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Actively Managed Mutual Fund Returns versus the S&P 500 Index

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Abstract
The purpose of this paper is to determine if active mutual fund managers provide value over passive fund managers through their stock picking ability. I examine the performance of funds that are "closet indexers" and I have developed several variables that measure how similar a fund is to the S&P 500 Index (as proxied by the Vanguard 500 Index). I regress fund returns on these measures, along with control variables. I use raw returns, characteristic benchmarked returns and four-factor model excess returns as the dependent variables in panel regressions. I use returns from the Center for Research in Security Prices mutual fund database, both before and after fees, as well as calculating fund returns using holdings data from Thompson Financial's CDA database. My main result is that active managers add value over the S&P 500 Index. The average active fund outperforms the S&P 500 Index by 1.29 to 1.96 percent per year before fees. The outperformance remains positive and significant after fees.

Keywords: Mutual funds; benchmarking; index funds; active management.

1. Introduction

Should investors buy actively managed mutual funds in the hopes of beating the market, or are they better off putting their money in a passive fund that mimics the return of the overall market? Do "closet" indexers have better performance than managers employing more active strategies? These are important questions, as mutual funds are the main investment vehicle for millions of people. The mutual fund industry is huge, with assets managed valuing in the trillions of dollars [1]. The investments made by fund managers can have important impacts on the economy as well as individuals' wealth. The purpose of this paper is to determine if active mutual fund managers provide value over the S&P 500 Index through their stock picking ability.

One of the easiest, cheapest ways for an individual investor to hold a diversified portfolio is to buy an index fund based on the S&P 500. What if an investor wants to "beat the market"? Investing in such an index fund would not work, since the S&P 500 is widely taken to be a good proxy for "the market." In order to increase their return while staying diversified and not having to do the legwork themselves, many investors turn to actively managed funds. These are funds whose managers claim to have enough skill to be able to pick the "right" stocks at the "right" time, and therefore provide investors with a higher return. Of course, they charge higher fees than index funds in return for this valuable service. What about funds that claim to have a specific strategy, but end up looking similar to the S&P 500 — the so-called "closet-indexers"? They are presumably charging the higher fees in return for calling themselves an active fund, but actually deviating little from the index. One reason managers might do this is to minimize their tracking error. Another, less honorable reason, would be to avoid doing the work of an active manager while still collecting the large fees. How is the individual investor supposed to sort this out? One must figure out if (truly) actively managed funds are worth the higher fees.

An important addition to the mutual fund benchmarking literature is that of Daniel, Grinblatt, Titman and Wermers [2] — hereafter referred to as DGTW — which develops benchmarks based on size, book-to-market and return momentum characteristics of the stocks held by a mutual fund. Using holdings data, they create "Characteristic Selectivity" and "Characteristic Timing" measures to break down performance into that due to a manager's stock picking capabilities and that due to his timing capabilities. In the application of these measures to equity mutual fund data, they find that managers show some stock-picking ability (especially in growth funds), but no ability to time the market. In this paper, I employ characteristic benchmarking based on the "Characteristic Selectivity" measure of DGTW to help determine if active fund managers are good stock pickers.

An important question addressed in mutual fund literature is: do active mutual fund managers create value for investors? Numerous studies have provided numerous answers to this question [3]. Grinblatt and Titman [4] utilize several mean-variance efficient benchmarks to determine that while some mutual funds outperform before fees, the fees investors must pay erase the gains. Malkiel [5] addresses the issue of survivorship bias in mutual fund research, and finds that this accounts for previous findings of persistence in mutual fund performance in the 1980s. He finds that on average, funds underperform benchmark portfolios even before fees.

Carhart [6] also studies persistence in mutual fund performance. He finds that the so-called "hot hands" phenomenon [7, 8] is entirely explained by a momentum effect. The only persistence in mutual funds is by the poorest performers. He concludes that fund managers do not exhibit skill.

