Inexperienced Investors and Bubbles [*]

Robin Greenwood
Harvard Business School

Stefan Nagel
Stanford University and NBER

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Abstract

It is a popular hypothesis that inexperienced investors play a role in the formation of asset price bubbles. Without first-hand experience of a downturn, these investors may underestimate the likelihood that stock prices can go down, and be more willing to buy overpriced stocks. Using age as a proxy for investment experience, we compare the portfolio holdings and returns of young and old mutual fund managers during and after the technology stock bubble. Around the peak of the bubble, mutual funds run by younger managers are more heavily invested in technology stocks, relative to their style benchmarks, than their older colleagues. Consistent with experimental evidence on inexperienced traders, we find that young managers, but not old managers, exhibit trend-chasing behavior in their technology stock investments. Our results are unlikely to be explained by standard career concerns models or by differences in the ability between younger and older managers to pick technology stocks.

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I. Introduction

Stock market folklore is rich in anecdotes about inexperienced investors drawn into the market during financial market bubbles. In his classic history of financial speculation, Kindleberger (1979) argues that bubbles bring in "segments of the population that are normally aloof from such ventures." Recalling the 17th century tulip bubble, Mackay (1852) reports that "even chimney-sweeps and old clotheswomen dabbled in tulips." More recently, Brennan (2004) proposes that an increase in participation by individuals with little investment experience may have been the driving factor of the internet stock price boom of the late 1990s. The common theme in these historical accounts is that inexperienced investors, who have not yet directly experienced the consequences of a stock market downturn, are more prone to the optimism that fuels the bubble.

In this paper, we study the portfolio decisions of experienced and inexperienced mutual fund managers during the technology bubble of the late 1990s.[1] Our main hypothesis is that inexperience affects investment decisions through its role in forming expectations. Using manager age as a proxy for experience, we examine whether younger managers were more likely to bet on technology stocks. At the start of the bubble, younger managers show little deviation from older managers. In fact, managers under age 35 have slightly lower technology stock exposure than the average manager in their Morningstar style category. But leading up to the peak in March 2000, younger managers strongly increase their holdings of technology stocks relative to their style benchmarks, while older managers do not.

Our findings are consistent with evidence from experiments and retail investor surveys. Smith, Suchanek, and Williams (1988) find that bubbles and crashes occur regularly in laboratory asset markets, but are less likely when subjects have experienced bubbles and crashes in prior trading sessions. Summarizing data from retail investor surveys, Vissing-Jorgensen (2003) shows that young, inexperienced investors had the highest stock market return expectations in the late 1990s. Our results show that the

[1] While our analysis is motivated by the idea that there seems to have been an asset price bubble during the late 1990s (e.g., Shiller, 2000; Ofek and Richardson, 2003; Hong, Scheinkman Xiong, 2005; Abreu and Brunnermeier, 2003), the question of whether young and old manager differed in their willingness to invest in these high priced stocks and, if so, what explains this heterogeneity, is relevant even if prices could perhaps be justified by fundamentals (e.g., as argued by Pastor and Veronesi, 2005).

effects of inexperience are not limited to participants in laboratory experiments, or to retail investors, but also influence professional money managers. *A priori*, the professionals in our sample are perhaps the least likely to be affected by behavioral biases.

Experimental findings provide cues about the channel through which inexperience affects portfolio decisions. The study by Smith et al. shows that inexperienced traders have adaptive expectations. Similarly, Haruvy, Lahav, and Noussair (2006) find that subjects extrapolate recent price movements. To see whether adaptive learning also plays a role for the young fund managers in our sample, we study how younger and older managers tilted their holdings in response to past returns of technology stocks. Younger managers increase their technology holdings following quarters in which technology stocks experience high returns, while older managers do not. Thus, during our sample period, younger managers appear to be trend chasers, in contrast with contrarian older counterparts. Interestingly, this pattern repeats during the crash of technology stocks in 2000 and 2001. Following low returns, younger managers are more likely to rebalance away from technology stocks.

