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Are Some Mutual Fund Managers Better Than Others? Cross-Sectional Patterns in Behavior and Performance

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ABSTRACT

We examine whether mutual fund performance is related to characteristics of fund managers that may indicate ability, knowledge, or effort. In particular, we study the relationship between performance and the manager's age, the average composite SAT score at the manager's undergraduate institution, and whether the manager has an MBA. Although the raw data suggest striking return differences between managers with different characteristics, most of these can be explained by behavioral differences between managers and by selection biases. After adjusting for these, some performance differences remain. In particular, managers who attended higher-SAT undergraduate institutions have systematically higher risk-adjusted excess returns.

THE FINANCIAL PRESS PRODUCES a tremendous volume and variety of information about the individuals who manage mutual funds. Profiles of fund managers are a staple of many financial magazines, and managerial changes at large funds merit front page stories in newspaper business sections. Recently, the Securities and Exchange Commission has allowed some funds to advertise the past records of their managers in the press, even though those track records were assembled while the managers were employed by other funds. Thus, one gets the impression that investors pay a great deal of attention to the individuals who are managing their money. In light of this behavior, an obvious question to ask is whether some managers are indeed better than others.

A large number of previous papers have addressed the related question of whether some mutual funds are better than others (from an investor's perspective) by looking for evidence of persistence over time in mutual fund

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performance. The consensus of this "hot hands" literature seems to be that there is some persistence in fund performance, which suggests that many mutual fund investors are not making wise selections.[1] However, a large part of the performance persistence is attributable to persistence in fund expense ratios, thus it is not clear whether we can also conclude that some funds have superior stock-picking ability. Carhart (1997), for example, suggests that most of the after-expenses performance persistence in his sample can be attributed to the one-year momentum effect of Jegadeesh and Titman (1993) in the underlying stock returns, with much of the remaining persistence attributable to the worst-performing funds.

In this paper we take a new approach to the question of whether some mutual fund managers are better than others by looking at the relationship between performance and manager characteristics. We use a sample of 492 managers who had sole responsibility for a growth or growth and income fund for at least some part of the 1988–1994 period. Our paper departs from the "hot hands" approach in two ways. First, we focus on fund managers instead of funds. Of course, if "ability" exists, it is not obvious whether it resides in the manager or in the fund organization. Because there is high managerial turnover in the fund industry, the empirical distinction between funds and managers need not be trivial.[2] Second, rather than looking at the correlation over time of each manager's performance, we look cross-sectionally at how performance is related to observable characteristics of the fund manager. Our approach has the disadvantage of requiring data on manager characteristics which leaves us with a much smaller sample of fund-years than the hot hands papers. However, our approach has a potential advantage in that power may be gained by pooling information across managers rather than treating each manager separately.

The characteristics data available to us include a manager's age, the name (and average student SAT score) of the institution from which a manager received his/her undergraduate degree, whether he/she has an MBA degree, and how long a manager has held his/her current position. If one thinks of mutual fund managers as skilled professionals whose job (like those of doctors or statisticians) involves gathering and analyzing data, it seems reasonable to hypothesize that some managers may perform better than others. Moreover, one could give a number of reasons why performance might be systematically related to these characteristics. For example, one could imagine that younger managers might do better because they are working harder to advance their careers (or worse because of a lack of experience), or that MBAs or graduates of more prestigious colleges might do better because

[1] Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), and Gruber (1996) find evidence of persistence in fund performance over relatively short horizons (one to three years). Grinblatt and Titman (1992), Elton et al. (1993), and Lehman and Modest (1987) suggest that a fund's current performance can predict performance 5 to 10 years into the future. In contrast, Malkiel (1995) concludes that mutual fund performance persistence was an important phenomenon in the 1970s, but broke down in the 1980s.

[2] In our sample 18 percent of the funds change managers in the period 1993 to 1994.

they are smarter, better educated, have better networks of contacts from whom to gather information, and/or work for firms that provide better support services.

We begin by showing that simple regressions of market excess returns on the managerial characteristics in our data with no other controls suggest relationships between education, age, and performance which are so strong as to make it seem unlikely that "ability" differences could be the whole story. The body of the paper is then devoted to the dual task of examining how systematic differences in behavior and selection effects may be responsible for the initial findings and whether there seem to be any residual differences that may reflect differences in "ability."

In the raw data, we find that managers with MBAs outperform managers without MBAs by 63 basis points per year. However, we find that the higher returns achieved by MBAs are entirely attributable to their greater holdings of systematic risk. Second, the raw data suggest that younger managers outperform older managers; a manager who is 12 years older than the mean manager is predicted to lag the mean manager by one percentage point per year. A substantial portion of the higher returns achieved by younger managers, however, is attributable both to their working for funds that charge lower expenses and to survivorship biases. The survivorship biases stem from the fact that separation from the managerial position is more sensitive to performance for younger managers, a relationship that we explore in more detail in Chevalier and Ellison (1999). We do, however, find a small degree of residual superior performance by younger managers which may be indicative of greater stock-picking "ability" in our regressions examining four-factor excess returns. One explanation for why such performance differences might exist is that younger managers may work harder, both because they are more likely to be fired for poor performance and because they have longer careers ahead of them.

The most robust performance difference we identify is that managers from undergraduate institutions with higher average student SAT scores obtain higher returns. Though some part of the higher returns of managers from higher-SAT colleges is attributable to risk/expense/survivorship differences, there remain significant differences for which our analysis of managerial behavior cannot account. There are many possible explanations for why college average SAT scores may predict performance. Obviously the result could be due to managers from higher-SAT schools having higher inherent abilities or receiving direct benefits from a better education. Alternatively, a high-SAT school may provide indirect benefits via the network of connections to other members of the financial community it provides. (Such connections could conceivably result in having better sources of information, improved access to IPOs, preferential execution of trades, etc.) It is also true that managers with different characteristics tend to work for different funds. Thus, the performance results also could reflect higher-SAT managers being hired into fund companies that have lower unreported expenses, that have better support staff, or that induce higher effort via better incentive packages, etc.

Some of the relationships we find in the raw data have also been noted elsewhere. First, related to our school quality results, a 1994 study by Morningstar, Inc. reported on by *Business Week* (July 4, 1994, p. 6) notes that over the previous five years diversified mutual funds managed by "Ivy League" graduates had achieved raw returns that were 40 basis points per year higher than those of funds managed by non-Ivy League graduates. Second, an independent paper by Golec (1996) has taken an approach very similar to our own in examining the relationship between a manager's age, tenure, and possession of an MBA degree on performance, risk-taking, and expenses in a sample of funds of various types which were in operation throughout the entire 1988–1990 period. His analysis of behavioral differences is fairly similar to ours (although some of the results differ). On the performance side, however, he does not try to account for selection effects and perhaps as a result reports finding several very strong significant predictors of performance.[3] His study also does not include the college quality variable, which we ultimately find is the only variable that clearly predicts risk-adjusted excess returns.

