Sector Fund Performance: Analysis of Cash Flow Volatility and Returns

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ABSTRACT

Sector funds are an important and growing segment of the mutual fund industry. This paper analyzes the performance of 609 actively managed stock sector funds listed on the CRSP Survivor-Bias Free US Mutual Fund Database during 1972-1999. We use a five-factor model to document the following results. First, sector funds as a group neither outperform nor underperform their benchmarks. Second, sector funds experience significantly higher cash flow volatility than non-sector funds. However, conditioning returns on lagged cash flows does not alter their neutral performance. This finding differs from previous literature that documents a significant decrease in diversified stock fund performance due to cash flow volatility. Third, sector fund investors as a group do not possess the ability to pick winning sector funds or winning sectors of the stock market. This finding differs from previous literature that documents the smart money effect. For comparison, we present the performance statistics of 3,227 diversified (non-sector) stock funds during the same period.

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I. Introduction

Beginning with the early studies by Sharpe (1966) and Jensen (1968), the performance of mutual funds has been extensively analyzed in the finance literature. However, there is little documented evidence on the performance of sector funds that constitute an important segment of the mutual fund industry.[1] Most studies focus on diversified stock funds and specifically exclude sector funds. A better understanding of the performance of sector fund managers and sector fund investors is of interest because sector funds differ from diversified mutual funds in several important respects. Some of these differences are more well-known, such as their investment strategy of making concentrated sector or industry bets and their higher fund expenses. Other differences are less well-known, such as the nature of investor clientele and the higher volatility of investor cash flows experienced by sector funds.

The differences between sector funds and diversified funds give rise to a number of logical questions. First, does the specialized and concentrated nature of sector fund investments translate into superior performance?[2] This possibility arises because certain sectors, such as real estate and technology, may be characterized by higher information asymmetries. Superior skill, if it exists, should be particularly valuable for picking stocks in such sectors. For example, Kallberg, Liu, and Trzcinka (2000) analyze real estate funds and find that they outperform their passive benchmarks by two percent a year. It is possible that there are gains to specializing in any particular sector of the stock market.

Second, do sector fund investors possess sector timing or sector rotation abilities? This question is particularly relevant given the favorable evidence on the fund selection ability of mutual fund investors in Gruber (1996) and Zheng (1999), a finding commonly known as the smart money effect. Casual observation suggests that sector funds attract a greater percentage of short-term investors who trade

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[1] The Investment Company Institute Fact Book reports that stock sector funds had total net assets (TNA) of $235 billion at the end of 2000, representing 5.9 percent of all stock fund assets. They also attracted $62 billion of new cash flow during 2000, representing 20.1 percent of all stock fund new cash flow during the year.

[2] The evidence on the performance of diversified mutual funds generally suggests that they either underperform the relevant benchmarks, or that they fail to outperform after expenses (see, for example, the studies by Jensen (1968), Gruber (1996), Carhart (1997), and Grinblatt and Titman (1993), among others).

actively in the belief that they possess such abilities. To cater to such investors, Fidelity Investments in fact offers several sector funds that allow short bets and are bought and sold at prices determined every hour instead of once at the end of the day.

Third, how does the cash flow volatility resulting from active trading by short-term investors affect the performance of fund managers? Ferson and Warther (1996) suggest that diversified mutual funds tend to realize positive cash flows during periods of higher expected market returns. This hurts the measured fund performance as fund managers are forced to carry higher cash holdings during times of higher returns.[3] Sector funds experience higher investor cash flow volatility than diversified stock funds and provide a natural out-of-sample test of the relationship between cash flow volatility and fund performance.

In this paper we conduct a comprehensive analysis of stock sector fund performance with a view to providing answers to these questions.[4] We identify 609 sector funds that existed at some time during a 28-year period, from 1972 to 1999, by using the CRSP Survivor-Bias Free US Mutual Fund Database. Most of these funds belong to one of the seven large sectors of the economy, which we define as energy, financials, health care, precious metals, real estate, technology, and utilities. However, a few funds are tied to smaller sectors of the economy, such as air transportation, leisure, and retailing. We include these in one miscellaneous category. We report the summary statistics for this category, but our return analysis is focused on the other seven categories for which we can find or construct sector index returns. For comparison, we also present the performance statistics of 3,227 non-sector funds during the same period.

Our findings are as follows. Sector funds charge higher expenses than non-sector funds. During 1999, sector funds charged annual expenses of 1.31 percent, compared to 0.80 percent charged by non-

[3] In this context, Edelen (1999) also argues that erratic cash flows force fund managers to deviate from their target efficient portfolios and thereby negatively impact the fund performance.

[4] As mentioned before, previous evidence on the performance of sector funds is scarce. Khorana and Nelling (1997) analyze a sample of 147 sector funds during 1976-1992. They use a one-factor model that gives conflicting results depending on whether the factor represents the S&P 500 returns or the sector index returns. They conclude that sector funds underperform relative to the first benchmark and overperform relative to the second benchmark. A few other studies focus on a single category of specialized funds, such as commodity funds (Elton, Gruber, and Rentzler (1987)), international funds (Cumby and Glen (1990)), bond funds (Elton, Gruber, and Blake (1993)), real estate funds (Kallberg, Liu, and Trzcinka (2000)), and the Japanese open-end funds (Brown, Goetzmann, Hiraki, Otsuki, and Shiraishi (2001)).

sector funds. It is not obvious that sector funds incur higher operating costs, which further raises curiosity as to whether these expenses are justified by their strong performance.

We test fund performance by using the Carhart (1997) methodology, which controls for the survivorship and look-ahead biases. Each month we calculate returns on a total net assets (TNA) weighted portfolio of all sector funds within each category. We use a five-factor model that regresses the excess returns on sector fund portfolios against the excess returns on market, size, book-to-market, momentum, and sector index portfolios. The resulting five-factor alphas are positive in two cases and negative in five cases. However, the highest t-statistic is barely significant at the 10 percent confidence level. Further, the five-factor alphas of equally-weighted fund portfolios are positive in three cases, negative in four cases, and significantly positive or negative in one case each. Thus, on a net return basis, the sector fund managers as a group neither underperform nor outperform their benchmarks. This finding differs from the previous evidence on non-sector funds that are known to earn significantly negative four-factor alphas in Carhart (1997), Carhart et al. (2002), and others, a result that we confirm for our sample period. However, the difference between sector fund and non-sector fund alphas is economically insignificant.

Unconditional alphas calculated by using net returns do not provide conclusive evidence against the existence of stock-picking skills. Following Ferson and Schadt (1996) and Ferson and Warther (1996), we next examine whether the performance is adversely affected by the cash flow volatility. Consistent with our prior beliefs, the standard deviation of quarterly cash flow scaled by fund assets is about 50 percent higher for sector funds than for non-sector funds, which strengthens this possibility. We next report two tests. The first test uses a fund-regression approach that measures five-factor alphas of individual funds conditional on their lagged cash flows. The conditional alphas from this approach are statistically indistinguishable from unconditional alphas for all seven categories of sector funds. The second test sorts all sector funds within each category into two portfolios based on their cash flow volatility over the last 12 quarters. We then use a portfolio-regression approach to measure the alphas of the low vs. high cash flow volatility portfolios. Once again, the difference between alphas is positive in four cases, negative in three cases, and insignificant in all seven cases. For comparison, we show that the two tests give similar results for non-sector funds.

Our evidence on cash flow volatility and returns has two implications. First, we infer that sector fund managers do not outperform or underperform relevant benchmarks even after accounting for the effects of investor cash flows. It appears that concentrating on one sector of the market does not produce superior returns. Second, in contrast to the previous findings in regards to non-sector funds, we find that cash flow volatility does not reduce sector fund performance. We analyze a larger dataset than previous studies, and we employ a multi-factor model for both sector and non-sector funds. We also calculate conditional performance by using the actual cash flows of individual funds, whereas Ferson and Warther (1996) use the dividend yield on market and the T-bill rate as instruments for cash flows of all funds. In further support of our results, we show that the cash flows are not related to subsequent sector returns.

The remaining tests focus on the fund selection and sector timing abilities of fund investors. To test the fund picking abilities of investors, we form two portfolios within each sector fund category at the beginning of each quarter. The first portfolio includes funds that realize positive net cash flow during the last quarter, and the second portfolio includes funds that realize negative net cash flow. Unlike Zheng (1999), we find that the difference between alphas of the two portfolios is insignificant. However, our performance model differs from Zheng (1999) in that we include the momentum factor. To test whether investors can pick the winning sectors, we regress the quarterly sector index return net of the riskfree return or the market return on the lagged values of quarterly net cash flow for all funds in that sector. The coefficient of lagged cash flow is about as likely to be positive as negative. The combined evidence suggests that sector fund investors do not possess fund picking or sector timing abilities.

Our evidence is largely consistent with market efficiency. But what then explains the popularity of actively managed stock sector funds? Apart from providing account maintenance and tax computation service, they allow investors to pick a portfolio of several stocks within a sector of the stock market at a short notice and with limited capital. Regardless of the merits of sector investing, there must be many investors who value this service, which is why their cash flow volatility is high. During the period of our study there were few alternatives to sector funds. However, in recent years many cost-efficient alternatives have emerged in the form of exchange traded funds (ETFs) on sector indexes. Whether these ETFs will reduce the lure of expensive but actively managed stock sector funds remains to be seen.[5]

The remaining paper proceeds as follows. Section II describes the data and methods. Section III presents tests of fund performance, and Section IV presents tests of the magnitude and the effects of cash flow volatility. Section V analyzes the fund selection and sector timing abilities of sector fund investors, and Section VI concludes. An Appendix reports the robustness tests.