To assess the economic significance of these results, we examine the total net assets and the flows into funds of young and old managers. If retail investors recognized younger managers' inexperience and withdrew their money from (or, at least, limited their flows into) these funds, the economic importance of younger managers' investment decisions would be limited. But this is not the case. At the end of 1997, younger managers start out with relatively small funds, but by the time of the market peak in March 2000, their assets under management had roughly quadrupled, even surpassing the average fund size of all other age groups. To some extent, this increase reflects rising technology stock prices, but much of it is driven by large abnormal inflows. As a result, at the peak of the market, a significant fraction of institutional money is controlled by young managers. Interestingly, during the subsequent downturn of technology stock prices, younger managers do not experience significant abnormal outflows compared with their Morningstar category peers, despite their poor performance. Thus, from the perspective of the mutual fund company, the relative underperformance of young managers in the post-bubble period turns out not to be that costly.

Our results fit well with adaptive expectations models of learning. According to this interpretation, the trend-chasing behavior of young managers reflects their attempts to learn and extrapolate from the little data they have experienced in their careers. Such extrapolation may be excessive if young managers don't properly adjust for the small sample of data at hand (e.g., as in Rabin 2002), or use simple models to forecast returns (e.g., as in Hong, Stein, and Yu, 2006). More broadly, our results are consistent with evidence that people learn how to solve decision problems primarily through learning-by-doing and behavioral biases become less prevalent as experience accumulates (Camerer and Hogarth 1999; List 2003; Feng and Seasholes 2005). It thus seems natural that inexperience affects investment decisions relating to rare and relatively long-term phenomena such as asset price bubbles. The development from bubble to crash can take years, and a similar pattern might not repeat for decades. In contrast, there is less of a role for inexperience in more frequent phenomena, such as earnings announcements, which young managers have ample opportunity to experience first-hand.

We also consider a variety of alternative explanations for our results. A natural place to look is in the set agency relationships between fund managers, fund management companies, and retail investors.

Career concerns, for example, could lead young and old managers to differ in their investment choices. In particular, career concerns may incentivize young managers to herd (Scharfstein and Stein, 1990; Zwiebel, 1995). Chevalier and Ellison (1999a) find that funds run by young managers have lower tracking error than funds run by older managers, which supports the herding theories (see also Hong, Kubik, and Solomon, 2000; and Lamont, 1995). In light of this earlier evidence, it is particularly remarkable that the young managers in our sample period *deviate* from their category benchmark towards technology stocks. Our results do not rule out that herding may help explain differences between young and old managers' investment choices more generally, but this deviation from benchmarks on the dimension of technology stock exposure appears inconsistent with herding.

We also consider the possibility that young managers possess specific human capital that allows them to analyze new technologies better than old managers. Analyzing internet-related technologies may have required considerable effort, and the costs may have been lower for younger managers. According to this view, not only would younger managers have shifted their focus towards technology stocks, but they should have been more successful at stock-picking within the technology sector relative to their older colleagues. Using various performance metrics, however, we don't find any evidence for systematic outperformance by younger managers. While younger managers outperform before the peak in March 2000, they significantly underperform after the peak, averaging out to about zero. Hence, there is no evidence that young managers were better at picking stocks during this period of high technology stock price volatility. Therefore, we doubt that human capital theories help explain our results.

One twist on the human capital story that could perhaps fit some of our results is suggested by Hong, Scheinkman, and Xiong (2005). Their model would suggest that young managers might better understand new technologies, but intentionally take excessive positions in technology stocks to signal to smart investors that they understand the new technology, as opposed to old managers, who are limited to downward biased signals. Somewhat similar implications follow from the model of Prendergast and Stole (1996), in which young managers want to acquire a reputation for quick learning, which leads them to exaggerate their information. It is not clear, though, whether these models are consistent with the fact that young managers did not perform better than the average investor in technology stocks once prices collapsed.

A final possibility is that part of our results could be driven by window-dressing by fund managers around the time of their reporting dates (Lakonishok, Shleifer, Thaler, and Vishny 1991). For example, Cooper, Gulen, and Rau (2004) show that during a period that overlaps with our sample period, funds could attract additional inflows merely by changing the name of their fund to reflect a popular investment style. To make sure our holdings-based results are not driven by pure window-dressing that is reversed once the holdings have been disclosed, we also analyze funds' return betas on a tech-stock index and find similar results.

