Value Funds we found that 48% of the $\hat{\gamma}$'s were significantly positive at the 10% level of significance and that all but two of the ninety-five $\hat{\gamma}$ were positive. See Table 11 for a summary of the results. Further, Table 12 shows that for the composite Large Value fund $\hat{\gamma}$ is significantly positive at the 10% level. Again, this provides evidence that Large Value Fund managers are able to forecast their style benchmark at quarterly frequencies.

4.2.3. Small Growth Fund Results: Quarterly Frequency Assessments

Using the style based model for the Small Growth Funds we found that only 11% of the $\hat{\gamma}$'s were significantly positive at the 10% level of significance and that only two of the nine $\hat{\gamma}$ were positive. See Table 11 for a summary of the results. The composite model estimates in Table 12 confirm this since $\hat{\gamma}$ is negative and not significant. Therefore, this provides little evidence that Small Growth Fund managers are able to forecast their style benchmark at quarterly frequencies. However the sample size limits our ability to draw firm conclusions about the population of Small Growth Fund managers.

4.2.4. Small Value Fund Results: Quarterly Frequency Assessments

Using the style based model for the Small Value Funds we found that only 15% of the $\hat{\gamma}$'s were significantly positive at the 10% level of significance but that all but 9 of the forty-eight $\hat{\gamma}$ were positive. See Table 11 for a summary of the results. However, the estimated composite style based Small Value fund results in Table 12 show that $\hat{\gamma}$ is significantly positive at the 5% level. Based on the quarterly rebalancing assumption, this provides some evidence that Small Value Fund managers may be able to forecast their style benchmark at quarterly frequencies.

Table 11
Quarterly Frequencies and Index as Benchmark

$$(R_I - R_f)_t = \theta_0 + \theta_1 (TB)_{t-2} + \theta_2 (D/P)_{t-2} + \theta_3 (YS)_{t-2} + \theta_4 (QS)_{t-2} + \eta (Cash)_{t-1} + \gamma \beta_{t-1} + \varepsilon_t$$

	$\hat{\gamma} > 0$	$\hat{\gamma}\ signif > 0$	$\hat{\gamma}\ signif < 0$
SV	81%	15%	0%
SG	22%	11%	0%
LV	98%	48%	0%
LG	94%	65%	0%

Notes: SV, SG, LV and LG are small growth, small value, large value and large growth respectively. TB, D/P, YS, QS and Cash are T-bill, dividend yield, yield spread, quality spread and cash flow respectively. The numbers in each row are the percentage of funds in the fund class, indicated by the row designation, for which $\hat{\gamma}$ satisfies the condition indicated by the column heading. $\hat{\gamma}\ signif > 0$ and $\hat{\gamma}\ signif < 0$ mean $\hat{\gamma}$ is significantly positive and negative respectively at the 10% level. We used White's (1980) heteroscedasticity consistent standard errors in our determinations.

Table 12
Composite Models - Quarterly Frequencies and Index as Benchmark

$$(R_I - R_f)_t = \theta_0 + \theta_1 (TB)_{t-2} + \theta_2 (D/P)_{t-2} + \theta_3 (YS)_{t-2} + \theta_4 (QS)_{t-2} + \eta (Cash)_{t-1} + \gamma \beta_{t-1} + \varepsilon_t$$

	θ_0	θ_1	θ_2	θ_3	θ_4	δ	γ
SV	-16.514	1.313	2.537**	-1.015	-0.231	-0.979**	13.157**
SG	22.936	-16.232*	2.921**	-5.160	-3.172	-0.557	-2.502
LV	4.083	-10.521	1.170	-2.545	-1.997	-1.139	14.405*
LG	15.630	-28.564**	-0.428	-3.524	-4.658	0.818	35.834**

Notes: For each of the fund classes, small value, small growth, large value and large growth, a single composite return series was obtained as the simple arithmetic average of the returns in that class in each period. The four composite series were then used to estimate model (2). The composite cash flow series was obtained similarly. The entries in the table are estimates of the parameters. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.. White's (1980) heteroscedasticitiy consistent standard errors were used in the determination of significance. The significance in the last column is based on an upper-tail test.

Overall it seems that we are only able to draw firm conclusions with respect to the Large Fund managers. For Large Growth and Large Value Funds the evidence strongly indicates that these fund managers are able to forecast their respective style benchmarks at quarterly frequencies. However, the evidence is far less promising for Small Fund managers.