II. Data and methods

A. Sample description

Our primary data source is the CRSP Survivor-Bias Free US Mutual Fund Database.[6,7] The sample consists of all equity sector funds that existed at any time during 1972–1999. We identify sector funds using the ICDI fund objective code, the Weisenberger fund type code, the Strategic Insight fund objective code, and a policy variable provided by CRSP. Besides general diversified stock funds, we exclude sector index funds, international funds, bond funds, and money market funds. This results in a sample of 609 stock sector funds. We classify all sector funds into eight categories: energy, financials, health care, precious metals, real estate, technology, utilities, and a miscellaneous category (acronyms EN, FN, HL, PM, RE, TC, UT, and MS are used in tables). We confirm the accuracy of our classification by examining each fund's investment objective and description from internet sources. The miscellaneous

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[5] For example, the American Stock Exchange lists the SPDR Funds (Standard & Poor's Depository Receipts). The SPDRs are designed to track the S&P 500 sector indexes that we use as benchmarks and charge annual expenses of 0.28 percent. However, an investor must pay brokerage and bid-ask spread just as in buying any other stock.

[6] Elton, Gruber, and Blake (2001) point out that the CRSP database is well constructed, but has a slight upward bias in net returns during months when a fund declared multiple distributions. To illustrate this bias, they cite the Windsor II fund, which declared a dividend of $0.24 per share and a capital gains of $0.86 per share on December 14, 1994. The fund had NAV (net asset value) of $13.71 as of November end, $12.59 as of December end, and $12.53 as of distribution date. CRSP calculates the net return as (12.59/13.71)×(1+0.24/12.53)×(1+0.86/12.53), or 0.000133, whereas the correct return should be (12.59/13.71)×(1+1.10/12.53), or –0.001075. We applied the needed correction to remove this bias.

[7] The CRSP database provides only annual returns on many non-surviving non-sector funds. We infer monthly returns in these cases by following a procedure similar to Carhart et al. (2002). We first calculate the ratio of the average annual gross return on funds with only annual returns to those with monthly returns. (The gross return is simply one plus the [net] return.) We then infer the monthly returns on funds with only annual returns as the average gross return of those funds with monthly returns multiplied by one-twelfth power of this ratio minus one.

category includes sector funds that are hard to classify and for which performance benchmarks are not available. For this reason, we restrict our detailed analysis to the first seven categories of sector funds.

Our sample of non-sector funds includes 3,227 domestic stock funds that are not sector funds. This sample is identified by using the same procedure as in Carhart et al. (2002). In fact, we use their exact sample for funds that exist before 1995.[8] For funds that exist only after 1995, we use the ICDI fund objective code to identify aggressive growth, growth and income, and long-term growth funds.

Table 1 describes the sample. Panel A shows that the number of sector funds increased steadily from 11 in 1972 to 530 in 1999, representing 2.0 and 18.2 percent of all stock funds (which includes both sector and non-sector funds). The aggregate TNA of sector funds increased from $1.6 billion to $157.6 billion during this period, representing 3.0 and 6.7 percent of the TNA of all stock funds.[9] Although not directly shown, it can be inferred that the average TNA for a sector fund has declined from about 1.5 times the average TNA for non-sector funds in 1972 to about 0.3 times the average TNA for non-sector funds in 1999.

Panel B of Table 1 shows the distribution of sector funds by category. Real estate funds are the most numerous, at 122, followed by technology funds, at 114. However, measured by TNA in December 1999, technology funds are dominant, accounting for $72.4 billion, or 45.9 percent of all sector fund assets. Next in size are the utilities funds, at $24.6 billion, and health care funds, at $23.4 billion. At the other end, precious metals funds have only $1.9 billion in assets, even though there are 66 funds in this category. Since our sample of sector funds includes many cases of two or more funds that differ mainly in their marketing to different types of investors (e.g., institutional shares vs. advisor shares), we further identify a sub-sample of 373 unique sector funds. This sub-sample includes the oldest of each group of two or more clone funds, or the biggest in case two or more clone funds start in the same year. Given the very time-consuming nature of this task involving internet searches, the identification of unique non-sector funds is not attempted.

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[8] We are obliged to Mark Carhart for providing this sample of non-sector funds.

[9] TNA information is missing for 8 percent of sector funds and 5 percent of non-sector funds, so the actual fund assets may be higher than reported here.

Panel C of Table 1 shows the largest fund within each category as of December 1999. The largest sector fund across all categories is the Vanguard Specialized – Health Care fund. It had $10.6 billion in assets, which represents 45.5 percent of all assets in the health care sector. The largest funds in other sectors manage between 11.2 and 27.8 percent of total assets in that sector. Among non-sector funds, Fidelity Magellan is the largest fund. It had $99.2 billion in assets as of December 1999, which represents 4.5 percent of all assets in the non-sector fund category.

Table 2 shows the summary statistics. For each data item, we first calculate the TNA-weighted average across all funds at the end of 1972, 1976, 1980, 1984, 1988, 1992, 1996, and 1999, and then report a simple time-series average of the cross-sectional averages. Panel A of Table 2 shows that the stock holdings of sector funds and non-sector funds are similar at 88.4 and 86.8 percent. The total load charges, consisting of the front-end load and the other load, are also similar at 4.3 and 4.1 percent for sector and non-sector funds. Front-end load represents the maximum percentage expense incurred at the time of purchase of fund shares, and other load usually represents the maximum deferred or rear-end charges. The annual turnover for sector funds at 67.0 percent is somewhat higher than at 59.8 percent for non-sector funds. But the biggest difference is in the expense ratio, defined as the percentage of total assets that investors pay in fund operating expenses every year. The expense ratio over the years averages 1.05 percent for sector funds and 0.79 percent for non-sector funds. The difference in expense ratios is not explained by the difference in fund turnover and fund size. Yearly cross-sectional regressions that include log transforms of both these variables show that the sector dummy is generally positive and significant. For example, such analysis shows that sector funds charge an extra 0.16 percent in 1999. The reasons behind this additional charge are not obvious. It is not clear that running a sector fund is more expensive than running a diversified stock fund.

Panel B of Table 2 reports summary statistics for different categories of sector funds. The average stock holdings lie between 86.3 percent for real estate funds and 91.8 percent for miscellaneous funds. The annual turnover rate lies in a wider range, from 34.5 percent for precious metals funds to 130.9 percent for miscellaneous funds. Technology funds have the second highest turnover at 94.1 percent. The expense ratios vary between 0.93 percent for energy funds and 1.62 percent for miscellaneous funds.

Panel C of Table 2 shows the time trend in expense ratios of sector funds and non-sector funds. In 1972 the expense ratios for the two groups were nearly identical at 0.58 percent for sector funds and 0.59 percent for non-sector funds. The expense ratios for both groups increased over the sample period, but the increase was much greater for sector funds. In 1999 the average expense ratio for sector funds was 1.31 percent as compared to 0.80 percent for non-sector funds.

B. Unconditional performance evaluation model

We examine sector fund performance by using a five-factor model. This includes the four broad-market factors employed by Carhart (1997) and a fifth factor that captures the return on a passive sector index as follows:

$$r_{p,t} - r_{f,t} = \alpha_p^5 + \beta_{1,p} RMRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} UMD_t + \beta_{5,p} INDRET_t + e_{p,t} \qquad (1)$$

Here, $r_{p,t} - r_{f,t}$ is the monthly return on a portfolio of sector funds in excess of the one month T-bill return, RMRF is the excess return on the value-weighted market portfolio consisting of all NYSE, AMEX, and NASDAQ stocks, and SMB, HML, and UMD are returns on factor-mimicking portfolios for the size, book-to-market, and one-year momentum in stock returns. The use of RMRF, SMB, and HML factors is inspired by Fama-French's (1993) 3-factor model. The use of momentum factor is inspired by Carhart (1997), who shows that it makes a large difference to the analysis of mutual fund performance.[10]

The fifth factor, INDRET, equals the excess return on a passive sector index. The choice of sector indexes is described in the following section. A passive sector index represents a natural benchmark for sector fund performance. Since sector funds make concentrated bets within industry segments, broad-market factors alone are not sufficient to explain the performance of sector funds. In this sense, our five-factor model can be interpreted as a performance attribution model.

We evaluate the performance of sector fund portfolios based on their five-factor alpha, α_p^5, estimated by using Equation (1). The five-factor alpha represents a multi-factor generalization of the well-known Jensen's alpha. As shown in Equation (1), our primary inference is based on a portfolio regression approach. Each month we form TNA-weighted portfolios of all funds within a sector, regardless of their history, and compute the portfolio returns. The TNA values used in this approach are as of the end of

[10] We wish to thank Ken French for making available the data on RMRF, SMB, HML, and UMD.

month *t-1*. As a robustness check we sometimes examine the performance of equally-weighted sector fund portfolios. Whereas the TNA-weighted approach includes all 609 unique and clone sector funds, the equally-weighted approach uses only the 373 unique sector funds.

We evaluate the performance of non-sector funds using the Carhart (1997) four-factor model that employs RMRF, SMB, HML, and UMD as factors. Each month we form a TNA-weighted (or equally-weighted) portfolio of all non-sector funds using all funds within the category. We use the time series of monthly portfolio returns to compute the four-factor non-sector fund portfolio alpha.

We use many other performance evaluation criteria in addition to the five-factor model shown in Equation (1). We use a one-factor model that contains only INDRET for sector funds and RMRF for non-sector funds. We also use a conditional performance evaluation version of Equation (1) in which we use a fund's normalized quarterly cash flow as a conditioning variable. These and the other performance models are described along with the results.

C. Sector index description

The choice of sector indexes is guided by two considerations. First, we desire value-weighted indexes that are relatively passive and require minimum rebalancing. Second, we desire broad-based indexes that account for a large part of the investment in the corresponding sectors. With this in mind, we use the S&P 500 sector indexes for energy, financials, health care, technology, and utilities. The S&P 500 sector indexes represent value-weighted portfolios of the S&P 500 stocks that belong to each of these sectors. Both the S&P 500 index and the S&P 500 sector indexes are popular benchmarks and viable investment portfolios. The S&P 500 index funds have existed for a long time, and recently it has become possible to invest in the S&P 500 sector indexes by purchasing the sector SPDR funds.