Our paper shares with some existing work the objective of getting a better understanding of investor behavior during the technology bubble, with the ultimate goal of understanding why and when bubbles might develop. Brunnermeier and Nagel (2004) find that hedge funds had invested heavily in technology stocks. Temin and Voth (2004) find similar results in the trading records of an English Bank during the South Sea Bubble of the 18th century. Their results differ from ours in that the investors studied in these papers strongly outperform benchmarks, suggesting they had some ability to anticipate price movements during the bubble and subsequent crash. Griffin, Harris, and Topaloglu (2005) examine the trading behavior of various investor groups at daily frequency and find evidence suggesting that it was largely institutional investors who drove and burst the technology bubble. Dass, Massa, and Patgiri (2005) show that mutual funds with high-incentive contracts had relatively lower exposure to technology stocks.

The paper proceeds as follows. Section II describes our data and provides summary statistics. Section III presents the results and relates them to theories about fund manager behavior. Section IV concludes.

II. Data

A. Defining the Bubble Segment

We follow Brunnermeier and Nagel (2004) and use the price/sales ratio to identify stocks affected by the technology bubble. For ease of reference, we use "high price/sales stocks" and "technology stocks" as synonymous in the rest of the paper. It is useful to have a continuous measure to classify stocks, as opposed to a discrete indicator for industry or internet stock index membership, for example. Moreover, Lewellen (2003) reports that almost all internet stocks in March 2000 had extremely high prices/sales ratios relative to other stocks, and so our P/S classification should do a good job of capturing the segment of the market most affected by the technology bubble. Figure 1 illustrates this by plotting the buy-and-hold returns of a value-weighted portfolio of Nasdaq stocks in the highest price/sales quintile (rebalanced monthly) from December 1997 to December 2002 (thick line) against the buy-and-hold return on the CRSP value-weighted index. Prices of high price/sales Nasdaq stocks almost quadrupled over a two-year period, only to lose all of these gains in the subsequent two years. For comparison, Ofek and Richardson (2003) report that their internet stock index increased by about 1000% from the end of 1997 to March 2000. The 40% gain in the CRSP value-weighted index over this time period pales in comparison with the gains of internet and high price/sales stocks. But it is useful to keep in mind that even for the market index valuations measured by price/sales or price/earnings reached unprecedented values around March 2000 (see, e.g., Shiller 2000).

B. Data on Funds and Characteristics of Managers

We require data on the characteristics and managers of all equity mutual funds in operation at the end of December 1997. We choose the end of 1997 as our pre-bubble cutoff because the following year is the first time when technology stocks meaningfully outperform the market.

Morningstar maintains a database of mutual funds and the identity of their managers, including their start and end dates. We identify all equity domestic mutual funds in existence at the end of 1997. Morningstar classifies funds according to benchmark based on their holdings and objectives identified in their annual reports to shareholders. Based on these benchmarks and fund names, we exclude index funds and specialty sector funds, such as “precious metals,” because the managers of these portfolios are unlikely to have any discretion over their allocation in technology stocks. This leaves the classifications “conservative allocation,” “moderate allocation,” “large blend,” “mid-cap blend,” “small blend,” “large growth,” “mid-cap growth,” “small growth,” “mid-cap value,” and “large value.”

Using these data, we identify at the end of each month (a) the number of managers running the fund, (b) the characteristics of the median manager of the fund. The characteristic we are most interested in is the age of the manager. We use it as a proxy for inexperience. Ideally, we would like to have the number of years of experience on the job, but since Morningstar does not have reliable manager personal data before 1994, it is not possible to construct managers’ career histories. We infer the age in the following way. For approximately 25 percent of the managers in its database, Morningstar reports the date of birth, which we then use to compute age. For others, we use the same approach as Chevalier and Ellison (1999a) and back out age by assuming that the manager was age 22 at college graduation. Rather than advance the age of managers month-by-month, we calculate the age of the manager as of December 1997 and permanently assign this age to the fund for the entire sample period. This means that if the fund manager changes at some point during the sample period, we still classify this fund based on the age of the manager that was in place in December 1997. This introduces some noise when managers switch jobs, but we deliberately use this method to avoid a potential endogeneity problem. Our aim is to track the investment policy of young and old managers over time. But if we were to update age of the fund manager over time, our results could be driven by a tendency of fund management companies to hire young managers in order to implement a shift towards technology stocks (for example, because fund management companies believe that young managers will be better at running a technology stock fund). In any case, untabulated robustness checks show that our main results are quantitatively similar if we update the fund manager age each month.