Note that since the realized betas are continuous record consistent, monthly betas based on around 21 daily observations per month are of questionable accuracy. However each quarterly beta is typically derived from around 63 daily observations. Thus the quarterly realized beta series used in Model (1) and Model (2) have far less measurement error.

We believe that our finding of a positive correlation of beta with the ensuing period excess index return is the result of a rebalancing of the portfolio based on superior private information. These results are not significantly affected by window dressing or portfolio pumping activities since, the monthly and quarterly returns and betas used in the analysis are realized over the entire monthly and quarterly periods. In other words we do not infer results based on intermittent reports of portfolio holdings.

Although our data is subject to survivorship bias we believe this does not affect the conclusion that some large capitalization fund managers are able to forecast their respective benchmarks.

Fifty-five percent of our sample of large capitalization fund managers was found to significantly forecast their respective benchmarks. Furthermore, since we identified a sample of 346 funds that met our selection criteria on January 1997 using the Morningstar database but unproblematic data for only 217 funds were available on December 2005 a dropout rate due to selectivity and survivorship bias may be only as high as 37%[3]. If we take the conservative approach that assumes that all the dropouts and funds with problematic data series that were dropped from the sample could not forecast their respective benchmarks than the percentage of funds for which forecasting ability was significant is still 34.7% $((0.55)(1-0.37)=0.347)$. For any test of the null hypothesis of no ability to forecast the index with α rejection probability we expect around α rejections. Since in our case a survivorship as low as even 10% will give a rejection rate larger than the traditional $\alpha = 5\%$ $((0.10)(0.55)=0.055)$ it is reasonable to conclude that some U.S. large-cap equity fund managers are indeed able to forecast their excess index return.

4.3. Market Timing and Fund Characteristics: a cross-sectional analysis

Table 13 provides the results of the Model (3) cross-sectional regressions. The first four rows give the results with p-values in parentheses beneath the estimates for each of the four fund style classes. In the last two rows we estimate Model (3) for all small funds as a group and all large funds as a group respectively. Interestingly, we found that for large capitalization funds there was a positive relationship between turnover ratios and timing coefficients and a negative relationship between expense ratios and timing coefficients. For small funds, on the other hand, the relationship between turnover ratios and timing coefficients was negative. This may indicate that the large funds (the funds that are able to forecast their index returns) in an effort to rebalance their funds in response to private information do so by turning over their assets. The small funds, (the funds that are unable to forecast their index returns) on the other hand, actually hinder their performance by turning over assets in response to false leads.

Table 13
Cross - Sectional Models

$$\hat{\gamma}_i = \phi_0 + \phi_1 TNA_i + \phi_2 Turnratio_i + \phi_3 Expratio_i + \phi_4 Inst_i + \phi_5 \mathrm{Re}\,tail_i + \varepsilon_i$$

	ϕ_0	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5
SV	Na	Na	Na	Na	Na	Na
SG	-25.362	0.016	-11.274	1803	6.191	3.122
LV	10.662***		5.213***	-379**		
LG	18.580*		11.347**	-721**	-6.912*	13.163*
All Small	6.762***		-5.371***			
All Large	10.632***		5.241***	-391***		

Notes: TNA, Turnratio, Expratio, Inst and Retail are total net assets, turnover ratio expense ratio and indicator variables for institutional and retail funds respectively. The entries in the table are estimates of the coefficients of the cross-sectional model ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. White's (1980) heteroscedasticitiy consistent standard errors were used in the determination of significance.

5. Stock Selection Ability Results

5.1. Stock Selection Ability Results: Monthly Frequency Assessments

Motivated by our findings in Section 4 and by the portfolio pumping and window dressing

[3] Our final sample was reduced to 217 not only because of unavailability on December 2005 but also because several series lacked variation over long spans of time or had missing data at intermediate dates. Therefore not all of the 37% were dropouts.

arguments, which suggest that there may be an increase in buying and selling activities at the beginning and end of the first and last months of the quarters, respectively, we begin our investigation of stock picking ability using monthly data. This investigation is conducted by regressing monthly abnormal returns, obtained from Model (4), on an intercept and dummy variables; one for the first and one for the last month of the quarters. The equation used is: $\alpha_{pt} = b_{p2} + b_{p1}M1_t + b_{p3}M3_t + \varepsilon_{pt}$ where α_{pt} is the realized alpha series obtained from Model (4) and $M1_t$ and $M3_t$ are dummy variables that indicate the first and last month of the quarter, respectively.