The remainder of the paper proceeds as follows. In Section I we describe our data. In Section II we present the basic stylized facts about performance. In Section III we examine the relationship between our managerial characteristics variables, holdings of systematic risk, and observable characteristics of the funds such as expenses and turnover. In Section IV we look at fund closings and the managerial labor market and examine the possibility that survivorship biases cause our measured differences in performance. Section V examines the possibility that the performance differences can be accounted for by differences in observable management styles. Section VI looks at whether "good" managers systematically beat the market. Section VII concludes.

I. Data

The majority of our data are obtained from Morningstar, Inc. We use as our starting sample the set of growth and growth and income mutual funds listed in Morningstar's March 1994 Mutual Funds OnDisc CD-ROM. From the March 1994 CD we obtain monthly returns, expense ratios, assets under management, and turnover ratios for these funds, along with information on their current managers. For each fund, Morningstar gives the name(s) of the fund's manager(s) along with a brief biographical sketch that includes the manager's start date, all undergraduate and graduate degrees received, the years in which the degrees were granted, and the names of the degree-granting institutions (as well as hobbies, etc.) Using the Morningstar CDs

[3] He finds that a manager's predicted risk-adjusted return is increased by one percentage point for each 5.5 years of tenure in his current position, he finds an age effect similar in magnitude to that in our initial regression, and in some specifications he finds a significant MBA effect. We would imagine that his focus on three-year returns makes survivorship biases larger than they are even in our initial regressions.

and the *Morningstar Mutual Fund Sourcebook* at approximately annual intervals, going backward to 1988 and forward through 1995, we check the information from the March 1994 CD and add information about earlier and later fund managers.[4] Records of fund name changes from Morningstar are used to verify our tracking of the funds.

We use the data from the biographical sketches to create four manager characteristic variables.[5] Using the information in the biographical sketches, we compile an MBA dummy and a manager tenure variable. We construct an approximate manager age variable by assuming that each manager was 21 years old upon graduation from college. Finally, with the hope of obtaining a variable that might reflect the manager's ability, effort, connections, or the quality of his training, we record the average SAT score of students at the institution from which the manager received his undergraduate degree.

The construction of this latter variable is somewhat involved. We first look up each manager's undergraduate institution in the 22nd (1993) edition of *Lovejoy's College Guide* (Straughn and Straughn 1993). Most schools report upper and lower bounds for the verbal and math SAT sections. The bounds are supposed to be constructed so that the middle 50 percent of students attending the school lie between the upper and lower bounds. We approximate each school's composite SAT score as the average of the upper and lower bounds for the verbal score plus the average of the upper and lower bounds for the math scores. In some cases the SAT scores are missing or reported only in different formats, or the college names found in the biographical sketches are ambiguous. The Appendix describes how we deal with these cases.

In order to compute risk-adjusted excess returns and explore management styles we use a number of monthly return time series provided to us by Kent Daniel. One of these variables is the return on the value-weighted NYSE/AMEX/Nasdaq composite index minus the risk-free rate, which we refer to as the RMRF series. The recent finance literature suggests that in addition to systematic risk, market capitalization, the book-to-market ratio, and past returns have significance in explaining cross-sectional patterns in stock returns.[6] For this reason we also obtain monthly returns on three other portfolios. The HML portfolio is a zero-investment portfolio constructed by subtracting the returns of low book-to-market ratio stocks from the returns of high book-to-market ratio stocks. The SMB portfolio is a zero-investment portfolio constructed by subtracting the returns of large market capitaliza-

[4] The starting date field in the Morningstar CD is the most error-prone category. By moving backward year by year for each fund, we believe that we are able to correct many of these errors.

[5] Our analysis focuses on those fund-years in which Morningstar records that, as of December 31st of the previous year, a single manager is responsible for the fund. Though the data sometimes list the names of each member of a management team, it is often not clear whether all of the managers listed contribute equally to the management of the fund, or whether one of the listed managers is the lead manager, and we thus feel that it would be problematic to generate metrics of manager characteristics in such cases.

[6] See Fama and French (1993), Jegadeesh and Titman (1993), and Carhart (1997).

Table I

Summary Statistics

Summary statistics for all of the variables used in the analysis are presented. The observations are fund-years. The manager characteristics variables include the SAT of matriculants at the manager's undergraduate institution (divided by 100), a dummy variable that takes the value of one if the manager has an MBA degree and zero otherwise, the manager's age, and the manager's tenure. The analysis also utilizes performance and risk characteristics of each fund. Alpha is the market model excess return, in percentage per year. Beta is the coefficient of the market portfolio in a regression of the fund's monthly returns minus the risk-free rate on the monthly returns of the market portfolio minus the risk-free rate. Unsys risk is the standard deviation of the residuals from this regression, expressed in percentage points per year. The HML, SMB, and PR1YR weights are the coefficients from a regression of the fund's monthly returns on the market returns minus the risk-free rate and the returns of three other factor portfolios. The HML portfolio is a zero-investment portfolio constructed by subtracting the returns of low book-to-market ratio stocks from the returns of high book-to-market ratio stocks. The SMB portfolio is constructed by subtracting the returns of large market capitalization firms from the stock returns of small market capitalization firms. The PR1YR portfolio is the spread between the performance of stocks in the top 30 percent of returns in the prior 12 months and those in the bottom 30 percent. Alpha4 is the excess return from this four-factor model in percent per year. Other fund characteristics utilized are a dummy variable that takes the value of zero for growth funds and one for growth and income funds, the log of total fund assets under management, and the fund's expense and turnover ratios, expressed as percentages.

Variable	# of Obs.	Mean	Std. Dev.
Simple excess return (%)	2029	−0.504	8.451
Manager college SAT (/100)	2029	11.416	1.436
Manager MBA	2029	0.596	0.491
Manager age	2029	44.176	9.684
Manager tenure	2029	3.793	5.058
Growth-income dummy	2029	0.374	0.484
Alpha	2029	−0.502	7.862
Beta	2029	0.971	0.247
Log of assets	1907	4.359	1.913
Expense ratio	1947	1.352	1.026
Turnover ratio	1885	76.813	69.368
HML weight	2029	−0.020	0.428
SMB weight	2029	0.151	0.389
PR1YR weight	2029	0.015	0.228
Unsys risk	2029	2.573	3.402
Alpha4	2029	−0.698	7.892

tion firms from the stock returns of small market capitalization firms. Finally, the PR1YR portfolio is a zero-investment portfolio constructed as the spread between the performance of stocks that are in the top 30 percent of returns in the prior 12 months and those that are in the bottom 30 percent. The exact construction of the portfolios is detailed in Daniel and Titman (1997). Summary statistics for all of the above variables on the sample of funds for which the return and manager characteristics variables are available are shown in Table I.

II. Do Manager Characteristics Predict Returns?

Our goal in this section is to present a simple first look at whether manager characteristics predict the cross-sectional distribution of mutual fund returns. The initial results are so striking as to be something of a puzzle. In the sections that follow we examine the extent to which the apparent differences in returns are in fact attributable to cross-sectional differences in risk, investment styles, expenses, and selection biases, in order to see whether differences in "ability" may also play a role.

For each fund-year in our sample, we calculate the simple excess return of the mutual fund. That is, we calculate the fund's annual return minus the annual return on the value-weighted NYSE/AMEX/Nasdaq composite index.