Wermers [9] finds that the average mutual fund holds a stock portfolio that beats the S&P 500 index by 1.3 percent per year, but the addition of expenses drops the return to about 1 percent below that of the benchmark. Chen *et al.* [10] examine both the holdings and the trades of mutual funds. In examining the trades, they find that stocks that are bought perform significantly better than stocks that are sold. In examining holdings, they find that stocks that are held by mutual funds do not outperform the average stock. Taken together, these results indicate that managers do possess some selection skill, but that the gains from that skill are short lived because they hold the stocks longer than they can predict returns for them. Barras *et al.* [11] base their analysis on the assumption that not all funds have a true value of alpha equal to zero, which is a common assumption made in mutual fund research. Their aim is to separate luck from skill in interpreting mutual fund performance. By employing Monte-Carlo tests, they find that less than 2 percent of funds have true alphas greater than zero, while 20 percent have true negative alphas. The implication is that it is very difficult for an investor to identify the truly good funds.

More recent research has begun to challenge the prevailing view that actively managed funds do not create value for investors [12-14]. Kacperczyk *et al.* [15] study actively managed equity funds. They create a measure of industry concentration and report that funds vary widely on their level of this measure. They find that managers who concentrate their holdings in a few industries outperform those who are more diversified both before and after fees. They then employ the characteristics benchmark of DGTW [2] and conclude that this outperformance results from superior stock selection within those industries. Similarly, Busse and Tong [16] study industry and stock selection by fund managers. They conclude that industry selection explains about half of a fund's abnormal returns. They also find that while industry selection ability persists, stock selection ability, after controlling for industry selectivity, does not. Kosowski *et al.* [17] find that there are a small number of "star" managers, mostly in funds with a growth strategy, who can persistently select stocks that offer superior returns, even after fees. They employ a bootstrap technique in order to address non-normality of mutual fund alphas. They conclude that luck alone cannot account for these managers' performance: there is evidence of stock-picking skill.

A paper related to mine is Cremers and Petajisto [18]. They create a variable that measures the similarity of holdings between a fund and a given benchmark. Their measure, called "Active Share" is essentially the difference in a stock's weight in the fund and in the index, summed over all stocks. There are several differences here from what I do. First, there are differences in benchmarks: I focus on the broad market, proxied by the S&P 500, while Cremers and Petajisto analyze 19 different indexes. While at first blush, using different indexes may seem more "correct," I look at the issue from the standpoint of an average investor. This investor is unlikely to be familiar with, for example, the Russell 3000 value index, or to care if his fund beats it. What he is likely to care about is "the market." In addition, Sensoy [19] shows that nearly one-third of funds' styles do not match their stated benchmarks. And, as Wermers [20] states, mutual fund managers' stock picks are "an attempt to beat the S&P 500 Index." Thus, it makes sense to evaluate all funds against the same broad benchmark, and it simplifies interpretation of results.

Instead of decomposing a given fund into a long-short portfolio of an index, as Active Share does, my intuitive measure of closet indexing is simply the percentage of a given fund that is made up of S&P 500 holdings. I create both equal-weighted and value-weighted measures of this percentage. I also use the r-squared of a regression of fund returns on S&P 500 returns as another measure of closet indexing. Another difference between the two papers is the funds we analyze. Cremers and Petajisto limit their study to 100 percent equity funds. While I, too, focus on primarily equity funds, I do allow for other holdings. In regression analysis, we also calculate standard errors differently. While my main results cluster by fund, which is perhaps more intuitive, I point out that if standard errors are clustered by month, some of the statistical significance goes away. Their standard errors are clustered by year, with some of the results only marginally significant, or not at all. The interpretations are also slightly different, given the different index benchmarks. In general, both studies find that more actively managed funds produce higher returns than the benchmark indices.

This study adds to this field of literature by examining active fund management relative to the broad market index. This provides useful context for mutual fund investors wishing to beat the market. The majority of my results indicate that active mutual fund managers do, indeed, provide value to their investors, on the order of two percent per year. However, if standard errors are calculated using clustering by month rather than by fund, then the statistical significance of some of the results disappears. The most intuitive means of determining managers' stock-picking ability, however, remains robust to the more conservative standard error approach.

The rest of this paper is organized as follows. Section 2 describes the data and methodology, Section 3 presents empirical findings, and Section 4 concludes.