We use S&P 500 sector index total returns that include dividends. We obtain data on index total returns during 1990-1999 from Telerate, which in turn obtained these data from the Standard & Poor's Corporation. In addition, we obtain the index total returns data for utilities during 1972-1989 and for financials during 1976-1989 from S&P publications. For the remaining sample during 1972-1989, we construct sector index returns as follows. We obtain a list of all stocks included in the S&P 500 index from February 1972. We obtain their sector classifications from Compustat, which are available from

1976. However, to construct as long an index series as possible, we assume that the sector classifications during 1972-1976 are the same as during 1976. This approximation is justified by the observation that only about four percent of the firms for which the Compustat data are available ever change their sector classification. Using CRSP returns, we next calculate the value-weighted sector index returns including dividend. We confirm that the returns constructed by using this procedure correspond closely to the sector index returns originating from the Standard & Poor's Corporation during 1990-1999.

Unfortunately, there are no S&P 500 sector indexes for the precious metals and the real estate sectors. For the precious metals sector, we use the Philadelphia Exchanges's Gold/Silver index (XAU). This is a value-weighted index of nine stocks in the precious metals sector. For the real estate sector, we use the Wilshire Real Estate Securities index (WRES). This is a value-weighted index of real estate investment trusts and real estate operating companies. Kallberg, Liu, and Trzcinka (2000) argue that WRES is the preferred benchmark for the real estate sector as it is broad-based and includes relatively liquid securities. We obtain the data on the XAU returns from the Philadelphia Exchange, and the WRES returns from the Wilshire Associates. Both of these return series include dividends.

Table 3 describes the sector indexes. Panel A reports the starting date and the ending date for each index and the correlation between the index and a portfolio of the corresponding sector funds. Monthly returns on the sector indexes for energy, health care, financials, technology, and utilities are available from February 1972, for precious metals from April 1989, and for real estate from January 1978. However, data on the first health care and real estate funds are available only from January 1982. The correlations between the monthly excess returns on sector indexes and sector fund portfolios are quite high. With TNA-weighted portfolios, the correlations range between 0.676 for the real estate sector and 0.943 for the precious metals, with a median of 0.874. The results are quite similar with equally-weighted portfolios. Overall, the chosen indexes seem to be reasonable benchmarks for analyzing the performance of sector fund portfolios. As expected, the correlation between the value-weighted market index and the non-sector fund portfolios is even higher, at 0.992 for the TNA-weighted portfolio and 0.983 for the equally-weighted portfolio. These higher correlations may be attributed to the much larger number of non-sector funds that collectively hold a large part of the market portfolio.

To further explore the characteristics of sector indexes, we conduct a regression of the monthly index excess returns on the four broad-market factors RMRF, SMB, HML, and UMD. The results are shown in Panel B of Table 3. The intercept term is significant in two cases, positive for the health care index and negative for the real estate index. The market factor is significantly positive for all indexes. Five of the seven indexes (energy, financials, health care, technology, and utilities) have negative loading on SMB, indicating that these indexes are dominated by large capitalization stocks. The health care and technology indexes have negative loadings on HML, reflecting that these sectors are dominated by growth stocks. Somewhat surprisingly, the energy and real estate sector indexes are the only ones with a positive loading on UMD.[11] Finally, the adjusted R-square values range between 0.054 for the precious metals index and 0.716 for the financials index, with a median of 0.624. This suggests that the four broad-market factors explain a large part of the variation in sector index returns, but there is enough left over that requires the inclusion of an INDRET factor in analyzing the performance of sector funds.

III. Do sector fund managers outperform the benchmarks?

We begin our analysis by examining the performance of sector funds as measured by the factor models discussed earlier. Table 4 reports the average excess returns, or alphas, from one-factor and five-factor models. These are denoted by α^1 and α^5. The subscript p is dropped for easier exposition.

Panel A of Table 4 shows the results for the TNA-weighted portfolios of sector funds. The α^1 is insignificant for all categories. In contrast, the non-sector fund portfolio has α^1 of –0.072 percent, which is significant at the 5 percent level. Looking further, we find that the coefficient of INDRET for each sector fund portfolio is smaller than its average percent stock holding shown in Table 2. For example, the financials sector fund portfolio has an INDRET coefficient of 0.708. If the stock holdings of financials funds were exactly similar to the index, the coefficient would be around 0.916, which is the same as the percent stock holdings of financials funds in Table 2. It appears that the one-factor model is not adequate

[11] This may seem odd, but can be explained. First, the strong association between the momentum factor and the health care and technology stocks is a 1990s phenomenon. Second, the univariate correlations between UMD and the EN, FN, HL, PM, RE, TC, and UT excess returns equal 0.082, –0.130, 0.103, –0.091, –0.036, 0.072, and –0.040 over the study period. However, due to correlations between RMRF, SMB, HML, and UMD, the UMD loadings of sector indexes in a four-factor model may be of a different sign compared to the univariate correlations.

to analyze the performance of sector funds. This may be due to non-sector stock holdings, or due to differences in the size, book-to-market, and momentum characteristics of sector stock holdings of the funds and the sector indexes.[12]

We next analyze the five-factor results for the TNA-weighted portfolios of sector funds, also shown in Panel A of Table 4. As expected, each of the sector fund portfolios has a significantly positive coefficient of INDRET. The coefficient of RMRF is also significantly positive for all portfolios except precious metals. Relative to the market and the sector indexes, real estate and utilities funds hold small value stocks as shown by the positive coefficients of SMB and HML. Energy, health care, precious metals, and technology funds hold small growth stocks, and financials funds hold large value stocks. However, the coefficients of SMB and HML used to make such inferences are not always significant. In five out of seven cases, we find a positive UMD coefficient. The UMD coefficient is significantly positive for technology and health care, suggesting that these funds hold momentum stocks relative to the market and indexes. The two sectors with negative but insignificant UMD coefficients are financials and utilities. The adjusted R-square of all regressions lies between 0.497 and 0.909, with a median value of 0.875. The non-sector funds tend to hold smaller, growth stocks relative to the value-weighted market index as evidenced by the significantly positive SMB coefficient and the significantly negative HML coefficient.

The central results concern α^5, which lies between –0.228 percent for precious metals and 0.086 percent for technology. It is negative in five cases and positive in two cases. However, the α^5 is insignificant in each case, with the sole exception of energy funds, where it equals –0.179 percent and is marginally significant at the 10 percent level. This shows that after accounting for style differences the sector fund managers as a group earn fair returns. The simple average of the seven α^5 values equals –0.080 percent, which translates into an annual excess return of –0.96 percent. This excess return is computed after subtracting the average fund expenses of 1.05 percent, but before subtracting the fund loads. Not subtracting fund expenses would give an annual excess return of around 0.09 percent, which would remain insignificant, judged by the precision of estimates in Table 4. In comparison, the non-sector

[12] The one-factor model may not capture all the systematic variation in sector-fund returns. Nevertheless, it may be the appropriate benchmark for an active investor who holds sector funds to invest efficiently in a chosen sector of the stock market.

fund portfolio alpha is significantly negative at –0.063 percent per month, or –0.76 percent annually. The significant underperformance of the non-sector funds is consistent with previous results in the literature. However, based on the relative magnitude of the alphas, the difference in the performance of sector funds and non-sector funds is economically insignificant in TNA-weighted tests. The difference in statistical significance reflects the greater precision of non-sector fund alphas.

Panel B of Table 4 shows the results for equally-weighted fund portfolios. The α^1 is positive and marginally significant for financials, real estate, and technology. Non-sector funds on the other hand, have a significantly negative alpha of –0.122 percent. The α^5 is much more relevant, and it is insignificant for all categories except energy and technology. It equals –0.263 percent (t-statistic –2.23) for energy, and 0.236 percent (t-statistic 2.18) for technology. The simple average of the seven α^5 values for equally-weighted portfolios of sector funds equals –0.042 percent. In comparison, the non-sector funds have a significantly negative α^5 of –0.104 percent.[13]

Based on the α^5 estimates, the results for energy funds are significantly negative with both TNA-weighted and equally-weighted portfolios. The results for technology funds are positive but significant only for the equally-weighted portfolio. The remaining results are insignificant, although for financials both alphas are positive, for precious metals, real estate, and utilities both are negative, and for health care one is negative and one is positive. Overall, the evidence suggests that the performance of sector funds is essentially neutral after accounting for the systematic factors in stock returns. It is fair to conclude that as a group the sector fund managers neither outperform nor underperform the relevant benchmarks. Our evidence is thus largely consistent with market efficiency.[14]

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[13] The four-factor alphas for the value-weighted and the equally-weighted portfolios of non-sector fund portfolios equal –0.089 percent and –0.136 percent (t-statistics –2.90 and –3.90) when the Carhart (1997) and Carhart et al. (2002) momentum factor PR1YR is used in place of the Fama-French UMD factor. This equally-weighted alpha compares favorably with Carhart et al. estimates over a different time period of 1962-1995.

[14] We note that Kallberg, Liu, and Trzcinka (2000) find that real estate funds earn significantly positive excess returns of two percent a year, while we find insignificant results. However, there are many differences between the two studies. First, their sample period is March 1987 to June 1998, while ours is January 1982 to December 1999. Second, they use a form of the fund regression approach, while we use the portfolio regression approach. The fund regression approach suffers from a look-ahead bias that can overstate the excess returns. Third, they use a five-factor model that includes the bond factor, but does not include the momentum factor. Fourth, their results are based on an equally-weighted average of individual fund alphas, while we base all our primary inferences on TNA-weighted portfolios of sector funds. Appendix A.2. discusses that our results for an equally-weighted portfolio of real estate funds over a shorter sample period are more in line with those reported by Kallberg, Liu, and Trzcinka.