Table 14
Stock Selection Models - Monthly Frequencies

$$\alpha_{pt} = b_{p2} + b_{p1}M1_t + b_{p3}M3_t + \varepsilon_{pt}$$

	b_{p1} $Signif > 0$ b_{p1} $Signif < 0$	b_{p2} $Signif > 0$ b_{p2} $Signif < 0$	b_{p3} $Signif > 0$ b_{p3} $Signif < 0$
SV	4% 34%	2% 3%	38% 3%
SG	8% 28%	1% 4%	31% 5%
LV	5% 14%%	6% 4%	12% 6%
LG	3% 16%	2% 2%	11% 4%

Notes: SV, SG, LV and LG are small growth, small value, large value and large growth respectively. M1 and M3 are dummy variables for the first and third months of the quarter respectively. The numbers in each row are the percentage of funds in the fund class, indicated by the row designation, for which b_{pj} satisfies the condition indicated by the column heading. b_{pj} $Signif > 0$ and b_{pj} $Signif < 0$ means b_{pj} is significantly positive and negative respectively at the 10% level. We used White's (1980) heteroscedasticity consistent standard errors in our determinations.

Using this model we found that although a significant portion of the Small Value and Small Growth funds exhibit significantly smaller risk adjusted abnormal returns in the first month these groups of funds exhibit significantly larger risk adjusted abnormal returns in the last month of the quarter. For the Large Value and Large Growth funds, however, the results do not indicate significant differences over the three months of the quarters. See Table 14 for a summary of the results. The numbers in each row are the percentage of funds in the fund class, indicated by the row designation for which the coefficients on the dummy variables satisfy the conditions indicated by the column headings.

5.1.1. Large Growth Fund Results: Monthly Frequency Assessments

Looking at the first column of Table 14 shows that for the Large Growth funds b_{p1} is significantly negative for 16% of the funds but significantly positive for only 3% of the funds. This indicates that only a slightly larger portion of the Large Growth funds abnormal returns are down in the month after the quarterly disclosure dates than is predicted under the null of no difference across the months. The last column of the table shows that for these same funds, b_{p3} is significantly positive for 11% of the funds and significantly negative for only 4% of the funds. This does not indicate that a larger portion of the Large Growth funds abnormal returns are up in the month before the quarterly disclosure dates than is predicted under the null of no difference across the months.

5.1.2. Large Value Fund Results: Monthly Frequency Assessments

Looking at the results for the Large Value funds the first column of Table 14 shows that b_{p1} is significantly negative for 14% of the funds but significantly positive for only 5% of the funds. Again, this indicates that only a slightly larger portion of the Large Value funds abnormal returns are down in the month after the quarterly disclosure dates than is predicted under the null of no difference across the months. The last column of the table shows that for these same funds b_{p3} is significantly positive for 12% of the funds and significantly negative for only 6% of the funds. Similar to the findings for Large Growth funds, this does not indicate that a larger portion of the Large Value funds abnormal returns are up in the month before the quarterly disclosure dates than is predicted under the null of no difference across the months.

5.1.3. Small Growth Fund Results: Monthly Frequency Assessments

Looking at the results for the Small Growth funds, the first column of Table 14 shows that b_{p1} is significantly negative for 28% of the funds but significantly positive for only 8% of the funds. Contrary to the findings for large capitalization funds, this indicates that a larger portion of the Small Growth funds abnormal returns are down in the month after the quarterly disclosure dates than is predicted under the null of no difference across the months. The last column of the table shows that for these same funds b_{p3} is significantly positive for 31% of the funds and significantly negative for only 5% of the funds. Therefore unlike large capitalization funds, this indicates that a larger portion of the Small Growth funds abnormal returns are up in the month before the quarterly disclosure dates than is predicted under the null of no difference across the months. These results, therefore suggest a strong return reversal at the ends of the quarters.

5.1.4. Small Value Fund Results: Monthly Frequency Assessments

Looking at the results for the Small Value funds the first column of Table 14 shows that b_{p1} is significantly negative for 34% of the funds but significantly positive for only 4% of the funds. This also indicates that a larger portion of the Small Value funds abnormal returns are down in the month after the quarterly disclosure dates than is predicted under the null of no difference across the months. The last column of the table shows that for these same funds b_{p3} is significantly positive for 38% of the funds and significantly negative for only 3% of the funds. Again this indicates that a larger portion of the Small Value funds abnormal returns are up in the month before the quarterly disclosure dates than is predicted under the null of no difference across the months. As is the case for Small Growth funds, these results also suggest a strong return reversal at the ends of the quarters.