2. Methods

Mutual fund data are taken from two databases. Quarterly after-fee fund returns and expense ratios are from the CRSP mutual fund database. If a fund is missing quarters (e.g., if it reports semi-annually), the quarter previous to the missing one is carried forward. Total net assets and fund equity holdings by stock are from Thompson Financial's CDA database. Access to this database was limited to the years 1981 to 2000. To ensure that I am focusing on equity funds, I require that a fund have at least 20 stocks and at least $20 million in equity holdings to be included in the sample. Stock return data are from CRSP, and accounting data are from Compustat. I exclude ADRs and closed-end funds; stocks require at least two years' worth of Compustat data to be included. Industry classifications are based on the 49 Fama-French industries. Industry classifications and market factors [21] are obtained from Ken French's website[1]. The final sample covers 1984 to 2000. Only funds covered by both the CRSP mutual fund and CDA databases are included. The final sample contains 92,031 fund-months.

The raw returns used in the analysis consist of before-fee and after-fee returns from the CRSP mutual fund database and before-fee holdings-based returns calculated using CDA fund holdings data and individual stock returns. Before-fee CRSP returns are calculated by multiplying the after-fee monthly return by one plus the monthly expense ratio. I employ several benchmarking methods to calculate excess returns. For characteristic-benchmarked returns, I follow the methodology of DGTW [2] in calculating their characteristic selectivity (CS) measure. For each stock, I begin by calculating the industry-adjusted book-to-market ratio, market equity at the end of the previous December and the past twelve-month return ending in May. Book-to-market is calculated as the log of last fiscal year's book equity divided by market equity at the end of the prior December. Industry-adjusted book-to-market is firm book-to-market minus industry book-to-market, normalized by the standard deviation of the difference. I calculate characteristic benchmark returns in the following manner. Each July, all NYSE, AMEX and NASDAQ stocks in CRSP are sorted into portfolios based on NYSE market-equity quintiles. Each of those portfolios is then sorted into book-to-market quintiles. Finally, each of the 25 resulting portfolios is sorted into quintiles based on the twelve-month return ending in May of the portfolio formation year. I end up with 125 portfolios each year, for which I calculate value-weighted monthly returns. Each month, each stock in a fund is assigned to a benchmark portfolio. The characteristic-benchmark return for each fund is the weighted average return of the benchmark portfolios to which its stocks are assigned. The fund's excess return is the CRSP before-fee return, the CRSP after-fee return, or the weighted average of its stock returns (using holdings data) minus the characteristic-benchmark return. I also use the four-factor model to benchmark the CRSP mutual fund returns. To calculate factor loadings, I require three years of past return and accounting data and run regressions using the four-factor model. The excess fund return is the raw fund return (both before-fee and after-fee) minus the predicted value from the regression.

To identify "closet indexers," I create three variables, using the Vanguard 500 holdings as a proxy for the S&P 500 holdings. The first step is to calculate the monthly value-weighted return of the Vanguard 500. I then calculate how closely a given fund's returns track those of the Vanguard 500 by using the r-squared of monthly OLS regressions. Two full years of monthly returns are used to calculate r-squared; funds that do not meet this data requirement are dropped from the sample. I use holdings-based returns in these regressions, but regressions run

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

using CRSP mutual fund returns yield nearly identical results. As shown in Table 1, the average r-squared is 0.4929. I also calculate equal-weighted and value-weighed measures based on how much a given fund's holdings overlap with those of the Vanguard 500. The equal-weighted measure is the total number of S&P stocks in a given fund divided by the total number of stocks in that fund. The value-weighted measure is the total value of S&P stocks held in a given fund divided by the total value of that fund. On average, 57.56 percent of a fund's stocks are S&P 500 constituents, and 63.12 percent of a fund's value is made up of S&P 500 constituents.

Table 1: Summary Statistics Means

This table reports the monthly means and standard deviations and the number of fund-month observations for all mutual funds in the sample covering 1984 to 2000. Statistics are reported for dependent and independent variables used in later regressions. Returns are on a monthly basis.