We report in Appendix A that our results are robust to a variety of cross-checks. First, following Kosowski et al. (2001), we use a bootstrap procedure to test statistical significance in the presence of potentially non-normal distributions of alphas. Most of our results are unchanged, except that the marginally significant five-factor alpha for TNA-weighted portfolio of energy funds becomes marginally insignificant. Our quantitative inference concerning the magnitude and significance of alphas thus change only slightly, and our qualitative inference concerning the neutral performance of sector funds remains unchanged. Second, we show that our results are robust to the choice of sub-sample or sub-period. Third, to address any potential concerns about the choice of S&P 500 sector index returns, we use DataStream sector index total returns and re-compute the five-factor alphas in Table 4. While occasionally there are some changes in the significance level of alphas, the overall nature of the results remains unchanged with the choice of a different sub-sample, sub-period, or sector index return.

IV. Does cash flow volatility adversely affect the sector fund performance?

A. Why cash flow volatility may affect performance

Edelen (1999) documents that around 70 percent of the cash inflow or outflow to a mutual fund during a six-month observation period results in contemporaneous purchases or sales. The remaining cash flow increases or decreases the cash position of the fund. Ferson and Warther (1996) suggest that cash inflows are more likely to occur when expected market returns are high, and cash outflows are more likely to occur when expected market returns are low. Not adjusting for the effect of cash flows on fund betas thus understates the fund performance as managers are forced to decrease beta during times when they should increase it, and vice versa. Ferson and Warther use data on aggregate fund flows, which they show are related to the dividend yield on the market portfolio and the T-bill rate. They employ the Ferson and Schadt (1996) conditional performance evaluation model to show that allowing betas to be related to the lagged values of these two macroeconomic variables, used partly as instruments for fund cash flows, makes some difference to the fund alphas. Below we present statistics on the cash flow volatility of sector funds and their five-factor alphas calculated by using the Ferson and Schadt model and allowing betas to be directly related to the lagged cash flows of individual funds.

B. Measuring the cash flow volatility of sector funds

We use changes in fund TNA adjusted for the effect of mergers and scaled by the starting TNA as our primary measure of cash flow. Specifically, for each fund *i*, we calculate the quarterly cash flow ratio for each quarter *q* as follows:

$$QCF_{i,q} = (TNA_{i,q} - TNA_{i,q-1} \times (1 + r_{i,q}) - MGTNA_{i,q}) / TNA_{i,q-1} \quad (2)$$

MGTNA refers to the increase in fund assets due to mergers, and the remaining variables are continued from before.[15] Since TNA data before 1991 are available only on a quarterly basis, we use quarterly intervals for measuring cash flows during the entire period of our study. To examine representative statistics for each category of sector funds, we first compute the time-series median and standard deviation of *QCF* values for each fund. We then report the cross-sectional medians of the individual fund statistics. The median standard deviation is our measure of cash flow volatility.

Panel A of Table 5 shows that the cash flow volatility for all 542 sector funds with available cash flow data equals 0.337. In comparison, the cash flow volatility for all 3,126 non-sector funds equals 0.226. The ratio equals 1.49, which is economically very significant. Looking across the seven categories of sector funds, the cash flow volatility in each case is higher than for non-sector funds, which is significant at the 5 percent level. In the case of financials, health care, and technology funds, the cash flow volatility is over twice as large as that for non-sector funds.

The above test implicitly assumes that the *QCF* values for a fund have a constant expected value over time. However, the expected value may change in an autoregressive fashion. We therefore examine the residual volatility from the following model:

$$QCF_{i,q} = \mu_i + \theta_i \times QCF_{i,q-1} + \varepsilon_{i,q} \quad (3)$$

As before, we first estimate this model for each fund, and then report the cross-sectional medians of the individual fund statistics. Panel B of Table 5 shows that the residual cash flow volatility for sector funds and non-sector funds equals 0.302 and 0.197. The ratio equals 1.53, which is similar to estimates from Panel A and remains economically very significant. Looking across the seven categories of sector funds,

[15] Elton, Gruber, and Blake (2001) point out that the merger dates provided on the CRSP database can sometimes be inaccurate. We therefore checked the merger dates reported by CRSP for possible errors. We found one case where the merger date appeared to be off by a quarter, and made the appropriate correction.

the cash flow volatility in each case is again higher than for non-sector funds, which is significant at the 5 percent level. Consistent with popular beliefs, both sets of figures show that sector funds experience high cash flow volatility. A $100 million sector fund realizes unpredictable cash flows each quarter with a standard deviation of around $30 million.

In light of the previous results in the literature, it is natural to ask what effect, if any, this high cash flow volatility has on the performance of sector funds. We examine this issue in more detail in the following two sub-sections.

C. Sector fund performance conditional on lagged cash flows

The effect of cash flow volatility on fund betas and performance can be analyzed by using the conditional performance evaluation model combined with the fund-regression technique of Gruber (1996) and Zheng (1999). For each fund *i*, we estimate the following model by using monthly returns:

$$\begin{aligned} r_{i,t} - r_{f,t} \;=\; & \alpha_i^{5c} + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} UMD_t + \beta_{5,i} INDRET_t + \delta_{1,i}\left(QCF_{i,q-1} * RMRF_t\right) \\ & + \delta_{2,i}\left(QCF_{i,q-1} * SMB_t\right) + \delta_{3,i}\left(QCF_{i,q-1} * HML_t\right) + \delta_{4,i}\left(QCF_{i,q-1} * UMD_t\right) + \delta_{5,i}\left(QCF_{i,q-1} * INDRET_t\right) + \varepsilon_{i,t} \end{aligned} \quad (4)$$

The model itself is inspired by Ferson and Schadt (1996) and Ferson and Warther (1996). In this model, the lagged cash flow ratio $QCF_{i,q-1}$ is the only conditioning variable. The sample includes only those funds for which at least 30 months of cash flow and returns data are available. The conditional fund-regression alpha for month *t* is obtained as the TNA-weighted average of $(\alpha_i^{5c} + \varepsilon_{i,t})$ across all funds belonging to a given category of sector funds. The final conditional alpha and its t-statistic are obtained by averaging the time-series of fund-regression alphas for all months. The unconditional alphas are estimated by a similar technique, but by dropping the interaction terms from Equation (4).

Table 6 shows that the conditional and unconditional alphas are insignificantly different for all seven sector fund categories. The difference between alphas is positive in five cases and negative in two cases. It ranges between –0.037 and 0.053. The conditional and unconditional fund-regression alphas of non-sector funds equal –0.056 and –0.060, both significant at the five percent level. The difference in this case is positive, but statistically insignificant. Although not reported in Table 6, we also verify that the results of Table 6 are similar if we obtain the conditional and the unconditional alpha for month *t* as an equally-weighted average of $(\alpha_i^{5c} + \varepsilon_{i,t})$ across all funds belonging to a category.

Overall, we document an insignificant effect of cash flows on the performance of sector funds. Our results in this respect are different from previous results documented for non-sector funds. The most likely explanation for this difference in results is that there is no systematic link between aggregate cash flows to funds within a sector and the future returns to that sector. As we show below in Section V, direct tests confirm this conjecture. In further support of our results, we find that the median $\delta_{1,i}$ from Equation (4) is positive in four out of seven sector fund categories, and the median $\delta_{5,i}$ is positive in three out of seven categories. This finding is inconsistent with the notion that sector fund betas decrease significantly during quarters in which cash flows are higher than expected, and vice versa.[16]

For non-sector funds we are, in fact, able to replicate the findings of Ferson and Warther (1996), despite differences in the sample, factor model, and test period. Following their conditional performance model, we interact each factor return with lagged dividend yield on the market portfolio and the Treasury bill yield. Similar to their evidence, we find that conditioning returns on these two variables makes a difference to the four-factor alphas of non-sector funds. Using the fund-regression approach of Table 6, we measure that the conditional alpha of non-sector funds is an insignificant –0.021 percent (t-statistic –0.73), while the unconditional alpha is a significant –0.060 percent (t-statistic –2.16). However, none of the alphas for sector funds change from significant to insignificant, or vice versa, by using the dividend yield and the Treasury bill yield as conditioning variables.[17]

D. Portfolios of sector funds with low vs. high historic cash flow volatility

We present another test to examine the effects of cash flow volatility on performance. In January of each year from 1975 to 1999, we calculate the historic cash flow volatility for each fund by using the standard deviation of the last 12 quarterly cash flow ratios as defined in Equation (2). We rank all funds within a sector fund category into two portfolios on the basis of their historic cash flow volatility. We then use the portfolio regression technique to measure the five-factor alphas of the low vs. the high cash

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[16] Yet another evidence is based on the percent stock holdings (or cash holdings) of sector and non-sector funds. The cross-sectional median of the time-series standard deviation of percent stock holdings equals 3.90 for all sector funds and 3.56 for all non-sector funds. Since the variation in stock holdings may be voluntary or involuntary, this suggests that the involuntary changes in fund betas caused by unpredictable cash flows may be small. Unfortunately, the stock or cash holdings data are available only on annual basis.

[17] Further details of all robustness tests mentioned in the text of this paper but not reported in a table are available from the authors on request.

flow volatility TNA-weighted portfolios. Table 7 shows that the two alphas and the difference between alphas are insignificant in all seven categories of sector funds. The difference is positive in four cases and negative in three cases. The results for non-sector funds are a little different. The alpha of the low volatility portfolio in this case is an insignificant –0.034 percent (t-statistic –1.09), while the alpha of the high volatility portfolio is a significant –0.096 percent (t-statistic –2.74). The difference between alphas has the right sign, but it is insignificant. As a cross-check, although not reported in Table 7, we find that the difference between the alphas of low vs. high cash flow volatility portfolios remains insignificant if we use equally-weighted fund portfolios of sector and non-sector funds.

The combined evidence of this section suggests that sector funds experience high cash flow volatility, but that this volatility does not adversely affect the measured fund performance. Combined further with the evidence from Section III, we conclude that as a group the sector fund managers do not possess superior stock selection skills.