In summary, the evidence indicates that small capitalization fund returns exhibit an end of month return reversal since abnormal returns are larger than average at the end of the quarter and are smaller than average at the beginning of the quarter. Portfolio pumping may play a minor part in these findings.

5.2. Stock Selection Ability Results: Quarterly Frequency Assessments

Next, we estimate Model (5) using quarterly data and find that abnormal returns are significantly positive, for small capitalization funds, more often than predicted under the null hypothesis of no ability to select undervalued securities. A summary of the results is found in Table 15.

Interestingly, the last two columns of Table 15 give an expected result. In particular the column headed $\delta_1 \; Signif < 0$ indicates that 68%, 57%, 71% and 68% of the δ_1 coefficients were significantly negative for the Small Value, Small Growth, Large Value and Large Growth funds respectively.

Additionally, the column headed $\delta_2\ Signif > 0$ indicates that 72%, 48%, 62% and 53% of the δ_2 coefficients were significantly positive for the Small Value, Small Growth, Large Value and Large Growth funds respectively.

Table 15
Quarterly Frequencies

$$a_{it} = d_0 + d_1\ \left(TB - \overline{TB}\right)_{t-1} + d_2\left(\frac{D}{P} - \overline{\frac{D}{P}}\right)_{t-1} + d_3\ \left(YS - \overline{YS}\right)_{t-1} +$$
$$d_4\ \left(QS - \overline{QS}\right)_{t-1} + d_5\ \left(cash - cash\right) + e_{pt}$$

	$\delta_0 > 0$	$\delta_0\ Signif > 0$	$\delta_0\ Signif < 0$	$\delta_1\ Signif < 0$	$\delta_2\ Signif > 0$
SV	78%	21%	2%	68%	72%
SG	72%	28%	0%	57%	48%
LV	54%	12%	7%	71%	62%
LG	58%	14%	5%	68%	53%

Notes: SV, SG, LV and LG are small growth, small value, large value and large growth respectively. TB, D/P, YS, QS and Cash are T-bill, dividend yield, yield spread, quality spread and cash flow respectively. The numbers in each row are the percentage of funds in the fund class, indicated by the row designation, for which $\hat{\delta}_0$ satisfies the condition indicated by the column heading. $\delta_0\ Signif > 0$ and $\delta_0\ Signif < 0$ mean $\hat{\delta}_0$ is significantly positive and negative respectively at the 10% level. We used White's (1980) heteroscedasticity consistent standard errors in our determinations.

Thus, as expected managers deliver higher risk adjusted abnormal returns relative to the CAPM when the dividend yield is high and short term interest rate are low. Thus, since high dividend yields and low interest rates both predict high stock returns, the coefficients indicate that conditional alphas of the funds tend to be positively correlated with expected stock market returns. Next, we will look at the stock selection testing coefficient for each class in detail.

5.2.1. Large Growth Fund Results: Quarterly Frequency Assessments

A summary of the Model (5) results, in Table 15, show that δ_0 is significantly positive at the 10% level for only 14% of the Large Growth funds. This is only slightly more than the proportion expected if the null of no stock picking ability true for all funds. Thus, the evidence is not strongly suggestive of stock selection ability for Large Growth funds.

5.2.2. Large Value Fund Results: Quarterly Frequency Assessments

Table 15 indicates that 12% of the Large Value funds have a significantly positive value for δ_0 at the 10% level of significance. This suggests that a slightly higher percentage of Large Value funds are able to select under valued stocks than predicted under the null hypothesis of no stock picking ability. However, as was the case for Large Growth funds the evidence is not strongly suggestive of stock selection ability for Large Value funds.

5.2.3. Small Growth Fund Results: Quarterly Frequency Assessments

For Small Growth funds the evidence does suggest some stock picking abilities. The results in Table 15 show that 28% of these funds were found to have stock picking abilities as indicated by the significance of δ_0. This is much more than the percentage expected under the null of no stock picking ability, tested at the 10% level.