Panel A: Independent Variables			
Variable	**Mean**	**Std Dev**	**N**
R-squared	0.4929	0.3055	92031
# of S&P stocks/Total # of stocks in mutual fund	0.5756	0.3045	92031
Value-weight % of mutual fund	0.6312	0.3079	92031
Log assets	19.6576	1.4127	92031
Turnover	0.0552	0.0579	92031
1/number of stocks	0.0184	0.0101	92031
Panel B: Dependent Variables			
Variable	**Mean**	**Std Dev**	**N**
Before-fee return	0.0141	0.0495	92031
After-fee return	0.0132	0.0494	92031
Four-factor model before-fee return	0.0005	0.0210	92031
Four-factor model after-fee return	-0.0004	0.0210	92031
CS benchmark before-fee return	0.0001	0.0214	92031
CS benchmark after-fee return	-0.0008	0.0214	92031
Holdings-based raw return	0.0150	0.0540	92031
Holdings-based CS benchmark return	0.0010	0.0209	92031

The main analysis is done using panel regressions. The control variables are log fund assets, the reciprocal of the number of stocks in a fund, and fund turnover, since prior studies have shown these to be correlated with fund returns. To be sure those outliers do not skew the analysis, I drop observations with values for control variables in the top and bottom 0.5 percent of the distribution. Regressions are all run using time fixed effects. The dependent variables are before-fee and after-fee CRSP returns minus the risk-free rate, before-fee and after-fee four-factor model excess CRSP returns, before-fee and after-fee CRSP returns minus the characteristic-selectivity benchmark return, holdings-based returns minus the risk-free rate, and holdings-based returns minus the characteristic-selectivity benchmark return. The average of each variable is reported in Table 1, and correlations are presented in Table 2. Each dependent variable is used in three regressions: on each of the closet-indexer independent variables with the inclusion of control variables.

3. Results and Discussion

The purpose of this paper is to determine if active mutual fund managers provide value over passive fund managers through their stock picking ability. The variables of interest in the regressions are those that indicate how closely a fund approximates the S&P 500 (the closet-index measures). The coefficients on these measures provide information about the manager's skill in picking stocks. Table 3 reports panel regression results for holdings-based returns calculated using CDA data.

Table 2: Summary Statistics: Correlations

This table reports matrices showing Pearson correlation coefficients for the dependent and independent variables used in the regression analysis.

Panel A: Independent Variables

	R-squared	# of S&P stocks/Total # of stocks in mutual fund	Value-weight % of mutual fund		
R-squared	1.0000				
# of S&P stocks/Total # of stocks in fund	0.2853	1.0000			
Value-weight % of mutual fund	0.2901	0.9729	1.0000		

Panel B: Dependent Variables (before-fee only)

	Before-fee	FF excess before-fee	Before-fee CS benchmarked	Holdings-based raw	Holdings-based CS benchmarked
Before-fee	1.0000				
FF excess before-fee	0.2274	1.0000			
CS benchmark before-fee	0.3641	0.4553	1.0000		
Holdings-based raw	0.9472	0.1703	0.1942	1.0000	
Holdings-based CS benchmark	0.4527	0.3669	0.6619	0.5402	1.0000

Table 3: Dependent Variable: Holdings-Based Returns

This table reports the results from panel regressions of returns calculated using a fund's reported holdings as the dependent variable. As such, the dependent variable is on a before-fee basis. Reported coefficients have been annualized, and t-statistics are shown in parentheses. All regressions include time fixed effects. Standard error calculations cluster by fund.

R-squared closet-index measure	-0.0262 (2.35)**		
# of S&P stocks/Total # of stocks in fund		-0.0339 (3.16)***	
Value-weight % of mutual fund			-0.0311 (2.83)***
Log assets	-0.0013 (0.56)	-0.0007 (0.28)	-0.0004 (0.16)
Turnover	0.0497 (0.96)	0.0710 (1.38)	0.0721 (1.40)
1/number of stocks	0.4456 (1.34)	0.5728 (1.70)	0.5488 (1.63)

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

These returns give the best picture of the manager's stock-picking skill. The returns are limited to equity, whereas the CRSP returns can include returns from other asset classes included in the fund. While managers may have skill in these other areas as well, my focus is on equities. The r-squared coefficient indicates that the S&P 500 underperforms a hypothetical fund with zero r-squared by 2.62 percent per year, significant at 5 percent. Thus the returns on the stock holdings of a fund with an average level of active management (hereafter referred to as an average fund), with an r-squared of 0.4929, beat the market by a significant 1.29 percent per year. The index underperforms funds with no S&P 500 stocks by 3.39 percent (equal-weight) or 3.11 percent (value-weight) per year. Both estimates are statistically significant at the 1 percent level. These numbers indicate that an average fund, in which S&P 500 constituents make up 57.56 percent of the holdings by number and 63.12 percent by weight, outperforms the S&P 500 by 1.95 percent and 1.96 percent per year, respectively.