We examine whether the fund's performance in year t is related to the characteristics of the manager who is in charge of the fund on December 31 of year $t - 1$.[7] The manager characteristics we use are: the mean composite SAT score at the undergraduate institution attended by the fund manager, a dummy variable that equals one if the manager undertook an MBA and zero otherwise, the manager's age, and the manager's tenure. We also include a dummy variable that equals one for growth and income funds and zero otherwise. The omitted category, then, is growth funds.

The regression results are reported in Table II. Heteroskedasticity-robust standard errors are shown in parentheses. The point estimates suggest that younger managers with MBAs from higher SAT schools earn higher returns. The coefficients of SAT scores and age are each significant at the 1 percent level, and the MBA coefficient is significant at the 11 percent level. The magnitudes of the coefficients are strikingly large. For example, a manager who attended the 4th highest SAT score school in our sample, Princeton (composite 1355), is expected to outperform a manager from the mean school in our sample (composite 1142), by about one percentage point per year.[8]

Older managers seem to fare much worse than their younger counterparts. A manager who is one year older than another is expected to achieve a return that is 8.6 basis points lower. Thus, the predicted performance difference between the youngest manager in our sample (26 years old) and the oldest manager (80 years old) is approximately 4.6 percentage points (or 460 basis points) per year. The point estimate of MBAs is that a manager who has an MBA outperforms a non-MBA manager by 63 basis points per year on average. The regression coefficients indicate that fund performance also in-

[7] If the manager of the fund changes during year t, we do not ascribe the fund's performance to the new manager until year $t + 1$. We make this decision because we do not want to use a methodology that introduces look-ahead biases. However, we rerun these specifications dropping out returns in years in which there were management changes (and in which, consequently, performance cannot cleanly be ascribed to a single manager). The fit and significance of the basic results we describe here improve somewhat, but are qualitatively similar to the results that we present.

[8] The University of Florida and the University of California at San Diego have SAT composites very close to the sample mean.

Table II

Mutual Fund Performance and Manager Characteristics

The dependent variable, calendar year simple excess return is regressed on a set of manager characteristics, including the average SAT score of matriculants at the manager's undergraduate institution (divided by 100), a dummy variable that takes the value of one if the manager has an MBA degree and of zero otherwise, the manager's age, and the manager's tenure with the fund. A dummy variable is also included that takes the value of one if the fund is a growth and income fund and the value of zero if the fund is a growth fund. The observations are fund-years. Heteroskedasticity robust standard errors are in parentheses.

Independent Variables	Coefficients
Constant	−1.704 (1.756)
Manager college SAT	0.463 (0.136)
Manager MBA	0.631 (0.391)
Manager age	−0.086 (0.022)
Manager tenure	0.005 (0.046)
Growth-income dummy	−1.836 (0.351)
R^2	0.031
No. of observations	2029

creases slightly with tenure, but this effect is not significantly different from zero at standard confidence levels.

Differences in stock-picking ability may be part of the explanation for the results above, although the magnitudes of the effects are so large as to suggest that other factors must be at work as well.

III. Risk, Expenses, Turnover, and Fund Size

Section II gives evidence that managers with different characteristics systematically produce very different returns. One potential explanation for this is cross-sectional differences in manager behavior, a subject we begin to explore in this section.

A. Systematic Risk

We calculate a beta for each mutual fund-year in our sample by regressing the fund's monthly returns in that year minus the risk-free rate on the monthly return of the market minus the risk-free rate. The 12-month horizon gives us fewer data points for the estimation than one might want, but we want to avoid longer horizons because of the possibility of a fund's riskiness changing over time.

In the first column of Table III, we list the coefficient estimates from a regression of funds' betas on the manager characteristics described previously. Newey-West standard errors are used throughout this section because we expect residuals for a single fund for different years to be serially correlated. Managers from higher-SAT schools and those who hold MBAs are more likely to manage higher beta funds. The latter estimate reflects the

Table III

Fund Characteristics and Manager Characteristics

Characteristics of and actions taken by mutual funds are regressed on characteristics of the funds' managers. The manager characteristics variables include the average SAT of matriculants at the manager's undergraduate institution (divided by 100), a dummy variable that takes the value of one if the manager has an MBA degree and zero otherwise, the manager's age, and the manager's tenure. The observations are fund-years. Newey-West standard errors are in parentheses.

	Dependent Variables			
Independent Variables	Beta	Log of Assets	Expense Ratio (%)	Turnover Ratio (%)
Constant	0.788	4.257	1.911	143.61
	(0.069)	(0.661)	(0.225)	(25.80)
Manager college SAT	0.011	0.063	−0.055	−5.09
	(0.005)	(0.054)	(0.029)	(2.19)
Manager MBA	0.067	0.393	−0.083	−1.88
	(0.016)	(0.149)	(0.054)	(5.18)
Manager age	0.0020	−0.0261	0.0211	−0.027
	(0.0009)	(0.0085)	(0.0076)	(0.351)
Manager tenure	−0.0055	0.054	0.023	−0.26
	(0.0020)	(0.019)	(0.017)	(0.58)
Growth-income dummy	−0.131	0.268	−0.006	−14.47
	(0.015)	(0.162)	(0.083)	(5.35)
Log of assets			−0.206	
			(0.031)	
R^2	0.102	0.036	0.238	0.020
No. of observations	2029	1907	1895	1885

fact that the mean beta in our sample for funds managed by a non-MBA manager is 0.93, and the mean beta among funds managed by an MBA is 1.00. Managers with longer tenure choose significantly lower betas. The point estimate indicates that older managers choose higher betas. The age effect is, however, not statistically significant at standard confidence levels.

We feel that behavioral differences are interesting in and of themselves, in part because they may shed some light on the labor market for mutual fund managers.[9] In this paper, however, we are most interested in the extent to which performance differences between managers persist when we control for behavioral differences. Table IV shows how the apparent relationship between excess returns and manager characteristics changes as we control for each of the behavioral factors we examine in the paper. At this point, the

[9] In Chevalier and Ellison (1999) we explore career concerns in more detail in relation to cross-sectional differences in risk-taking and herding behavior. One conclusion of that paper is that young managers on average hold less unsystematic risk than older managers, and this may reflect a desire to minimize the probability of job loss. Though unsystematic risk holdings have no clear connection to apparent excess returns, it is perhaps interesting to note also that managers from high-SAT schools tend to hold less idiosyncratic risk and that there are no significant differences in the idiosyncratic risk holdings of MBA and non-MBA managers.

Table IV

More Performance Regressions

Column 1 regresses simple excess return on manager and fund characteristics; columns 2–5 regress risk-adjusted excess returns on manager and fund characteristics. In columns 3–5, instrumental variable estimation is used, treating fund expenses and turnover as endogenous variables. Column 4 displays the same regression as column 3 utilizing only the reduced survivorship bias subsample of the data. Column 5 displays the same specification again, except the full dataset is used and a Heckman-like procedure is used to correct for survivorship biases. Finally, columns 6 and 7 show the same specifications as columns 4 and 5, replacing the dependent variable with the excess returns from a four-factor model. The regressors are manager and fund characteristics. The included manager characteristics are the average SAT score of matriculants at the manager's undergraduate institution (divided by 100), a dummy variable that takes the value of one if the manager has an MBA degree and zero otherwise, and the manager's age. A dummy variable that takes the value of one for growth and income funds and zero for growth funds is also included as a regressor. Columns 3 through 7 also include the fund's log of assets, expense ratio (%), and turnover ratio (%) as regressors. In all cases, the observations are fund-years and heteroskedasticity-robust standard errors are shown in parentheses.