In circumstances where there is more than one manager, we assign the median age of the team to the fund.[2] In a small fraction of cases, our data indicate that the fund is run by more than one manager, but demographic information is not available for every one of the managers. In these cases, we use the available data to form our best estimate of age. This type of data omission is rare, however, as demographic data is more commonly available for either all or none of the managers of a particular fund. Where no data at all is available, we drop the observation

We further collect other demographic variables that might proxy for training, ability, or the willingness of managers to take risks. These, too, are measured in December 1997. For the subset of managers who report data on college graduation, we use data from Business Week on the average SAT scores of entering university students to calculate the mean SAT score for each school, which we then match to the managers of the fund. Of our manager characteristics, the SAT score has the lowest data coverage. Where this data item is missing, but data is available for the other measures, we replace it with the sample mean SAT. We also check whether the manager has passed the certified financial analyst (CFA) exam. If there are multiple managers, we take the mean of the CFA and SAT variables for the team. We also calculate the number of women managers.

[2] We obtain similar results using the mean. The choice of the median could be motivated by the median voter theorem-- if we assume that investment decisions within a team are made by majority voting and that age is closely related to a managers opinion on how much to invest in technology stocks.

Thomson Financial maintains a database of mutual fund holdings between 1980 and 2005, collected from semi-annual SEC filings and from quarterly reports of mutual funds. We match these holdings to our Morningstar sample. Our objective is to measure the manager's allocation to technology stocks at the end of each quarter. For about two-thirds of the funds the data is available quarterly, and for a most of the others semi-annually. We first align all data at quarter-ends by assuming that funds did not trade until the end of the quarter. Thus, if a fund reports holdings as of May 31 (Thomson RDATE), for example, we assume that holdings (in terms of number of shares) stay the same until June 30. For funds that have missing data because the data is available only at semi-annual frequency, we substitute in the holdings from the previous quarter for the missing quarter. As a result, there is some staleness in our holdings data, and it's useful to keep this in mind when interpreting the holdings-based results. We then match each fund's stock holdings to CRSP and Compustat to calculate quarterly returns, prices, the price/sales ratio, and market capitalization for each stock. There is variation across funds in the fraction of holdings for which we are able to calculate price/sales ratios. We exclude funds for which we have data on less than 10 stocks, or less than 30 % of their holdings by value.

Finally, we also match each fund in our Morningstar data to the CRSP mutual funds database to collect monthly total net assets and monthly fund returns. In some of our tests, we also use data on portfolio turnover and fees from the CRSP mutual funds database. For all of our tests, we then aggregate the CRSP and Morningstar data for different share classes to fund-level observations.

While the data we obtained from Morningstar contains information on dead funds, it drops identifying information (fund tickers) once the fund has been delisted, or the fund class discontinued. Therefore, if one were to mechanically match the data with fund returns from the CRSP mutual funds database, for example, the resulting data would exhibit survivor bias. To counter this, we lookup all missing tickers manually before attempting to match to other sources. We did extensive checks to ensure that there is no survivor bias introduces in the process of matching the Morningstar data with CRSP and with the Thomson Mutual funds data. The Appendix provides some information on the outcome of our matching process. The bottom line is that we have no reason to suspect that our matched data set should be affected by survivor bias.