V. Do sector fund investors possess fund selection or sector timing abilities?

Recent evidence suggests that some mutual fund investors may have the ability to detect funds with superior future performance. Gruber (1996) and Zheng (1999) provide evidence of such selection ability among diversified mutual fund investors, a finding known as the smart money effect.[18] It is possible that sector fund investors possess similar fund selection ability. This would partly explain the popularity of sector funds. Another argument in favor of sector funds is based on sector timing or rotation ability. It is possible that sector fund investors are able to pick the right sector at the right time. This would also explain the popularity of sector funds, especially since low-cost indexing alternatives tied to sector indexes did not exist until the late 1990s. Below we test both of these possibilities with cash flow and returns data.

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[18] This is the central message of Gruber's (1996) presidential address to the American Finance Association. He argues that it is not irrational for investors to choose actively managed open-end mutual funds, even though collectively they underperform the indexes. He suggests that since managerial ability is not reflected in the prices of open-end funds, mutual fund performance may be predictable. This would enable some investors to direct their investments to managers with superior ability and away from those with inferior ability. Hence, the return on new cash flow should be superior to the average return on all funds.

We analyze the fund selection ability of sector fund investors by examining the performance of new-money portfolios formed on the basis of the net cash flow realized by funds within each sector. At the beginning of each quarter, we group all funds within a sector into two portfolios. The positive cash flow portfolio includes all funds with positive net cash flow during the previous quarter, and the negative cash flow portfolio includes all funds with negative net cash flow during the previous quarter. Similar to Equation (2), the net cash flow to fund *i* during quarter *q* is defined as follows:

$$TNA_{i,q} - TNA_{i,q-1} \times \left(1 + r_{i,q}\right) - MGTNA_{i,q} \tag{5}$$

All notations have the same meaning as before. We compute monthly cash-flow-weighted returns for the two sets of new-money portfolios within each sector. The cash-flow-weighted returns are computed using all funds within a portfolio and the net cash flows during the previous quarter as defined above. For each sector we limit the analysis to the number of months during which observations are available for both the positive and the negative cash flow portfolios for the sector.

We use the five-factor model to compare the performance of the positive cash flow and the negative cash flow portfolios. If sector fund investors have fund selection ability, then we would expect the difference between the two alphas to be positive. However, Table 8 shows that the difference between alphas is positive in three cases (energy, health care, and utilities), negative in four cases (financials, precious metals, real estate, and technology), and insignificant in all seven cases. There is no evidence of fund selection ability on the part of the sector fund investors. A similar conclusion emerges when we examine the difference between the alphas for the positive cash flow and the negative cash flow non-sector fund portfolios. The difference is positive, but insignificant. Our findings for non-sector funds may differ from Zheng (1999) because we use a four factor model that includes the momentum factor.[19]

We next examine the question of sector timing or rotation ability. Analogous to market timing, we define sector timing as successful shifting of funds between sector stocks and cash.[20] We define sector

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[19] In this respect our finding is similar to Sapp and Tiwari (2004), who analyze non-sector funds during 1970-2000 and find that the momentum factor explains the smart money effect.

[20] In the context of diversified mutual funds, the question of market timing ability of fund managers has also been extensively examined (see, for example, Henriksson (1984), Jagannathan and Korajczyk (1986), Goetzmann, Ingersoll, and Ivkovic (2000), and Bollen and Busse (2001)). However, we focus on the sector timing and sector rotation abilities of sector fund investors.

rotation as successful shifting of funds between one sector and the remaining sectors. The first definition suggests that the dependent variable should be the difference between the sector index return and the riskfree return. The second definition suggests that it should be the difference between the sector index return and the market return. In both cases we use quarterly returns. The independent variable is the last quarter's aggregate cash flow to all funds within that sector, normalized by the aggregate TNA at the beginning of that quarter. A significantly positive coefficient of the independent variable will indicate that sector fund investors direct excess cash flow to those sectors that realize greater subsequent returns, which can be interpreted as evidence in favor of sector timing or rotation ability.

Panel A of Table 9 reports the tests of sector timing ability. In three cases (financials, health care, and technology) the relation between the sector index return minus riskfree return and the aggregate cash flow of the last quarter is positive. In four cases (energy, precious metals, real estate, and utilities), the relation is negative. The slope coefficient is positive and significant only in the case of technology funds. Panel B presents similar evidence on sector rotation ability. Here again the relation between the sector index return minus market return and the aggregate cash flow of the last quarter is positive in three cases and negative in four cases. Two slope coefficients are now significantly different from zero, but one is positive and one is negative. The slope coefficient for technology is significantly positive (similar to Panel A), and the slope coefficient for health care is significantly negative.

The combined evidence on sector returns vs. sector cash flow shows that as a group the sector fund investors have neither sector timing ability nor sector rotation ability. It appears that information trading does not explain the active trading of sector funds. This finding is also related to our main results from Section IV that conditioning returns on lagged cash flows does not improve the measured fund performance. If the aggregate cash flows during this period are not correlated with expected sector returns during the next period, then any changes in fund betas caused by erratic cash flows would be random and would not adversely affect the fund performance.

VI. Conclusions

Sector funds are an important and growing segment of the mutual fund industry. This segment has not received much attention in the academic finance literature. We provide the first comprehensive analysis of sector fund performance by using a five-factor return model. Our sample includes all actively managed stock sector funds listed on the CRSP Survivor-Bias Free US Mutual Fund Database during 1972-1999. Most of our tests are based on the portfolio-regression technique that controls for the look-ahead bias. We investigate several issues related to the performance of both the sector fund managers and investors. In particular, we examine the effects of higher cash flow volatility of sector funds. We test whether it adversely affects the performance of fund managers, and we test whether it reflects trading by smart investors who are able to identify winning sector funds or winning sectors of the stock market. For comparison, we also analyze the performance of all non-sector funds listed on the CRSP database during 1972-1999.

We first examine whether the specialized and concentrated nature of sector fund investments translates into superior performance. Our main finding is that while sector funds charge higher expenses than non-sector funds, their net returns after expenses and transaction costs are not superior to their benchmarks. We conclude that sector funds as a group earn fair returns.

We next document that the volatility of cash flows experienced by sector funds is nearly 50 percent higher than that for non-sector funds. We examine whether the high cash flow volatility adversely impacts sector fund performance and hides superior stock-picking skills of sector fund managers. We present two tests of the relation between cash flow volatility and fund performance. The first test uses Ferson and Schadt (1996) conditional performance model in which betas are related to the last quarter's cash flow. The five-factor alphas from the conditional model are statistically indistinguishable from alphas from the unconditional model. The second test examines whether the fund performance is related to the historic cash flow volatility. The five-factor alphas of low cash flow volatility portfolios are also statistically indistinguishable from the five-factor alphas of high cash flow volatility portfolios. Our findings in regards to non-sector funds differ from previous literature that documents a substantial reduction in non-sector fund performance as a result of cash flow volatility.

A final question concerns whether the cash flow volatility arises because some investors are successfully able to pick the winning sector funds or the winning sectors of the stock market. As pointed out using anecdotal evidence in the introduction and supported by the higher cash flow volatility, many sector fund investors and prominent fund management companies seem to behave as if the answer is in the affirmative. Our evidence on this issue differs from the smart money effect documented for non-sector funds in previous literature. We find an insignificant difference between the performance of sector funds that realize positive new cash flow during the last quarter and sector funds that realize negative new cash flow, which suggests that sector fund investors cannot pick the winning sector funds. We also find that future sector index returns are not related to past values of aggregate cash flow to the corresponding sector funds, which suggests that sector fund investors cannot pick the winning sectors of the stock market. The combined evidence suggests that the higher cash flow volatility of sector funds is not information related. We conclude that our evidence is largely consistent with market efficiency.

Appendix A

A.1. Bootstrap procedure to test for non-normal distributions of alphas

Kosowski et al. (2001) suggest the use of bootstrap procedure in performance evaluation studies to handle potentially non-normal distributions of alphas. So we bootstrap the distribution of the Newey-West t-statistics associated with alphas of each sector fund and non-sector fund portfolio in Table 4. The procedure is explained as follows. We draw repeatedly, with replacement, from the observed time-series of residual terms obtained from Equation (1), $e_{p,t}$, to create a time-series of pseudo portfolio residual terms, $e^*_{p,t}$, of equal length. We compute the pseudo portfolio excess return, $(r^*_{p,t} - r_{f,t})$, for month *t* as the sum of the factor loadings times the factor realizations during month *t* and the pseudo portfolio residual term as follows:

$$r^*_{p,t} - r_{f,t} = \beta_{1,p}RMRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}UMD_t + \beta_{5,p}INDRET_t + e^*_{p,t} \quad \text{(A1)}$$

Consistent with the null hypothesis, the portfolio alpha, α^5, is set equal to zero (or missing) in the above pseudo portfolio excess return. For non-sector funds, we use a similar procedure with a four-factor model. We now use the pseudo portfolio excess returns and the original set of factor returns to compute a pseudo five-factor alpha and the associated Newey-West t-statistic. We repeat this procedure 5,000 times and compute the proportion of times when this bootstrap t-statistic exceeds the actual t-statistic. We assess the significance of the alpha estimates reported in Table 4 using these empirical p-values.

The bootstrap results show that our general conclusions regarding the insignificant performance of sector fund portfolios and the significant underperformance of non-sector fund portfolios are quite robust. For TNA-weighted portfolios of sector funds, none of the alphas are significant based on the bootstrap p-values. Recall from Panel A of Table 4 that in the only case of energy funds the α^5 is marginally significant at the 10 percent level based on the asymptotic distribution of the t-statistic. However, its bootstrap p-value is 0.1090. For equally-weighted portfolios, the results are unchanged. The α^5 for energy funds remains significantly negative at the 5 percent level, and the α^5 for technology funds remains significantly positive at the 5 percent level. Overall, our quantitative inference concerning the magnitude and significance of alphas change only slightly, and our qualitative inference concerning the neutral performance of sector funds remains unchanged.