	Excess Return Measure / Sample / Estimation Technique						
Independent Variables	Simple/Full/ OLS	Alpha/Full/ OLS	Alpha/Full/ IV	Alpha/RSB/ IV	Alpha/Full/ Heck-IV	Alpha4/RSB/ IV	Alpha4/Full/ Heck-IV
Constant	−1.730	−0.882	−0.237	−2.134	−1.007	−0.540	1.149
	(1.787)	(1.658)	(1.988)	(2.401)	(1.753)	(1.959)	(1.492)
Manager college SAT	0.462	0.376	0.306	0.253	0.291	0.248	0.363
	(0.135)	(0.127)	(0.133)	(0.160)	(0.120)	(0.143)	(0.102)
Manager MBA	0.630	0.042	−0.254	0.056	−0.279	0.437	0.417
	(0.390)	(0.363)	(0.388)	(0.494)	(0.346)	(0.415)	(0.295)
Manager age	−0.084	−0.082	−0.042	−0.015	−0.029	−0.043	−0.043
	(0.022)	(0.021)	(0.021)	(0.025)	(0.019)	(0.020)	(0.017)
Growth-income dummy	−1.835	−0.766	−0.512	0.888	−0.431	0.416	−0.788
	(0.351)	(0.331)	(0.356)	(0.460)	(0.336)	(0.388)	(0.288)
Expense ratio			−1.524	−1.579	−1.504	−1.949	−2.251
			(0.325)	(0.491)	(0.350)	(0.298)	(0.292)
Log of assets			−0.061	0.138	−0.018	0.206	−0.267
			(0.124)	(0.179)	(0.116)	(0.142)	(0.098)
Turnover ratio			0.014	0.013	0.013	−0.003	0.003
			(0.005)	(0.005)	(0.004)	(0.005)	(0.003)
R^2	0.03	0.02	0.05	0.05	0.05	0.16	0.10
No. of observations	2029	2029	1705	872	1705	872	1705

columns are of interest. The first reports a basic regression that uses simple excess returns as the dependent variable (from which we have dropped the insignificant tenure variable.) The second shows the effect of using risk-adjusted excess returns rather than simple excess returns as the dependent variable. Given the patterns in risk-taking noted above, it should not be surprising that the risk adjustments affect the return-characteristics relationship. Most notably, the coefficient of MBA drops from 0.63 to 0.04, indicating that the higher returns achieved by MBAs are essentially completely attributable to their taking on more systematic risk. The SAT effect is reduced in magnitude by approximately one-fifth when differences in systematic risk are controlled for, but remains highly statistically significant and large in practical terms. As expected, given that younger managers do not appear to take on more systematic risk, their performance advantage remains large and highly significant.

B. Expenses and Other Fund Characteristics

As mentioned earlier, one conclusion of the hot hands literature is that expense differences between funds seem to be associated with performance differences. One potential explanation for our findings then is that there are systematic differences in the jobs held by different types of managers, which result in their having different expense ratios.

To look at potential sources of differences in expenses, the second through fourth columns of Table III report regressions in which the dependent variables are the logarithm of a fund's assets under management at the start of the year, its expense ratio, and its turnover. The estimates are that managers from higher-SAT schools have lower expenses and turnover and manage larger funds than managers from lower-SAT schools. The expense and turnover effects are significantly different from zero at the 1 percent level. Note that an indirect benefit of working for larger funds is that such funds also have lower expenses. Managers who have MBAs also manage larger funds with lower expenses and lower turnover rates, although here only the fund size effect is statistically different from zero at standard confidence levels. Finally, older managers are associated with smaller, higher expense funds. Both of these effects are statistically different from zero at the 1 percent confidence level. The magnitudes of some of these effects are substantial. For example, even after controlling for fund size differences, a fund with a 55-year-old manager is expected to have an expense ratio that is more than 50 basis points per year higher than the expense ratio of a fund managed by a 30-year-old.

Turning to the question of whether these differences in expenses are sufficient to account for the performance differences found earlier, we report in the third column of Table IV a regression of risk-adjusted returns on manager characteristics which include a fund's expense ratio, start-of-year assets under management, and turnover ratio as explanatory variables. Lagged values of the expense ratio and the turnover ratio are used as instruments for these variables in the estimation. We find expenses to be highly significant. That the point estimate of the coefficient of the expense variable is greater than one in magnitude suggests that funds with high expense ratios may also have high unreported expenses. In connection with this it is noteworthy that turnover has a positive coefficient whenever it is included along with expenses. One story consistent with this is that the combination of high expenses and low turnover is indicative of managerial slack, whereas high expenses and high turnover may mean that investors are paying to have a lot of research done.

Although expenses are of tremendous practical importance, controlling for expense differences is still not sufficient to explain the superior performance of managers from higher-SAT schools and of younger managers. The coefficient of the SAT variable is reduced in magnitude by a bit less than one-fifth by the inclusion of the three extra variables, but remains significantly different from zero at the 5 percent level. Comparing columns 2 and 3 we see that controlling for the higher expenses charged by older managers reduces the age coefficient by about half of its former magnitude, but that it also remains statistically different from zero at the 5 percent level.

The one observation we would like to make from the last column of Table III is that managers from higher-SAT schools have lower rates of portfolio turnover. If one believes that mutual fund performance often suffers due to excessive churning, this result may suggest that these managers have benefited from their education.[10]

IV. Survivorship Issues

A number of researchers have noted that estimates of the average performance of mutual funds are biased upward by the fact that poorly performing mutual funds are more likely to liquidate or merge with other funds, thus leading the fund's history to be omitted from the many datasets that provide past histories of active funds only.[11] In this section, we look at whether survivorship biases in our data might account for some of the cross-sectional patterns we have observed.

A. Cross-Sectional Differences in Fund and Manager Survival

Although in recent years Morningstar has greatly improved the quality of its data on dead funds, there are three ways in which our estimates may be affected by survivorship biases. First, the 1994 Morningstar CD, which we use to construct our base sample, does not contain data for funds that were no longer in business in early 1994. Our base sample therefore has the stan-

[10] Though we do not have the exact data that one would like to test this, the turnover result is at least suggestive that the tax-adjusted performance of higher-SAT managers could eclipse the tax-adjusted performance of lower-SAT managers by an even greater margin than the differences between the non-tax-adjusted performances.

[11] See, for example, Brown et al. (1992), Brown and Goetzmann (1995), Carhart (1997), and Malkiel (1995).

dard survivorship problems. Second, Morningstar did not begin publishing educational information on managers until 1990. The observations from 1988 and 1989 in our sample are obtained by backfilling educational data reported in 1990 or later, and thus the sample is further selected by the requirement that the manager remain in the industry until 1990. Third, throughout the entire period there remains the problem that our regressions include annual returns and a number of other fund characteristics, and thus we ignore partial-year data on a fund in the year of its death and fund-years for which expenses or other variables are missing. If fund closure or variables missing from our dataset are related to performance in the same calendar year, this creates an additional survivorship problem.