Using raw before-fee CRSP fund returns, Panel A of Table 4 shows that the S&P 500 underperforms a hypothetical fund with zero r-squared by 2.74 percent per year, significant at the 5 percent level, implying that the average fund beats the S&P 500 by 1.35 percent per year. The index underperforms funds with no S&P 500 stocks by 4.68 percent (equal-weight) or 4.42 percent (value-weight) per year (both statistically significant at 1 percent). These numbers indicate that an average fund outperforms the S&P 500 by 2.69 percent and 2.79 percent per year, respectively. After-fee regressions, shown in Panel B, produce similar coefficients, although the gap between index and non-index fund returns narrows slightly. The S&P 500 underperforms a zero r-squared fund by 2.48 percent per year after fees (significant at 5 percent), and underperforms a fund with no S&P 500 stocks by 4.36 percent (equal-weight) or 4.12 percent (value-weight) per year (both significant at 1 percent). My conclusion from the results shown in Tables 3 and 4 is that actively managed funds on average provide significant value to investors. The more the manager deviates from the S&P 500, the higher the returns tend to be.

Table 4: Dependent Variable: CRSP Raw Returns

This table reports the results from panel regressions using CRSP raw returns as the dependent variable. Reported coefficients have been annualized, and t-statistics are shown in parentheses. All regressions include time fixed effects. Standard error calculations cluster by fund.

Panel A: Before Fees			
R-squared closet-index measure	-0.0274 (2.56)**		
# of S&P stocks/Total # of stocks in fund		-0.0468 (4.16)***	
Value-weight % of mutual fund			-0.0442 (3.82)***
Log assets	-0.0042 (1.82)**	-0.0032 (1.36)	-0.0027 (1.15)
Turnover	0.1194 (2.54)**	0.1419 (3.00)***	0.1435 (3.03)***
1/number of stocks	0.1559 (0.50)	0.3140 (0.99)	0.2827 (0.89)
Panel B: After Fees			
R-squared closet-index measure	-0.0248 (2.32)**		
# of S&P stocks/Total # of stocks in fund		-0.0436 (3.88)***	
Value-weight % of mutual fund			-0.0412 (3.56)***
Log assets	-0.0034 (1.46)	-0.0024 (1.02)	-0.0020 (0.83)
Turnover	0.1137 (2.42)**	0.1341 (2.83)***	0.1356 (2.86)***
1/number of stocks	0.1179 (0.38)	0.2639 (0.83)	0.2346 (0.74)

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

The next step is to see how these regressions change when excess returns calculated using various benchmarks are used in place of raw returns as the dependent variables. Using DGTW's characteristic selectivity measure as a benchmark for the CRSP data produces the same signs and significance levels as the original regressions, and the overlap variables' coefficients have a similar magnitude as well. Panel A of Table 5 shows that the before-fee coefficients are -4.65 percent (equal-weight) and -4.71 percent (value-weight), both significant at 1 percent. Panel B shows the after-fee coefficients: -4.33 percent (equal-weight) and -4.41 percent (value-weight), also significant at 1 percent. The r-squared coefficient is lower in magnitude, at –1.25 percent per year before fees, significant at 5 percent and -0.99 percent per year after fees, which is not statistically significant at conventional levels. Panel C presents the results using holding-based returns and the CS benchmark. The coefficient on r-squared is -1.13 percent, significant at 5 percent. The coefficients on the equal-weight and value-weight measures are -3.35 percent and -3.40 percent, respectively, both significant at 1 percent. Using the characteristic selectivity benchmark to calculate excess returns does not materially alter the results using raw returns. This adds credence to the conclusion that active managers can pick stocks that ultimately outperform other stocks that have similar size, book-to-market, and past returns.