A.2. Evidence over different sub-periods and sub-samples

We next examine if our results are sensitive to the choice of sample or time period. As a first cross-check, we start our study period only when at least five funds in any given category of sector funds become available. The five-factor alphas of this sub-sample are qualitatively similar to those reported in Table 4. An exception is the equally-weighted portfolio of real estate funds, for which the five-factor alpha equals 0.237 percent over the period May 1989 to December 1999, which is significant at the 10 percent level. This is more in line with the Kallberg, Liu, and Trzcinka (2000) results.

We next replicate our tests for two other sub-periods, 1976-1999 and 1990-1999. The first sub-period analysis becomes necessary since the sector classifications used for calculating the S&P 500 sector indexes only become available from 1976. The second sub-period analysis focuses on the more recent evidence. We find that over 1976-1999 the results are nearly identical to those reported in Table 4. Over 1990-1999, we find that none of the alphas of TNA-weighted or equally-weighted sector fund portfolios remain significant. The four-factor alphas for the TNA-weighted and the equally-weighted portfolios of non-sector funds continue to be negative, and in both cases are significant at the 10 percent level.

A.3. Evidence using DataStream sector index total returns

Our results on sector fund performance are based on the use of S&P 500 sector index returns for energy, financials, health care, technology, and utilities sectors. We believe that the S&P 500 sector index returns are the most appropriate for our purpose. However, as a robustness check, we replicate our results concerning the five-factor alphas in Table 4 by using DataStream sector index returns, which are monthly total returns on value-weighted portfolios of representative stocks from each sector.

We find that the results are nearly identical when we use DataStream sector index returns in place of S&P 500 sector index returns. For TNA-weighted portfolios, the only change is that the α^5 for utilities becomes significantly negative while the α^5 for energy becomes insignificant. For equally-weighted portfolios, the results are unchanged. The α^5 remains significantly negative for energy and significantly positive for technology, while for all other sectors it remains insignificant.

In summary, all our robustness checks uphold the conclusions of Section III concerning the performance of sector fund portfolios. Detailed test results are available from the authors on request.

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Table 1

Sample of sector funds

Panel A: Sector and non-sector funds during 1972-1999

Item	1972	1976	1980	1984	1988	1992	1996	1999
Number of non-sector funds	541	425	372	489	852	1102	1618	2385
Number of sector funds	11	13	18	58	129	175	360	530
Sector funds as percent of all funds	2.0	3.0	4.6	10.6	13.1	13.7	18.2	18.2
TNA of non-sector funds	51.3	39.0	45.1	78.8	169.5	392.0	1102.4	2209.9
TNA of sector funds	1.6	1.2	2.4	6.3	12.4	27.8	70.9	157.6
Sector funds as percent of all funds	3.0	3.0	5.1	7.4	6.8	6.6	6.0	6.7

Panel B: Different categories of sector funds in existence at any time during 1972-1999

Category acronym	Category name	Number of all funds	Number of unique funds	TNA as of December 1999	Percent of all sector funds
EN	Energy	43	30	5.6	3.5
FN	Financials	59	38	14.6	9.3
HL	Health care	42	25	23.4	14.8
MS	Miscellaneous	59	42	8.6	5.5
PM	Precious metals	66	49	1.9	1.2
RE	Real estate	122	65	6.5	4.1
TC	Technology	114	66	72.4	45.9
UT	Utilities	104	58	24.6	15.6
All sectors		609	373	157.6	100.0

Panel C: Biggest fund in each category in 1999

Category	Fund name	Fund TNA as of December 1999	Percent of TNA for category
EN	Neuberger Berman Sel Sector – Energy	1.5	27.8
FN	Freedom Inv Trust I – Regional Bank B	3.4	22.9
HL	Vanguard Specialized – Health Care	10.6	45.5
MS	Flag Investors – Telephone Income Shares/A	2.0	22.6
PM	Vanguard Specialized – Gold	0.4	18.9
RE	Cohen & Steers Realty Shares	1.4	21.8
TC	Price (T. Rowe) Sci & Tech	10.0	13.8
UT	Fidelity Utilities Income Fund	2.8	11.2
Non-sector	Fidelity Magellan Fund	99.2	4.9

The sample of 609 sector funds is obtained from the CRSP Survivor-Bias Free US Mutual Fund Database. It includes all sector funds that existed at any time during 1972-1999. We use the ICDI's fund objective code, Strategic Insight's fund objective code, Wiesenberger fund type code, and policy variables to identify sector funds from the universe of all US mutual funds, and then hand-check each sector fund with internet sources. We exclude bond funds, money market funds, sector index funds, and international funds. The resulting sample of sector funds is divided into eight categories based on the fund specialization. Since this sample includes many cases of two or more funds that differ mainly in their marketing to different types of investors (e.g., institutional shares vs. advisor shares), we further identify a sub-sample of unique funds, which includes the oldest of these clone funds, or the biggest in case two or more clone funds start in the same year. The sample of 3,227 non-sector funds includes all diversified stock funds that are not classified as sector funds. This sample is identified by using the same procedure as in Carhart et al. (2002). In fact, we use their exact sample for funds that exist before 1995. For funds that exist after 1995, we use the ICDI fund objective code to identify aggressive growth, growth and income, and long-term growth funds. TNA (total net assets) refers to the year-end market value of fund assets and is shown in billions of dollars. TNA information is missing for approximately 8 percent of the sector funds and 5 percent of non-sector funds, so the actual fund assets may be somewhat higher.

Table 2

Summary statistics of sector funds

Panel A: Characteristics of sector and non-sector funds

Item	Sector funds	Non-sector funds	Difference
Percent stock holding	88.4	86.8	1.6
Percent cash holding	7.5	7.6	-0.1
Percent other securities	4.1	5.6	-1.5
Turnover	67.0	59.8	7.2
Front-end load	3.6	4.2	-0.6
Other load	0.5	0.1	0.4
Expense ratio	1.05	0.79	0.26

Panel B: Characteristics of different categories of sector funds

Item	EN	FN	HL	MS	PM	RE	TC	UT
Percent stock holding	88.1	91.6	91.1	91.8	88.4	86.3	87.2	90.7
Percent cash holding	9.1	6.2	8.2	5.4	9.1	3.7	7.9	3.5
Percent other securities	2.8	2.2	0.7	2.8	2.5	10.0	4.9	5.8
Turnover	46.4	67.0	61.1	130.9	34.5	39.2	94.1	63.9
Front-end load	0.5	3.5	3.5	2.4	3.5	0.5	5.4	4.6
Other load	0.3	0.6	0.6	0.7	0.3	0.2	0.5	0.7
Expense ratio	0.93	1.13	1.09	1.62	1.48	1.39	1.04	1.24

Panel C: Time trend in expense ratio of sector and non-sector funds

Year	1972	1976	1980	1984	1988	1992	1996	1999
Sector funds	0.58	0.68	0.78	1.17	1.35	1.23	1.33	1.31
Non-sector funds	0.59	0.66	0.72	0.79	0.90	0.91	0.90	0.80

The sample of 609 sector funds and 3,227 non-sector funds during 1972-1999 is described in Table 1. Turnover is the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA, front-end load is the maximum percent charges applied at the time of purchase, other load is the maximum deferred or rear-end charges, and expense ratio is the percentage of total investment that shareholders pay for the fund's operating expenses. For each data item in Panels A and B, we first calculate the TNA-weighted average across all funds at the end of 1972, 1976, 1980, 1984, 1988, 1992, 1996, and 1999, and then report a simple time-series average of the cross-sectional averages.

Table 3

Sector index description

Panel A: Index description

Category	Description	Start date	End date	Correlation between sector index and TNA-weighted sector fund portfolio	Correlation between sector index and Equally-weighted sector fund portfolio
EN	S&P 500 Energy Index	Feb-1972	Dec-1999	0.818	0.855
FN	S&P 500 Financials Index	Feb-1972	Dec-1999	0.900	0.885
HL	S&P 500 Health Care Index	Jan-1982	Dec-1999	0.874	0.803
PM	Philadelphia Exchange Gold/Silver Sector Index	Apr-1989	Dec-1999	0.943	0.953
RE	Wilshire Real Estate Securities Index	Jan-1982	Dec-1999	0.676	0.760
TC	S&P 500 Technology Index	Feb-1972	Dec-1999	0.866	0.867
UT	S&P 500 Utility Index	Feb-1972	Dec-1999	0.890	0.894
Non-sector	Value-weighted market index	Feb-1972	Dec-1999	0.992	0.983

Panel B: Regression estimates from a regression of sector index excess returns against four factors

Category	α^4	RMRF	SMB	HML	UMD	Adj-Rsq
EN	-0.021	0.911	-0.358	0.214	0.073	0.487
	(-0.08)	(16.55)	(-4.08)	(2.05)	(0.72)	
FN	-0.081	1.324	-0.209	0.369	-0.278	0.716
	(-0.35)	(23.11)	(-2.76)	(4.40)	(-3.24)	
HL	0.415	0.865	-0.651	-0.384	-0.025	0.673
	(1.98) **	(16.84)	(-6.96)	(-2.95)	(-0.21)	
PM	-0.311	0.545	0.631	0.133	-0.247	0.054
	(-0.32)	(2.05)	(2.28)	(0.35)	(-0.79)	
RE	-0.442	0.744	0.550	0.583	0.002	0.624
	(-2.59) **	(16.05)	(7.43)	(7.44)	(0.04)	
TC	0.306	0.938	-0.049	-0.527	-0.031	0.689
	(1.58)	(17.06)	(-0.60)	(-4.91)	(-0.40)	
UT	-0.188	0.767	-0.288	0.547	-0.025	0.538
	(-1.05)	(16.45)	(-4.46)	(7.11)	(-0.46)	

The sample of 550 sector funds and 3,227 non-sector funds during 1972-1999 is described in Table 1. It excludes the 59 funds belonging to the MS category. Panel A describes the sector indexes and their correlations with TNA-weighted portfolios of all funds and equally-weighted portfolios of unique funds by using monthly excess returns. (The sub-sample of unique sector funds excludes all clone funds that differ from the included funds only in their marketing to a different investor group.) In the case of non-sector funds, Panel A presents the correlations between excess returns on the market index and the fund portfolios. The data on the S&P 500 sector indexes for the later part of our study period is retrieved from Telerate, and for the earlier part is constructed by using CRSP returns and Compustat sector classifications as described in Section III.C. The market index represents a value-weighted portfolio of all NYSE, AMEX, and NASDAQ stocks. Panel B presents α^4, the intercept, and the regression coefficients from a four-factor model of sector index excess returns. The four factors are explained as follows. RMRF is Fama and French's (1993) excess return on the market portfolio, and SMB, HML, and UMD are the returns on the mimicking portfolios for the common size, book-to-market, and momentum factors in stock returns. Alphas are expressed in percentage terms. The t-statistics based on the Newey-West covariance matrix are shown in parentheses. The notations *, **, and *** represent statistical significance levels of 10 percent, 5 percent, and 1 percent in two-tailed tests. To avoid clutter, the significance levels are shown only for alphas.