Because we are interested in cross-sectional patterns of returns rather than the level of excess returns, survivorship biases will affect our results only if the fund death or manager disappearance processes differ for managers with different characteristics (or across segments of funds that tend to hire different types of managers). For example, our result that managers with higher SAT scores have better risk-adjusted performance could possibly be an artifact of our data's survivorship biases if higher-SAT managers work for firms that are more aggressive about firing managers with poor performance. Alternatively, our SAT results could understate the true relationship between SAT and performance if fund executives give high-SAT managers the benefit of the doubt, and do not fire them as quickly as low-SAT managers following poor performance. Because one could construct several plausible hypotheses about how survivorship biases might affect our results, we undertake survivorship corrections.

To examine whether survivorship issues bias our results, we construct a second sample of mutual funds. This sample has as its starting point all mutual funds that were active in 1992. We trace the performance of these funds forward through 1994, being careful to match up funds that had changed names over the 1992–1994 time period. This yields a starting sample of 606 mutual funds that were in existence at the end of 1992. By the end of 1995, 507 of these funds were still active.

To look at the fund survival process, we employ the subsample of fund-years for which a fund had complete data for a year $t \in \{1992, 1993, 1994\}$ (942 fund-years). We use a specification that is similar to the base specification in our paper on career concerns of fund managers (Chevalier and Ellison (1999)). Here, we perform a probit regression with the dependent variable being a dummy for whether the fund survived until the end of year $t + 1$.[12] The explanatory variables for the survival probit are the fund's risk-adjusted excess return in year t (called Alpha in Table V), the characteristics of the manager who was managing the fund on December 31st of year $t - 1$ (age, SAT, and MBA), the characteristics interacted with the excess return, and control variables for the fund's size and age and the manager's tenure.

[12] In order to include the 1994 observations in these regressions, we look to see whether these funds survived to the end of 1995. We have not made any other use of the data from 1995 because in the data available to us expense and/or turnover figures are missing for the majority of funds.

Table V

Manager Characteristics and Survivorship

Two probit specifications are estimated. The first estimates the probability that a fund survives from year $t-1$ to year t. The second estimates the probability that a manager who is in our sample in year $t-1$ remains in our sample in year t. The observations are fund-years. The independent variables are managerial characteristics, performance measures, and fund characteristics. The managerial characteristics included are the average SAT score of matriculants at the manager's undergraduate institution (divided by 100), a dummy variable that takes the value of one if the manager has an MBA degree and zero otherwise, the manager's age, and the manager's tenure with the fund. Jensen's Alpha is included as the performance measure. Interactions of this performance measure and manager SAT, MBA, and age variables are also included. The fund characteristics included are the log of fund assets and the age of the fund in years. The survival process is estimated using the subset of our data from 1992–1994 for which we have more complete data on nonsurviving funds and managers. Standard errors are in parentheses.

	Dependent Variables for Probit	
Independent Variables	Fund Survival	Manager Found
Constant	−0.065	0.871
	(0.773)	(0.491)
Alpha	0.111	0.117
	(0.058)	(0.046)
Manager college SAT	0.069	0.061
	(0.060)	(0.037)
Manager MBA	0.215	−0.217
	(0.168)	(0.113)
Manager age	0.010	−0.0075
	(0.010)	(0.0061)
Alpha*(SAT-10)	0.0055	0.0037
	(0.0076)	(0.0056)
Alpha*MBA	0.024	−0.021
	(0.022)	(0.017)
Alpha*Mgr. age	−0.0023	−0.0021
	(0.0012)	(0.0009)
Log of assets	0.109	−0.017
	(0.049)	(0.032)
Fund age	0.021	−0.0063
	(0.011)	(0.0033)
Manager tenure	−0.037	0.042
	(0.020)	(0.014)
No. of observations	942	903

Note that in this model there are two channels through which survivorship biases might arise. First, if the coefficient of SAT were negative, it would be more difficult for a fund managed by a higher-SAT manager to survive, and such funds that did survive would be expected to display superior performance. Second, if the coefficient of the SAT-excess return interaction were positive then survival would be more performance-sensitive for higher-SAT funds. Again in such a situation the higher-SAT funds would display superior performance in the sample of survivors.

The results of the probit regression are reported in the left column of Table V. The positive significant coefficient of period t excess returns indicates as expected that better performing funds are more likely to survive. Neither the SAT variable nor the SAT-return interaction is statistically significant, with the point estimates on both being positive (in which case the two selection biases would work in opposite directions). The age-return interaction is negative and significant, indicating that fund survival is more performance sensitive for funds managed by younger managers. This negative coefficient suggests that survivorship bias would make younger managers appear to outperform older managers.

The right column of Table V examines the process by which fund managers disappear from the universe of funds in our data. This process is relevant because for the 1988–1989 period we fill in a manager's characteristics only if that manager is still managing some growth or growth and income fund listed in Morningstar in 1990. The set of observations in the regression is the 903 fund-years for which the fund had complete data for a year $t \in \{1992, 1993, 1994\}$ and the fund survived to the end of year $t + 1$. The dependent variable is a dummy variable for whether the December 31st of year $t - 1$ manager remained in our dataset (at this fund or another) at the end of year t. The explanatory variables are as in the previous regression. Again we find a performance effect—poorly performing managers are more likely to disappear. The coefficients of SAT and of the SAT-return interaction are again positive and insignificant. A negative and statistically significant age-return interaction indicates that, conditional on the fund surviving, the survival of the manager (or his ability to get another job) is also again more performance sensitive for younger managers. The backfilling of the manager characteristics in the 1988–1989 sample may thus create an additional bias toward finding that younger managers perform better.

So far we have considered the possibility that poor performance this year may lead to a fund or manager disappearing next year. An additional potential source of survivorship bias is that a manager's poor performance early in a year might lead to the fund's closure or his disappearance later that year. As one test for whether such selection might be important, we examine whether a fund's death anytime between March and December of year t can be linked to January and February performance in year t. Further, we check whether a fund's within-year disappearance probability is linked to the manager's age or SAT or an interaction between the manager's age or SAT and January–February performance. We find no significant evidence of such linkages.

B. Effects of Survivorship

We take two separate approaches to assess whether survivorship biases might be responsible for the cross-sectional patterns we find in excess returns. The first approach is to rerun our regressions on the 1992–1994 reduced-survivorship bias sample discussed in the preceding subsection. The fourth column of Table IV reports the results of reestimating the regression in the

Table VI

Management Styles and Manager Characteristics

A fund-year's weightings in a four-factor model are regressed on the characteristics of fund managers. The HML, SMB, and PR1YR weights are the coefficients from a regression of the fund's monthly returns minus the risk-free rate on the market returns minus the risk-free rate and the returns of three other factor portfolios. The HML portfolio is a zero-investment portfolio constructed by subtracting the returns of low book-to-market ratio stocks from the returns of high book-to-market ratio stocks. The SMB portfolio is constructed by subtracting the returns of large market capitalization firms from the stock returns of small market capitalization firms. The PR1YR portfolio is the spread between the performance of stocks in the top 30 percent of returns in the prior 12 months and those in the bottom 30 percent. These factor weightings are regressed on fund and manager characteristics. The included manager characteristics are the average SAT score of matriculants at the manager's undergraduate institution (divided by 100), a dummy variable that takes the value of one if the manager has an MBA degree, the manager's age, and the manager's tenure with the mutual fund. The log of fund assets and a dummy variable that takes the value of one for growth and income funds and zero for growth funds are also included as regressors. Observations are fund-years. Newey-West standard errors are in parentheses.