When using the four-factor model as a benchmark, the signs from the previous regressions do not change. However, the magnitudes and significance decrease, as shown in Table 6. Before fees, the coefficient on r-squared is close to zero and insignificant. The coefficients on the equal-weighted and value-weighted measures are -0.94 percent and -0.85 percent, respectively, both significant at the 5 percent level. After fees, none of the coefficients are significant. This indicates that once the variation due to the overall market, book-to-market, size, and momentum is removed, the returns of actively managed funds barely outperform the S&P 500 before fees, and essentially match it after fees. For the average investor, these results still suggest that it is better to purchase an actively managed fund, since the fees associated with purchasing an index fund are not accounted for in this analysis. However, the benefit to doing so is not economically large.

When using the more conservative approach of clustering standard errors by month instead of by fund, some of the statistical significance of the results goes away. As an example of the typical results using this method of standard error calculation, Table 7 shows that all of the t-statistics on the closet index measures have dropped below one.

A notable exception to this pattern is when excess returns are calculated using the CS benchmark. These results are reported in Table 8, which shows that the closet index measure coefficients have maintained their levels of significance for all three types of dependent variable: before-fee CRSP, after-fee CRSP and holdings-based returns. Because this benchmark is the best method of determining stock-picking ability, and (according to DGTW [2]), "characteristic-matching should have more statistical power to detect abnormal performance than factor models," the ultimate conclusion of this paper is that actively managed mutual funds do provide value to investors when compared with the broad market index.

4. Conclusion

The average mutual fund outperforms a pure index fund by nearly two percent per year, which is statistically significant. The most intuitive means of determining managers' stock-picking ability — the DGTW [2] characteristic selectivity benchmark — remains robust to a more conservative standard error approach. The general conclusion of this paper is that actively managed funds provide higher returns, both before and after fees, than index or closet index funds. Thus, the do provide a good investment vehicle for an investor wishing to "beat the market".

Competing Interests

None declared.

References

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Table 5: Dependent Variable: CS Benchmark Excess Returns			
This table reports the results from panel regressions using characteristic-selectivity benchmark excess returns as the dependent variable. Reported coefficients have been annualized, and t-statistics are shown in parentheses. All regressions include time fixed effects. Standard error calculations cluster by fund.			
Panel A: CRSP Before Fees			
R-squared closet-index measure	-0.0125 (1.99)**		
# of S&P stocks/Total # of stocks in fund		-0.0465 (6.87)***	
Value-weight % of mutual fund			-0.0471 (6.82)***
Log assets	-0.0021 (1.61)	-0.0009 (0.65)	-0.0003 (0.22)
Turnover	0.0871 (2.87)***	0.0980 (3.24)***	0.0997 (3.30)***
1/number of stocks	0.1820 (0.85)	0.3094 (1.43)	0.2836 (1.32)
Panel B: CRSP After Fees			
R-squared closet-index measure	-0.0099 (1.58)		
# of S&P stocks/Total # of stocks in fund		-0.0433 (6.39)***	
Value-weight % of mutual fund			-0.0441 (6.37)***
Log assets	-0.0013 (0.97)	-0.0001 (0.06)	0.0005 (0.35)
Turnover	0.0813 (2.69)***	0.0901 (2.98)***	0.0918 (3.03)***
1/number of stocks	0.1440 (0.67)	0.2593 (1.20)	0.2355 (1.09)
Panel C: Holdings-Based Returns			
R-squared closet-index measure	-0.0113 (1.92)*		
# of S&P stocks/Total # of stocks in fund		-0.0335 (5.49)***	
Value-weight % of mutual fund			-0.0340 (5.45)***
Log assets	0.0008 (0.59)	0.0016 (1.28)	0.0020 (1.60)
Turnover	0.0174 (0.58)	0.0270 (0.93)	0.0283 (0.97)
1/number of stocks	0.4718 (2.18)**	0.5683 (2.57)**	0.5497 (2.50)**
***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.			