Table 4

Jensen's alphas of a portfolio of sector funds

Panel A: Portfolio excess returns calculated as the TNA-weighted average of all fund excess returns

Category	One-factor model			Five-factor model						
	α^1	INDRET	Adj-Rsq	α^5	RMRF	SMB	HML	UMD	INDRET	Adj-Rsq
EN	-0.034	0.737	0.669	-0.179	0.539	0.256	-0.011	0.005	0.433	0.875
	(-0.21)	(18.07)		(-1.66) *	(13.85)	(5.75)	(-0.25)	(0.15)	(14.48)	
FN	0.202	0.708	0.809	0.083	0.299	-0.002	0.093	-0.005	0.548	0.825
	(1.61)	(20.27)		(0.68)	(4.31)	(-0.03)	(1.02)	(-0.10)	(11.52)	
HL	0.033	0.892	0.763	-0.001	0.333	0.422	-0.172	0.076	0.669	0.897
	(0.16)	(18.49)		(-0.00)	(6.42)	(7.46)	(-2.58)	(1.68)	(16.50)	
PM	-0.182	0.757	0.888	-0.228	-0.017	0.124	-0.116	0.056	0.750	0.889
	(-0.78)	(30.09)		(-0.94)	(-0.25)	(1.77)	(-1.19)	(0.70)	(29.51)	
RE	0.214	0.691	0.454	-0.184	0.325	0.256	0.390	0.133	0.428	0.497
	(1.03)	(6.70)		(-0.73)	(3.09)	(2.57)	(3.27)	(1.56)	(4.51)	
TC	0.172	0.837	0.750	0.086	0.664	0.255	-0.392	0.154	0.307	0.909
	(1.01)	(24.35)		(0.81)	(13.93)	(6.14)	(-7.72)	(3.96)	(7.35)	
UT	-0.089	0.763	0.792	-0.139	0.189	0.052	0.067	-0.036	0.632	0.826
	(-0.96)	(21.90)		(-1.61)	(5.08)	(1.38)	(1.52)	(-1.13)	(14.48)	
Non-sector	-0.072	0.936	0.984	-0.063	0.911	0.060	-0.049	0.019		0.987
	(-2.37) **	(110.55)		(-2.12) **	(93.67)	(4.65)	(-2.96)	(1.48)		

The sample of 550 sector funds and 3,227 non-sector funds during 1972-1999 is described in Table 1. It excludes the 59 funds belonging to the MS category. This table analyzes whether an investor can earn abnormal returns by investing in a portfolio of sector funds and as measured by Jensen's alphas in one-factor and five-factor models. Jensen's alphas are the intercepts in regressions, denoted by α^1 and α^5 for the one-factor and five-factor models. The dependent variable is the portfolio excess return, calculated as the TNA-weighted average of monthly excess returns of all sector funds belonging to a category in Panel A and the equally-weighted average of unique sector funds belonging to a category in Panel B. (The sub-sample of unique sector funds excludes all clone funds that differ from the included funds only in their marketing to a different investor group.) The five factors in return models are explained as follows. RMRF is Fama and French's (1993) excess returns on the market portfolio, SMB, HML, and UMD are the returns on the mimicking portfolios for the common size, book-to-market, and momentum factors in stock returns, and INDRET is the excess return on the sector index for a category (described in Table 3). The EN, FN, TC, and UT regressions include 335 monthly observations from February 1972 to December 1999, the HL and RE regressions include 216 monthly observations from January 1982 to December 1999, and the PM regressions include 129 monthly observations from April 1989 to December 1999. Both panels also report the one-factor and four-factor alphas of portfolios of all non-sector funds. For non-sector funds, the one-factor model uses RMRF as the single factor and the four-factor model employs RMRF, SMB, HML, and UMD. Alphas are expressed in percentage terms. The t-statistics based on the Newey-West covariance matrix are shown in parentheses. The notations *, **, and *** represent statistical significance levels of 10 percent, 5 percent, and 1 percent in two-tailed tests. To avoid clutter, the significance levels are shown only for alphas.

Panel B: Portfolio excess returns calculated as the equally-weighted average of unique sector fund excess returns and all non-sector fund excess returns

Category	One-factor model			Five-factor model						
	α^1	INDRET	Adj-Rsq	α^5	RMRF	SMB	HML	UMD	INDRET	Adj-Rsq
EN	-0.210	0.817	0.730	-0.263	0.360	0.359	-0.020	-0.047	0.616	0.864
	(-1.34)	(20.30)		(-2.23) **	(8.03)	(7.81)	(-0.38)	(-1.27)	(15.70)	
FN	0.248	0.686	0.783	0.114	0.355	0.053	0.149	-0.028	0.494	0.809
	(1.96) *	(21.64)		(0.94)	(5.66)	(0.91)	(1.98)	(-0.66)	(11.51)	
HL	0.086	0.824	0.643	0.025	0.442	0.564	-0.235	0.123	0.526	0.883
	(0.31)	(12.39)		(0.20)	(6.77)	(9.21)	(-3.22)	(2.29)	(8.39)	
PM	-0.257	0.707	0.907	-0.327	0.023	0.131	-0.059	0.049	0.697	0.908
	(-1.28)	(33.35)		(-1.61)	(0.37)	(2.00)	(-0.69)	(0.68)	(32.66)	
RE	0.338	0.712	0.575	-0.026	0.364	0.201	0.347	0.068	0.428	0.629
	(1.93) *	(9.43)		(-0.13)	(4.56)	(2.76)	(3.64)	(1.07)	(5.80)	
TC	0.315	0.885	0.751	0.236	0.692	0.395	-0.382	0.136	0.327	0.923
	(1.76) *	(24.96)		(2.18) **	(15.34)	(10.09)	(-7.26)	(3.53)	(8.18)	
UT	-0.056	0.766	0.799	-0.055	0.161	0.052	0.046	-0.070	0.653	0.829
	(-0.60)	(23.12)		(-0.65)	(4.19)	(1.39)	(1.07)	(-2.14)	(15.37)	
Non-sector	-0.122	0.926	0.967	-0.104	0.875	0.198	-0.059	0.022		0.985
	(-2.55) **	(73.06)		(-3.11) ***	(73.89)	(13.81)	(-3.20)	(1.50)		

Table 5

Quarterly cash flow volatility of sector funds

Panel A: Unadjusted quarterly cash flow ratio and cash flow volatility of sector and non-sector funds

Category	Number of funds	Cross-sectional median of time-series medians of quarterly cash flow ratios for individual funds	Cross-sectional median of time-series standard deviations of cash flow ratios for individual funds
EN	43	-0.0113	0.302 (1.34)
FN	57	0.0253	0.492 (2.18)
HL	41	0.0158	0.466 (2.07)
PM	66	0.0041	0.339 (1.50)
RE	121	0.0398	0.297 (1.32)
TC	110	0.1177	0.486 (2.15)
UT	104	-0.0010	0.264 (1.17)
All sector funds	542	0.0190	0.337 (1.49)
All non-sector funds	3126	0.0219	0.226 (1.00)

Panel B: Residual quarterly cash flow volatility and other autoregressive model parameters of sector and non-sector funds

Category	Number of funds	Median μ_i	Median θ_i	Median standard deviation of $\varepsilon_{i,q}$
EN	36	0.088	0.256	0.253 (1.28)
FN	44	0.236	0.422	0.399 (2.03)
HL	37	0.145	0.084	0.345 (1.75)
PM	62	0.102	0.099	0.327 (1.66)
RE	93	0.147	0.138	0.272 (1.38)
TC	82	0.231	0.139	0.377 (1.91)
UT	96	0.108	0.258	0.214 (1.08)
All sector funds	450	0.145	0.194	0.302 (1.53)
All non-sector funds	2676	0.084	0.207	0.197 (1.00)

The initial sample of 550 sector funds and 3,227 non-sector funds during 1972-1999 is described in Table 1. It excludes the 59 funds belonging to the MS category. The final sample used in this table is smaller than the initial sample due to the requirement of cash flow data. For each fund *i*, we calculate the quarterly cash flow ratio for each quarter *q* as follows:

$$QCF_{i,q} = (TNA_{i,q} - TNA_{i,q-1} \times (1 + r_{i,q}) - MGTNA_{i,q}) / TNA_{i,q-1}$$

TNA refers to the total net assets, *r* refers to the net return, and MGTNA refers to the increase in fund assets due to mergers. Panel A reports the unadjusted quarterly cash flow ratio and the cash flow volatility calculated as follows. For each fund, we first calculate the time-series median and standard deviation of its *QCF* values. The reported figures are the cross-sectional medians of the individual fund statistics. Panel B reports the adjusted or residual cash flow volatility from an autoregressive model as follows:

$$QCF_{i,q} = \mu_i + \theta_i \times QCF_{i,q-1} + \varepsilon_{i,q}$$

We first estimate this model for each fund. The reported figures are the cross-sectional medians of the individual fund statistics. Figures in parentheses are the standardized cash flow volatilities, calculated by assuming a value of 1.00 for all non-sector funds.