	Dependent Variables		
Independent Variables	HML Wgt	SMB Wgt	PR1YR Wgt
Constant	−0.062	0.288	−0.015
	(0.118)	(0.101)	(0.053)
Manager college SAT	−0.007	−0.011	−0.001
	(−0.009)	(0.008)	(0.004)
Manager MBA	−0.053	−0.020	−0.013
	(0.024)	(0.023)	(0.012)
Manager age	−0.0012	0.0013	0.0012
	(0.0014)	(0.0014)	(0.0007)
Manager tenure	0.0072	0.0031	−0.0006
	(0.0032)	(0.0030)	(0.0014)
Growth-income dummy	0.158	−0.188	−0.013
	(0.023)	(0.021)	(0.010)
R^2	0.044	0.059	0.004
No. of observations	2029	2029	2029

third column on this sample. Comparing the two columns we see that the SAT coefficient is somewhat smaller and given the smaller sample size it is no longer significant at the 5 percent level. The age coefficent loses almost two-thirds of its former magnitude and becomes insignificant.

Given that the above approach entails throwing out more than half of our data, we try also to obtain more precise survivorship-corrected estimates by using Heckman-style corrections. Thus, these specifications use our original, larger dataset but correct the estimates for survivorship biases. The goal of these Heckman-style specifications is to correct for the fact that our 1990–1992 data exclude funds that did not survive to 1993, and the 1988–1989 subsample excludes both managers who did not survive to 1990 and funds that did not survive to 1993. Our sample selection problem does not correspond exactly with the textbook truncated regression model because the selection equation includes an interaction between the manager characteristics and excess returns. Given the availability of the later sample, which is not subject to these selection biases, however, the selection model is not hard to estimate.

Formally, suppose that the pre-1993 data generating process takes the form

$$s_i = (x_{1i}\gamma)r_i + x_{2i}\delta + \epsilon_{1i}, \tag{1}$$

$$s_i^* = 1 \quad \text{if } s_i > 0 \text{ and } 0 \text{ otherwise}, \tag{2}$$

$$r_i = x_{3i}\beta + \epsilon_{2i}, \tag{3}$$

where s_i^* is an indicator for whether a fund (and manager) survives, r_i is the fund's excess return, and ϵ_{1i} and ϵ_{2i} are independent mean zero normal random variables. Suppose also that $\mathrm{Var}(\epsilon_{1i}) = 1$, $\mathrm{Var}(\epsilon_{2i}) = \sigma_{2i}^2$, and the various x's and the dependent variables are only observed if $s_i^* = 1$. In this model we have

$$E(\epsilon_{2i}|s_i^* = 1, x_{1i}, x_{2i}, x_{3i}) = \frac{(x_{1i}\gamma)\sigma_{2i}^2}{\sqrt{1 + (x_{1i}\gamma)\sigma_{2i}^2}}\,\lambda\left(\frac{(x_{1i}\gamma)x_{3i}\beta + x_{2i}\delta}{\sqrt{1 + (x_{1i}\gamma)\sigma_{2i}^2}}\right), \tag{4}$$

where $\lambda(z) = \phi(z)/\Phi(z)$ is the ratio of the standard normal pdf to the standard normal cdf. We can thus obtain consistent estimates of β on the full sample by a two-step process: first, using the survivorship bias-free sample we estimate γ, δ, β, and $\sigma_2(x)$. For each of the pre-1993 observations we form a Heckman-style correction term h_i by plugging the first-stage parameter estimates into equation (4). On the full sample we can then estimate β by regressing $r_i - h_i$ on x_{3i}.

The particulars of our estimation procedure are that the Heckman terms for the 1990–1992 period are generated by taking fund survival as the dependent variable in the selection equation; the 1988–1989 terms use the interaction of fund and manager survival as the selection variable. The x_1, x_2, and x_3 variables are those used previously in the regressions in Tables IV and V, and ϵ_{2i} is assumed to be possibly heteroskedastic with a variance that is linear in a fund's unsystematic risk level, $Unsys\ Risk_i$. The unsystematic risk variable is the standard deviation of the residuals from a regression of the fund's monthly returns on the monthly returns of the value-weighted NYSE/AMEX/Nasdaq composite.

The survival equation is estimated by a simple probit regression. The first-stage regression of returns on characteristics is estimated by GMM using lagged values of expenses and turnover as instruments for current values of expenses and turnover. The final estimates are then obtained from another instrumental variables regression, with the standard errors being corrected for the presence of the Heckman term. The mean value of the Heckman correction for the 1988–1989 sample is 0.34 (i.e., survivorship bias is predicted to make us overestimate the performance of the mean fund by 34 basis points in these years), and the mean value for the 1990–1992 sample is 0.15.[13]

The results of this estimation are presented in the fifth column of Table IV. The new estimate of the SAT coefficient lies between the previous two estimates, and is again significant at the 5 percent level. The results on age are also intermediate. The regression with the Heckman correction suggests that one-third of the age effect in column 3 is due to survivorship, which is less of an attenuation than was apparent in the fourth column. With the larger sample, the age coefficient is statistically significant at the 15 percent level.

V. Investment Styles

Recent literature in finance has described characteristics of portfolios which consistently have power in explaining cross-sectional stock returns. For example, Fama and French (1992) emphasize the fact that the stocks of small firms have consistently outperformed the shares of large firms. They construct a zero-investment portfolio in which shares of small firms are bought and shares of large firms are sold. This portfolio is the SMB portfolio. They argue also that the shares of firms with a high book value of assets divided by market value of assets outperform the market portfolio. They construct a zero-investment portfolio in which shares of high book-to-market stocks are purchased and shares of low book to market stocks are sold. This portfolio is the HML portfolio.

Jegadeesh and Titman (1993) show that firms which outperformed the market portfolio last year also tend to outperform the market this year. They construct a portfolio, PR1YR, in which last year's winners are bought and last year's losers are sold.

We remain agnostic on the question of whether the portfolios appear to be priced in the market because they truly represent risk factors or whether these portfolios simply classify categories of stock-selection styles that have performed well in the past. In either case, however, we feel that it is interesting to explore cross-sectional patterns in management styles and valuable to know what fraction of the differences between managers of different characteristics is attributable to the covariance of the manager's portfolio with these four factors. Residual excess performance can be characterized as the stock-picking ability on the manager's part which is orthogonal to his choice of weights on these factors.