5.2.4. Small Value Fund Results: Quarterly Frequency Assessments

Small Value funds also exhibit some stock picking abilities. The results in Table 15 show that 21% of these funds were found to have stock picking abilities as indicated by the significance of δ_0. Again, this is much more than the percentage expected under the null of no stock picking ability, tested at the 10% level.

One possible explanation for the greater proportion of small capitalization funds with stock selection abilities as compared to large capitalization funds is that small capitalization companies are less information efficient. In other words small companies provide less information to the public and therefore an analysis of company statements may prove fruitful.

In summary, although the monthly findings indicate a transfer of wealth from the first to the last month for small capitalization funds, it amounts to a net positive abnormal return at quarterly frequencies.

6. Concluding Remarks

In this paper we assess the performance of fund managers using a new technique that avoids potential bias in the estimated timing and selectivity coefficients. In the market timing context, we ran regressions of each funds associated excess index return on lagged values of the funds realized betas along with lags of the predetermined publicly available information variables that have been found to be useful in forecasting stock market returns. We also controlled for cash flow in our regressions. Using the four corners of the Morningstar Principia style boxes we sorted our sample into large growth, large value, small growth and small value funds. Regressions involving monthly observations indicated that fund managers are unable to forecast their respective style benchmarks. However, when the regression included a three-month lag of the realized betas on the right hand side, the coefficients were significantly positive for most funds. This prompted us to consider the possibility that fund managers are performing their rebalancing activities with month by month look ahead planning on a quarterly basis. Therefore we aggregated the data up to the quarterly level and re-ran the regressions with the quarterly realized betas as data and found that the vast majority of large growth and large value funds are able to forecast their respective style benchmarks at quarterly frequencies. However, the evidence regarding the small growth and small value funds is less clear.

Interestingly, cross-sectional regressions of the estimated timing coefficients on characteristics of the funds indicate that for large capitalization funds there is a positive relationship between turnover ratios and timing coefficients. For small funds, on the other hand, the relationship between turnover ratios and timing coefficients is negative. This may indicate that the large funds (funds that are able to forecast their index returns) in an effort to rebalance their funds in response to private information do so by turning over their assets. The small funds (funds that are unable to forecast their index returns) actually hinder their performance by turning over in response to false leads.

We believe that our findings of a positive association between large capitalization fund betas and the ensuing period excess index returns is not due to window dressing activities. We believe this because a performance effect, found at quarterly frequencies using realized returns based market timing models is most likely due to month by month active rebalancing activities designed to enhance performance rather than to fool the public. Window dressing effects, on the other hand, will be minimal, cosmetic and confined to the final month. We also dismiss portfolio pumping as a basis for our results since we found large capitalization fund managers were the ones who were able to significantly forecast their excess index return. Since they hold large company stocks they should not be able to affect the prices of the securities they hold with large buy and sell orders.

In the stock selectivity skills context we regressed the monthly realized abnormal returns on first and third month dummy variables and found an end of month return reversal for small capitalization funds. This finding indicates a transfer of wealth from the first to the last month for these funds. When we regressed quarterly abnormal returns on the demeaned publicly available information variables and cash flow we found that small capitalization funds exhibit stock picking abilities. Thus the end of month return reversal found using monthly data nets out as a positive abnormal return at quarterly frequencies. Regressions using quarterly data show a net positive abnormal return at quarterly frequencies. One possible explanation for the greater proportion of small capitalization funds with stock selection abilities, as compared to large capitalization funds, is that small capitalization companies are less information efficient. In other words small companies provide less information to the public and therefore an analysis of company statements may prove fruitful.

Although window dressing can not provide an explanation for the stock picking abilities of small capitalization fund managers, portfolio pumping may provide a partial explanation for the end of quarter return reversal.

In order to broaden the interest one can look at betas on macro risks such as inflation and industrial production. One can also investigate lagged performance relative to a benchmark in discrete quantiles with tournament incentives in mind. Also, since growth funds may focus more on indicators of economic growth a proxy for economic growth may be important as a predetermined variable for these funds. Since proxies for macro risks such as inflation and industrial production are not available at daily frequencies a tracking portfolio approach such as that suggested by Lamont (1998) could be used to develop proxies for the macro risk variables with daily frequencies. Another extension to this study involves an examination of performance persistence. For example one could apply tests for nonstationarity to the realized alpha series. If an alpha series is found to be I(1) nonstationary this would imply that performance is persistent.

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