C. Alternative Measure of Exposure to Technology Stocks: Return Regressions

Most of our tests use the (value-weighted) average price/sales ratios for each fund, calculated based on the Thomson stock holdings data. But for robustness, we also employ an alternative measure of technology stock exposure. One shortcoming of the holdings data is that we cannot observe the positions held by the fund between quarterly or semi-annual reporting dates. To rule out that the holdings reported in the Thomson database are substantially different from the intra-period holdings, we estimate the technology exposure by running a regression of fund returns on a the value-weighted market return (R_{Mt}) and a zero-investment portfolio return that proxies as a technology factor: The return on high P/S quintile stocks on Nasdaq (R_{Tt}) minus R_{Mt}.

$$R_t = \alpha + \beta R_{Mt} + \gamma_{\text{Tech}} (R_{Tt} - R_{Mt}) + \varepsilon_t . \qquad (1)$$

For each fund in our sample, we estimate γ_{Tech} using monthly return data between January 1998 and March 2000. Funds with a high proportion of technology stocks in their portfolios should have a large positive γ_{Tech}. Funds that avoid technology stocks should have a large negative γ_{Tech}, funds that hold approximately the market portfolio should have $\gamma_{\text{Tech}} = 0$. In the full sample, our estimates of γ_{Tech} range from -0.79 (Goldman Sachs Large Value) to 1.94 (ProFunds Ultra). Empirically, we find an average cross-sectional correlation of 49% between γ_{Tech} and the value-weighted average price/sales ratio of a fund at the peak of the bubble (March 2000), and a 62% correlation between γ_{Tech} and the value-weighted average price/sales quintile of the stocks held by a fund.

D. Summary Statistics

Table 1, Panel A, reports some basic summary statistics on our fund manager data. A couple of points are noteworthy here. First, the number of observations varies depending on data requirements. For our basic sample, we require Morningstar and CRSP data, which we have for 1,079 funds (where we aggregated multiple share classes of a fund). For the price/sales ratio in March 2000, we need Thomson holdings data, too, and the fund must have survived until March 2000, which leaves 855 funds.

Second, the distribution of total net assets is highly skewed (mean $880 million; median $152 million). In our analyses, we want to avoid that results are driven by the smallest funds, which are economically less important. For this reason, in most of our tests, we weight observations by the lagged total net assets of the fund, but for robustness checks we also report some equal-weighted results.

Third, the mean and median fund manger is close to 45 years old. Figure 2, Panel A, plots the distribution of mutual fund manager age. Naturally, the number of funds with managers aged 30 and lower is small, but the category from 31 to 35 years contains more funds. Together, the two groups account for about 12% of the total number of funds.

Fourth, the median fund is run by a single manager, while the mean number of team members is 1.85. Panel B of Figure 1 provides the distribution. It shows that having more than 3 managers in a team is rare. We also verify that within the group of funds that are run by a single manager, the age of the manager is distributed similarly to Panel A of Figure 1, with a slightly greater percentage of younger managers.

Panel A of Table 1 also shows that the distribution of fund-level price/sales ratios, calculated as the value-weighted average of price/sales ratios of the stocks in a fund's portfolio, is extremely skewed, with a median of 12, a minimum greater than zero, and a standard deviation of 130. This raises the concern that averages of the price/sales ratio across funds may be susceptible to excessive influence by outliers. For this reason, most of our tests are run with the natural logarithm of the funds' price/sales ratios. The table indicates that the log price/sales ratio has a roughly symmetric distribution.

Panel B of Table 1 shows that the log price/sales ratio varies significantly by benchmark, with large value portfolios averaging approximately 1.24 in March 2000, and small growth portfolios averaging approximately 3.51. The table also reveals some variation within benchmark groups, but the spread between the means of value and growth categories is roughly twice the typical within-group standard deviation, suggesting that the Morningstar benchmarks capture a sizeable share of the variation. This highlights the need to make sure that our results are robust to adjusting for style benchmarks. Young managers could be more likely to be in control of a growth fund, which would then automatically imply a higher (unadjusted) price/sales ratio for young managers. The distribution of fund manager age by Morningstar style category shown Panel C of Table 1 suggests that young managers are indeed a bit more likely to be in charge of a growth fund, but not by much.

III. Results

A. Holdings of technology stocks of young and old managers

We start by describing some basic statistics that foreshadow our main results. Panel A of Figure 3 plots the value-weighted average log price/sales ratio, by age group, starting in the 4th quarter of 1997 and ending in the 4th quarter of 2002. Log price/sales ratios drift upwards for all groups through early 2000, a simple consequence of the broad stock market rally. While the figure reveals some differences between young and old managers in 1998, the spread widens significantly in late 1999 and early 2000, reaching its peak in the second and third quarters of 2000.