Table 6

Sector fund performance conditional on last quarter's cash flow

Category	Months of data	Conditional estimates Alpha	Conditional estimates t-statistic	Unconditional estimates Alpha	Unconditional estimates t-statistic	Difference in alphas	t-statistic of difference
EN	335	-0.098	-1.18	-0.109	-1.25	0.011	0.09
FN	335	0.082	0.75	0.119	1.07	-0.037	-0.24
HL	210	0.010	0.09	0.031	0.28	-0.021	-0.14
PM	129	-0.210	-0.92	-0.231	-0.98	0.021	0.07
RE	213	0.138	0.81	0.085	0.47	0.053	0.21
TC	335	0.039	0.47	0.016	0.19	0.023	0.19
UT	335	-0.156	-2.46 **	-0.178	-2.70 ***	0.022	0.25
Non-sector	335	-0.056	-2.10 **	-0.060	-2.17 **	0.004	0.10

The initial sample of 550 sector funds and 3,227 non-sector funds during 1972-1999 is described in Table 1. It excludes the 59 funds belonging to the MS category. The final sample used in this table includes only the 372 sector funds and the 2,216 non-sector funds for which at least 30 months of returns and cash flow data are available. This restriction is necessary in the calculation of conditional and unconditional alphas by using the fund regression approach. For each sector fund *i*, the conditional model is estimated as follows:

$$r_{i,t} - r_{f,t} = \alpha_i^{5c} + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} UMD_t + \beta_{5,i} INDRET_t + \delta_{1,i}\left(QCF_{i,q-1} * RMRF_t\right)$$
$$+ \delta_{2,i}\left(QCF_{i,q-1} * SMB_t\right) + \delta_{3,i}\left(QCF_{i,q-1} * HML_t\right) + \delta_{4,i}\left(QCF_{i,q-1} * UMD_t\right) + \delta_{5,i}\left(QCF_{i,q-1} * INDRET_t\right) + \varepsilon_{i,t}$$

In this equation, $r_{i,t} - r_{f,t}$ is the fund's excess return for month *t*, $QCF_{i,q-1}$ is the fund's cash flow ratio for the last quarter *q-1*, RMRF is Fama and French's (1993) excess returns on the market portfolio, SMB, HML, and UMD are the returns on the mimicking portfolios for the common size, book-to-market, and momentum factors in stock returns, and INDRET is the excess return on the sector index for a category. The conditional fund-regression alpha for month *t* is obtained as the TNA-weighted average of $(\alpha_i^{5c} + \varepsilon_{i,t})$ across all funds belonging to a given category. The unconditional fund-regression alpha for month *t* is obtained by a similar procedure, but by dropping the interaction terms. For non-sector funds, the INDRET terms are also dropped (which means a four-factor model is used). The alphas and t-statistics reported below are the time-series averages and t-statistics of the monthly fund-regression alphas, expressed in percentage terms. The notations *, **, and *** represent statistical significance levels of 10 percent, 5 percent, and 1 percent in two-tailed tests.

Table 7

Performance of low vs. high cash flow volatility sector funds

Category	Months of data	Low cash flow volatility portfolio		High cash flow volatility portfolio		Difference in alphas	t-statistic of difference
		Alpha	t-statistic	Alpha	t-statistic		
EN	300	-0.127	-1.13	-0.235	-1.15	0.108	0.46
FN	192	0.129	1.25	0.125	1.01	0.004	0.02
HL	168	0.002	0.02	0.268	1.37	-0.266	-1.21
PM	129	-0.124	-0.48	-0.382	-1.44	0.258	0.70
RE	120	-0.410	-1.20	0.254	1.13	-0.664	-1.62
TC	300	0.164	1.35	-0.030	-0.21	0.194	1.03
UT	216	-0.182	-1.59	0.060	0.45	-0.242	-1.38
Non-sector	300	-0.034	-1.09	-0.096	-2.74 ***	0.062	1.32

The initial sample of 550 sector funds and 3,227 non-sector funds during 1972-1999 is described in Table 1. It excludes the 59 funds belonging to the MS category. The final sample and estimation period used in this table is smaller than the initial sample and estimation period due to the requirement of historic cash flow volatility data. In January of each year from 1975 to 1999, we calculate the historic cash flow volatility for each fund by using the last 12 quarterly cash flow ratios as defined in Table 5. We rank all funds within a category into two portfolios each year by using their historic cash flow volatility. We measure performance by Jensen's alphas, which are the intercepts in return models. The dependent variable is the portfolio excess return, calculated as the TNA-weighted average of monthly excess returns of all funds belonging to each portfolio. The five factors in the return model for sector funds are explained as follows. RMRF is Fama and French's (1993) excess returns on the market portfolio, SMB, HML, and UMD are the returns on the mimicking portfolios for the common size, book-to-market, and momentum factors in stock returns, and INDRET is the excess return on the sector index for a category. The return model for non-sector funds includes only the first four factors. The estimation period is chosen such that at least one fund is included in both the low and the high cash flow volatility portfolios during the entire period. Alphas are expressed in percentage terms. The t-statistics based on the Newey-West covariance matrix are shown in parentheses. The notations *, **, and *** represent statistical significance levels of 10 percent, 5 percent, and 1 percent in two-tailed tests.

Table 8

Performance of new-money portfolios

Category	Months of data	Positive cash flow portfolio		Negative cash flow portfolio		Difference in alphas	t-statistic
		Alpha	t-statistic	Alpha	t-statistic		
EN	266	-0.096	-0.39	-0.341	-1.66 *	0.245	0.76
FN	216	-0.007	-0.06	0.016	0.13	-0.023	-0.14
HL	168	0.186	0.95	-0.130	-0.71	0.316	1.18
PM	129	-0.319	-1.08	0.037	0.14	-0.356	-0.90
RE	141	-0.097	-0.28	0.191	0.56	-0.288	-0.59
TC	267	-0.095	-0.55	0.078	0.55	-0.173	-0.77
UT	231	0.100	0.74	-0.010	-0.07	0.109	0.58
Non-sector	335	-0.084	-1.62	-0.119	-2.76 ***	0.035	0.52

This table tests investors' ability to pick winning sector funds by analyzing the performance of fund portfolios formed on the basis of net cash flows realized during the previous quarter. The initial sample of 550 sector funds and 3,227 non-sector funds during 1972-1999 is described in Table 1. It excludes the 59 funds belonging to the MS category. Table 3 describes the sector indexes and the beginning and ending date for each index. The final sample used in this table for each category is limited to the number of months during which observations are available for both the positive and the negative cash flow portfolios for the category. Each quarter, funds within a category are grouped into either the positive cash flow portfolio or the negative cash flow portfolio based on the sign of the net cash flow experienced by each fund during the previous quarter. The cash-flow-weighted monthly excess returns are computed for each of these portfolios using all funds belonging to a category. The performance of sector fund portfolios is measured by using a five-factor model. The five factors are explained as follows. RMRF is Fama and French's (1993) excess returns on the market portfolio, SMB, HML, and UMD are the returns on the mimicking portfolios for the common size, book-to-market, and momentum factors in stock returns, and INDRET is the excess return on the sector index for a category. The performance of non-sector fund portfolios is measured by using a four-factor model that uses RMRF, SMB, HML, and UMD. The table reports the alphas for the positive and negative cash-flow portfolios, the differences in the alphas, and the corresponding t-statistics based on the Newey-West covariance matrix. The alphas and differences in alphas are expressed in percentage terms. The notations *, **, and *** represent statistical significance levels of 10 percent, 5 percent, and 1 percent in two-tailed tests.

Table 9

Sector timing and rotation abilities of sector fund investors

Panel A: Sector timing: Regression of sector index return minus risk-free return on last quarter's cash flow

Category	Intercept	SQCF1	Adj-Rsq
EN	2.009	-0.029	-0.009
	(2.46) **	(-0.19)	
FN	1.804	0.065	-0.006
	(1.46)	(0.65)	
HL	3.773	0.031	-0.014
	(3.24) ***	(0.55)	
PM	-0.609	-0.469	0.038
	(-0.32)	(-1.41)	
RE	1.307	-0.014	-0.013
	(1.19)	(-0.41)	
TC	2.008	0.250	0.013
	(1.79) *	(1.92) *	
UT	1.474	-0.093	0.001
	(2.04) **	(-1.46)	

Panel B: Sector rotation: Regression of sector index return minus market return on last quarter's cash flow

Category	Intercept	SQCF1	Adj-Rsq
EN	0.079	0.079	-0.006
	(0.11)	(0.75)	
FN	-0.004	-0.008	-0.009
	(-0.01)	(-0.16)	
HL	0.793	-0.002	-0.007
	(1.00)	(-5.82) ***	
PM	-3.961	-0.342	-0.001
	(-1.68) *	(-1.00)	
RE	-1.950	0.013	-0.013
	(-2.17) **	(0.38)	
TC	0.107	0.171	0.023
	(0.17)	(2.00) **	
UT	-0.465	-0.073	-0.002
	(-0.69)	(-1.03)	

This table presents parameter estimates from regressions of sector index excess returns on lagged cash flows experienced by funds within the corresponding sectors. The sector indexes are described in Table 3. The dependent variable in Panel A is the quarterly sector index return minus the riskfree return. The dependent variable in Panel B is the quarterly sector index return minus the market return. The independent variable in both panels is SQCF1, which is the last quarter's cash flow to all funds within a sector fund category. SQCF1 is computed as the aggregate net cash flow to all funds within a category during the last quarter divided by the aggregate TNA for the category in the beginning of the quarter. The EN, FN, TC, and UT regressions include 111 quarterly observations from April 1972 to December 1999, the HL and RE regressions include 71 quarterly observations from March 1982 to December 1999, and the PM regressions include 43 quarterly observations from April 1989 to December 1999. The intercept term is expressed in percentage terms. The t-statistics based on the Newey-West covariance matrix are reported in parenthesis. The notations *, **, and *** represent statistical significance levels of 10 percent, 5 percent, and 1 percent in two-tailed tests.