First, in order to look at whether there are any systematic differences in investment styles among managers with different characteristics, we con-

[13] Our results are thus similar to those of Grinblatt and Titman (1989a) and Brown and Goetzmann (1995) (in the later years of their sample) who find that survivorship bias adds 10 to 40 basis points per year to average performance. Malkiel (1995) argues that biases in this period are much larger—50 to 100 basis points.

struct factor weightings for each fund-year in our sample by regressing the monthly return of the mutual fund on the monthly return of the RMRF portfolio, the HML portfolio, the SMB portfolio, and the PR1YR portfolio.

Table VI shows the results of regressions of the factor weights for each fund-year on the characteristics of the manager who was in charge on January 1. We again use Newey-West standard errors because we expect the residuals for a given fund to be correlated across years. In light of our findings so far that managers from higher-SAT schools exhibit superior performance, it is notable that no particular tendencies of the higher-SAT managers reveal themselves in this table.

Two interesting tendencies are apparent in the table. First, managers with MBAs show a statistically significant tendency to purchase "glamour" stocks—that is, stocks with low book-to-market ratios. Second, it appears that older managers may have a greater tendency to use momentum strategies, as evidenced by the positive association between age and PR1YR.

The sixth and seventh columns of Table IV examine the possibility that style differences might explain some of the systematic performance differences we find. The dependent variable for each of the regressions is the excess return for a fund in a given year, $Alpha4_{it}$, and is calculated using a four-factor model with year-specific weights.[14] The use of four-factor excess returns is motivated by a desire to know whether the superior performance of managers from higher-SAT schools is attributable to a "market timing" effect of being in the right categories in the years we study or whether it reflects superior stock picking within categories. If, for example, their superior performance is entirely attributable to their having invested more heavily in growth stocks (which outperformed value stocks in the years we study), then the coefficient of the SAT variable will drop to zero when HML is included as a factor. Other than having a different dependent variable, the regression reported in column 6 of Table IV is specified like that of column 4—that is, it is an IV regression on the 1992–1994 reduced-survivorship bias sample. Column 7 is comparable to column 5 with the results being those obtained by applying a Heckman-selection correction to the full sample. In both columns, it is clear that the overperformance of higher-SAT managers is not diminished at all by using the four-factor residuals as the performance measure. This is not surprising because the SAT variable is not highly correlated with loadings on the factor portfolios.

The coefficient for MBA is positive in this specification but not statistically significant. Recall that in our prior analysis we find that the tendency of MBA managers to manage high-beta funds fully explains all of the excess

[14] Specifically, the dependent variable is $Alpha4_{it} \equiv r_{it} - rf_t - X_t\hat{\beta}_{it}$, where X_t is a vector giving the realized return in year t of each of the four-factor portfolios (RMRF, HMB, SMB, and PR1YR) and $\hat{\beta}_{it}$ are the fund-year specific factor weights obtained from a regression of monthly excess returns on a constant and the four factors. This procedure for constructing the dependent variable is similar to that of Sharpe (1992), with the primary difference being that Sharpe uses 12 factors and weights estimated from the previous 60 months but we use four factors and estimate the weights from the concurrent 12-month period.

returns of MBA managers which are apparent using simple excess returns. The positive point estimates of the within-category stock-picking ability in the four-factor model stems from the fact that the MBA managers are earning roughly average returns, despite having loaded up on "glamour" stocks.

Finally, the greatest change resulting from looking at four-factor excess returns is that the coefficient for the age variable becomes more strongly negative and is significant at the 5 percent level in both samples. The coefficient of the age variable indicates that each additional year in manager age is expected to erode manager performance by approximately four basis points. Thus, the predicted performance difference between a 30-year-old manager and a 55-year-old manager is about one percentage point per year.

VI. Do Good Managers Beat the Market?

The previous sections have shown that some of the puzzle of large systematic cross-sectional differences in fund performance are explained by risk-taking, expenses, survivorship biases, and investment styles. However, we do find that some residual amount of the cross-sectional differences (particularly between managers who attended colleges with different average SAT scores) are not explained away by these factors. In this section, we provide some sense of the practical relevance of these performance differences by examining whether predicted differences are big enough for managers with "good" characteristics to be predicted to beat the market. The question is also motivated by a desire to know whether some consumers may be acting rationally in choosing actively managed funds over index funds.

Because interpretation of our results will vary with one's view of market efficiency, it is worth noting that in our sample the funds on average earn above market returns on their investments which partially offset their expenses. In our one-factor Heckman-corrected model, the predicted risk-adjusted excess return of a fund with the mean characteristics is −0.41 percent per year. This is 95 basis points higher than expected if funds match the market on their investments given that the mean expense ratio is about 1.36 percent. The difference is significant at the 1 percent level. This result is roughly consistent with the previous literature.[15] However, we would like to be cautious in drawing conclusions about average performance levels. Our analysis ignores those survivorship biases that result from ignoring partial year returns in the year of a fund's death, and the standard errors are cal-

[15] In the earliest study of this question, Jensen (1968) does not find significant evidence of excess pre-expense performance in the 1945–1964 period. More recent studies that control for survivorship bias typically find positive pre-expense excess performance and negative post-expense excess performance. For example, in the most recent study we have seen, Carhart (1997) finds that mutual fund simple excess returns from 1961 to 1993 average −0.5 percent per year and the average expense ratio is 1.14 percent. Malkiel (1995) appears to be the exception in claiming that pre-expense excess returns are negative.

culated assuming all fund returns are independent. Further, our sample does not extend to 1995—a year in which mutual funds on average trailed the market.

Although the average fund earns back less than three-quarters of its expenses in excess returns on its investments, our previous results naturally lead one to wonder whether better managers are able to beat the market. Our answer to this question depends on what level of expenses a manager is trying to overcome. If one looks at a fund with the mean expense ratio we find very weak evidence that managers from higher-SAT schools are able to beat the market. Our point estimates indicate that a fund that otherwise has the mean characteristics is expected to beat the market if its manager attended a school with an average SAT score above 1283. However, even for a manager from a school with the highest SAT score in our sample (1420), the predicted excess return (39 basis points) is not statistically different from zero at standard confidence levels.

Because expenses are a very important predictor of returns, it is much easier for funds with lower expenses to beat the market. If one looks, for example, at a hypothetical fund with expenses at the 25th percentile in our sample (0.91 percent) our point estimates are that even a manager from a school with an average SAT score of 1046 (which is 100 points below the sample mean) would be expected to beat the market.[16] The predicted excess performance of a manager from a school with an SAT score of 1205 is 45 basis points per year, which is significantly greater than zero at the 5 percent level. Forty-seven of the 189 schools in our sample have SAT scores this high, and their alumni manage about one-third of the funds.

Overall, the distribution of expenses, SAT scores, etc. in our data is such that 38 percent of the funds are predicted to beat the market, and for approximately 14 percent of the funds the predicted excess performance is sufficiently large to be significant at the 5 percent level. We do not want to emphasize these results too much, however, both for the reasons noted above and because they involve making predictions away from the sample mean while maintaining the assumption of linearity.