Panel B presents the same results, but adjusted by the value-weighted Morningstar category mean. Relative to other managers with the same benchmark, younger mutual fund managers start out neutral, and sometimes underweighted in technology stocks, but they increase their price/sales ratios rapidly between March 1999 and June 2000. The difference between Panel A and the adjusted results in Panel B underscores the importance of controlling for the benchmark. Without the adjustment, younger managers appear to start with a relatively larger allocation to technology stocks, but this is a consequence of the fact that young managers disproportionately manage small capitalization and growth oriented funds. The adjustment eliminates this bias, showing that the differences between young and old develop only after technology stocks began to outperform in 1998. Looking across the other age categories, we have, at the peak of the bubble in March 2000, an almost monotonic relationship between age and adjusted log price/sales. Only the age > 65 category breaks the monotonicity. But then, the number of managers in this category is also very small (Figure 2, Panel A).

Table 2 presents the regression results corresponding to Figure 3. We estimate cross-sectional regressions of log price/sales ratios in March 2000 on manager age and a set of controls,

$$Log(P/S)_i = a + bAge_i + cFemale_i + dCFA_i + eSAT_i + fTeam_i + gZ_i + u_i \,. \tag{2}$$

Log price/sales ratios are measured in March 2000, the peak of the bubble.[3] The control variables include a dummy variable indicating whether the manager is a woman (*Female*), a dummy variable indicating whether the manager completed the Certified Financial Analyst exam (*CFA*), the mean SAT score of the university attended by the manager (scaled by total maximum score), and a dummy variable indicating whether the fund was managed by more than person (*Team*). For funds managed by more than one person, *Female* and *CFA* are expressed as a share of the number of managers and *SAT* is given by the average of the managers who report the name of their university.

The first column shows the basic result. Age is significantly related to technology exposure, with each year reducing log price/sales by 0.02. To put this in perspective, the implied spread in log price/sales ratios between a 25-year old and 65-year old manger is 0.80, approximately a quarter of the median log price/sales ratio of 2.47 (Table 1, Panel A), and about 70% of the typical benchmark-adjusted standard deviation of fund-level log price/sales ratios (Table 1, Panel B). Hence, the effect of age is clearly economically significant.

As in Figure 3, one would like to control for the benchmark faced by each manager to eliminate the possibility that we are simply picking up a composition effect because younger managers are in charge of more growth-oriented funds. We do this in two different ways. First, we estimate loadings on the three Fama-French (1993) factors (SMB, HML, and RMRF) by running regressions of monthly fund returns on the contemporaneous returns of the three factors. The time period for these regressions is January 1995 through December 1997. The combination of these factor loadings (β_{HML}, β_{SMB}, β_{RMRF}) provides a proxy for the prior benchmark of these funds without relying on possibly self-serving reported classifications. Not surprisingly, value funds tend to have higher β_{HML}, and small stock funds tend to have higher β_{SMB}. As the

[3] Similar results obtain for all quarters in the year 2000.

table shows, controlling for these loadings, there is still a negative correlation between log price/sales in March 2000 and the age of the manager.

A simpler and probably more effective way to control for benchmark is to add fixed effects for each of the Morningstar style categories. These results are shown in specification (3), yielding almost identical coefficients on manager age. The R-squared is higher than in specification (2), suggesting that the fixed effects better categorize funds than the lagged Fama-French factor coefficients.

Finally, we re-estimate the baseline regression, weighting each observation by total net assets in December 1997. These regressions correspond most closely with the value-weighted results shown in Figure 3 and attest to the economic relevance of our findings. It is reassuring that the value-weighted results are as strong as the equal-weighted results, as it confirms that our principal findings are not driven by a few small funds.

Although not our main focus, it is worth pausing to look at the sensitivity of technology exposure to the control variables. Funds that are run by teams are more likely to invest in high price/sales stocks, although the effect is only significant in one instance. *CFA* and *SAT*, two variables that proxy for cognitive ability (e.g., Frey and Detterman, 2004), do not enter consistently.