Table 6: Dependent Variable: CRSP Four-Factor Model Excess Returns			
This table reports the results from panel regressions using CRSP four-factor model excess returns as the dependent variable. Reported coefficients have been annualized, and t-statistics are shown in parentheses. All regressions include time fixed effects. Standard error calculations cluster by fund.			
Panel A: Before Fees			
R-squared closet-index measure	-0.0020 (0.54)		
# of S&P stocks/Total # of stocks in fund		-0.0094 (2.32)**	
Value-weight % of mutual fund			-0.0085 (2.06)**
Log assets	-0.0014 (1.83)*	-0.0011 (1.48)	-0.0011 (1.38)
Turnover	-0.0127 (0.70)	-0.0110 (0.61)	-0.0107 (0.59)
1/number of stocks	-0.1691 (1.45)	-0.1445 (1.22)	-0.1514 (1.28)
Panel B: After Fees			
R-squared closet-index measure	0.0007 (0.19)		
# of S&P stocks/Total # of stocks in fund		-0.0063 (1.56)	
Value-weight % of mutual fund			-0.0055 (1.34)
Log assets	-0.0005 (0.71)	-0.0003 (0.43)	-0.0003 (0.38)
Turnover	-0.0184 (1.01)	-0.0188 (1.03)	-0.0186 (1.02)
1/number of stocks	-0.2065 (1.77)*	-0.1941 (1.64)	-0.1990 (1.68)*
***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.			

Table 7: Dependent Variable: Holdings-Based Returns			
This table reports the results from panel regressions using returns calculated using a fund's reported holdings as the dependent variable. As such, the dependent variable is on a before-fee basis. Reported coefficients have been annualized, and t-statistics are shown in parentheses. All regressions include time fixed effects. Standard error calculations cluster by month.			
R-squared closet-index measure	-0.0262 (0.81)		
# of S&P stocks/Total # of stocks in fund		-0.0339 (0.82)	
Value-weight % of mutual fund			-0.0311 (0.73)
Log assets	-0.0013 (0.59)	-0.0007 (0.31)	-0.0004 (0.17)
Turnover	0.0497 (0.90)	0.0710 (1.19)	0.0721 (1.21)
1/number of stocks	0.4456 (1.78)*	0.5728 (2.28)**	0.5488 (2.24)**
***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.			

Table 8: Dependent Variable: CS Benchmark Excess Returns			
This table reports the results from panel regressions using characteristic-selectivity benchmark excess returns as the dependent variable. Reported coefficients have been annualized, and t-statistics are shown in parentheses. All regressions include time fixed effects. Standard error calculations cluster by month.			
Panel A: CRSP Before Fees			
R-squared closet-index measure	-0.0125 (2.32)**		
# of S&P stocks/Total # of stocks in fund		-0.0465 (5.00)***	
Value-weight % of mutual fund			-0.0471 (5.00)***
Log assets	-0.0021 (1.58)	-0.0009 (0.62)	-0.0003 (0.20)
Turnover	0.0871 (2.90)***	0.0980 (3.37)***	0.0997 (3.41)***
1/number of stocks	0.1820 (0.85)	0.3094 (2.08)**	0.2836 (1.93)*
Panel B: CRSP After Fees			
R-squared closet-index measure	-0.0099 (1.84)*		
# of S&P stocks/Total # of stocks in fund		-0.0433 (4.66)***	
Value-weight % of mutual fund			-0.0441 (4.68)***
Log assets	-0.0013 (0.95)	-0.0001 (0.06)	0.0005 (0.33)
Turnover	0.0813 (2.71)***	0.0901 (3.08)***	0.0918 (3.13)***
1/number of stocks	0.1440 (1.03)	0.2593 (1.75)*	0.2355 (1.61)
Panel C: Holdings-Based Returns			
R-squared closet-index measure	-0.0113 (1.91)*		
# of S&P stocks/Total # of stocks in fund		-0.0335 (3.19)***	
Value-weight % of mutual fund			-0.0340 (3.19)***
Log assets	0.0008 (0.53)	0.0016 (1.19)	0.0020 (1.50)
Turnover	0.0174 (0.77)	0.0270 (1.24)	0.0283 (1.29)
1/number of stocks	0.4718 (3.13)***	0.5683 (3.72)***	0.5497 (3.62)***
***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.			

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