VII. Conclusion

The results in this paper suggest that there are some systematic cross-sectional differences in fund manager performance that cannot easily be attributed to differences in managerial behavior. In particular, we find that mutual fund managers who attended more selective undergraduate institutions have higher performance than mutual fund managers who attended less selective undergraduate institutions, after correcting for differences in risk characteristics, survivorship biases, differences in expense ratios, and

[16] Although expenses of 0.91 percent are only the 25th percentile expenses in our sample, they are close to the expenses that the typical investor faces. On an asset-weighted basis, the mean expense ratio in our sample is 0.89 percent.

differences in factor loadings in a four-factor model. Of course, we cannot rule out explanations such as the performance differences being due to differences in unreported expenses. However, these results are somewhat suggestive that "stock-picking" ability does exist for a subgroup of managers. Perhaps more surprising is that our data also suggest that some managers may be expected to beat the market even taking into account the expenses they charge.

As we mention earlier, there are many possible explanations for our finding that SAT scores are predictive of performance. Among others, this finding could reflect differences in inherent stock-picking ability, direct benefits from a better education, differences in the value of the social networks that different schools provide, or it could be related to characteristics of the fund companies that tend to hire managers from different types of schools. We, of course, wish that we could do more to distinguish between these explanations.

One interesting idea for potentially distinguishing the social-networks explanation from the others which was suggested to us would be to examine whether the performance of women managers is less strongly related to the SAT score of the college they attended. One might expect that this would be the case if the value that a high-SAT school provides is a social network and if women have a harder time getting plugged in to these networks. Unfortunately, given that only 7 percent of the managers in our sample are women, we are unable to provide clear evidence on this question. When we add a dummy for being a woman and a woman dummy-SAT interaction to our model, we cannot reject the hypothesis that the SAT-performance relationship is as strong for women as it is for men, nor can we reject the hypothesis that there is no relationship at all for women.[17]

We also find (although the result is somewhat more fragile) that older managers have worse performance than younger managers. Once again, a number of distinct mechanisms could account for the performance result. The explanation we find most plausible is that this could be a result of career concerns—younger managers may work harder because they have a longer career ahead of them and because, as we show, they are more likely to be fired for poor performance. Alternatively, it is also consistent with the hypothesis that older managers are less well educated as well as with a reverse selection effect in which "better" managers tend to exit the industry (perhaps to manage institutional money) before they get old.[18]

[17] In our Heckman-corrected regression with *Alpha* as the dependent variable (i.e., in a specification that is otherwise like that of column 5 of Table IV) the point estimate is that the SAT effect is about half as large for women as it is for men. With *Alpha*4 as the dependent variable, the point estimate is that the SAT effect is slightly stronger for women managers. In our reduced survivorship bias sample, the point estimate with either dependent variable is that the SAT effect is weaker for women than for men.

[18] Separating different hypotheses about why age matters is not as easy as it might at first appear. For example, one natural test might be to add "fixed effects" and ascertain whether a given manager's performance deteriorates over time. Although this pattern does clearly exist in the data, it would be expected even if ability does not decline, given that managers tend to be fired following poor performance.

The finding that some managers are better than others would be paradoxical in a world with perfectly efficient asset markets, but we find it perfectly natural in a world of informationally efficient markets. If the job of a mutual fund manager is to gather and analyze information in a nearly efficient market, the claim that some managers are better than others need not be any more surprising than a claim that some physicians or some economists are better than others.

Appendix

The first problem that occurs in matching managers to institutional SAT scores is the situation in which several institutions share the same or similar names, and the managers' biographies do not make it clear which institution the manager attended. The following procedure (in order) is adopted in these circumstances:

(1) If the manager's biography indicates the birthplace of the manager, and one of the candidate institutions is located in the manager's home state, or a state adjacent to the manager's home state, the manager is assumed to have attended that institution. For example, one manager who attended "Miami University" and whose birthplace is listed as Ohio is assumed to have attended Miami University in Ohio, rather than the University of Miami in Florida.

(2) If (1) does not apply, but the manager's graduate degree is from a school located in the same state, or a state adjacent to one of the candidate institutions, the manager is assumed to have attended that institution. For example, a manager whose birthplace is not listed, but who received an MBA from Ohio State University, is also assumed to have attended Miami University in Ohio.

(3) If neither (1) nor (2) applies, the manager is assumed to have attended the larger school. This problem was most common for schools with religious affiliations. For example, there are six St. Joseph's Colleges in the United States. Any biases introduced by such misassignments should be small, in part because the candidate institutions tend to have very similar SAT scores.

Once a manager is assigned to an undergraduate institution, the undergraduate institution is assigned an SAT score. The modal form of SAT assigment is described in the text. Of the 235 institutions attended by our fund managers, this methodology can be used for 144 of them. When the data in the standard form are not available, one of the following procedures is used to assign an SAT score to each school. The methodologies are listed in their preferred order; if a lower-numbered methodology is available, it is used in preference to a higher-numbered methodology.

(1) Forty schools submitted a listing of the percentage of students scoring in certain ranges. For example, a listing for verbal scores might be Verbal: 700+ 2 percent; 600—699, 20 percent; 500—599, 50 percent; 400—499, 20 percent; 300—399, 5 percent; below 300, 3 percent. In this case, mid-50-percent ranges are estimated by interpolating. The mid-50-percent ranges are treated as described in the text.

(2) Fourteen other schools reported mean SAT scores (sometimes composite, sometimes verbal and math) in place of mid-50-percent ranges. The mean scores are taken in place of the midpoint of the mid-50-percent ranges and are treated as in the text. This methodology was used to calculate SAT numbers for 14 schools.

(3) Twelve other schools (most in the Midwest or Southwest) report ACT score mid-50-percent ranges. Using data from the schools in our sample which report mid-50-percent ranges for both the ACT and SAT math and English/verbal tests, we construct predicted mid-50-percent math and verbal SAT score ranges for the 12 schools that reported only ACT scores and then form a composite SAT score as before. For example, to construct the high endpoint of the SAT math range we use predicted values from a regression of SAT math high on ACT math low, ACT math high, ACT math low squared, and ACT math high squared.

(4) Five other schools report ACT English and math averages rather than mid-50-percent ranges. There are not enough schools reporting both SAT averages and ACT averages to run regressions as above. Thus, the regressions in (3) are rerun on the same data, using the midpoint of the SAT-50-percent ranges as the dependent variable, and the midpoint of the ACT-50-percent ranges and the midpoint squared as the independent variables. The ACT means are inserted in place of the midpoint of the ACT-50-percent ranges in order to calculate predicted SAT scores.

(5) Eight schools report only ACT composite score numbers, rather than ACT English and math numbers. This poses some difficulty, because the ACT composite score includes a science test that has no analogue in the SAT (the ACT composite score is a mean, rather than a sum). Nonetheless, the ACT composite scores are treated as if they represented only English and math scores, and are treated as in (3).

(6) Twelve schools report no standardized test scores. For these schools, we do have available Lovejoy's selectivity index, which ranges from 1 to 5 and is supposed to represent Lovejoy's information about the SAT scores of admitted students as well as the GPAs of admitted students. We assign to each of these schools the mean SAT score for the schools in our sample which have the same selectivity index and have reported SAT scores.

One drawback of using SAT scores as our measure of college quality is that all managers who attended foreign universities must be dropped from the dataset. Our final performance specifications (columns 5 and 7 of Table IV) use 1705 fund-year observations. We drop 31 additional observations solely because the manager attended a foreign institution.

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