The right-hand-side columns of Table 2 re-estimate the cross-sectional regressions, replacing the log price/sales ratio with γ_{Tech}, our regression-based measure of technology stock exposure. Because γ_{Tech} is based on correlations of funds returns with technology returns over the entire pre-peak period, not just a snapshot in March 2000, we might expect these results to be somewhat weaker. On the other hand, γ_{Tech} is a cleaner measure of technology exposure if funds were taking offsetting short positions in other technology stocks, in which case our previous results would be overstated. Moreover, it also provides a bigger sample size, because we don't need data from the Thomson holdings database for these test. As the table shows, the age effect is strong and significant in specifications (5) – (8), with and without the category-level controls.

Robustness

A number of variations of the basic specification confirm our main result. For each set of tests listed below, we repeat the results in both equal-weighted (OLS) and value-weighted (WLS) regressions, and category-level fixed effects are included in each case.

i. Alternative measures of technology exposure: We first experiment with different measures of technology stocks exposure. We re-run our tests with the simple price/sales ratio, which has considerably more cross-sectional dispersion than the log price/sales ratio due to a number of growth fund outliers. Nevertheless, specifications (1) and (2) show that our basic results go through. We also try a quantile-based measure, using the value-weighted average of the price/sales quintiles of stocks in the fund portfolio as the dependent variable (Specifications (7) and (8)).

ii. Single managers v. Teams of managers: Chevalier and Ellison (1999b) restrict their sample to funds run by a single manager. For our main tests, we include team-managed funds, too, but (3) and (4) show that the results are similar for single manager funds and team-managed funds. Unsurprisingly, the results are stronger among single manager funds, for which we have a more precise measure of inexperience.

iii. Within age groups: As Figure 3 suggests that our main results are primarily driven by differences between the youngest (below 35) and older managers, it is worth breaking the data into finer cuts. Specifications (9) and (10) show that the slope of the age relationship is about twice as big among the group of managers under 40 (young) as among the managers above 40 (old), but the standard error is bigger in the young group. Taking the point estimates at face value, one could speculate that this may have to do with the fact that the very youngest managers are those that experienced an almost constantly rising stock market during their short careers.

iv. Other: In addition to the basic robustness tests reported in Table 3, we repeat our basic tests with the following variations (untabulated): (a) quantile-based age measures; (b) controlling for technology exposure at the end of 1997; (c) restricting the sample to large funds only. We obtain similar results.

B. Sensitivity of holdings to past performance of technology stocks

What explains increases and decreases in technology holdings over the rise and fall of technology stock prices? Young managers start in 1998 without overweighting tech, but then strongly increase their technology stock holdings as the bubble progresses. The aim of this section is to understand the factors that may be driving this change.

Smith, Suchanek, and Williams (1988) find that the price forecasts of the traders in their asset market experiments tend to be adaptive – forecast changes are correlated with forecast errors in the previous period. Haruvy, Lahav, and Noussair (2006) investigate adaptive expectations formation in more detail, using an experimental set-up similar to Smith et al., and find that inexperienced individuals form their beliefs about future price changes by extrapolating past price trends. Applied to our setting with mutual fund managers, the conjecture is that younger managers are more likely to be trend chasers: they believe that past high returns imply high future returns.

To see whether this hypothesis is consistent with our data, we change our focus from cross-sectional differences in log price/sales ratios, to time-variation in log price/sales ratios within a fund. To start, we recognize that increases in the price/sales ratio can occur for two reasons. The first is mechanical: if prices of a fund's current holdings of high price/sales stocks increase relative to the prices of low price/sales stocks, then without doing any trading (and by allocating inflows in the same proportion as existing portfolio weights), the price/sales ratio of the portfolio increases. The second is by rebalancing: funds can purchase stocks with higher price/sales ratios, selling stocks with lower price/sales ratios. In some respects, both are interesting, because both active re-allocation and passive price effects affect portfolio weights. In the analysis that follows, however, we focus on active decisions only to make sure that we don't simply capture inertia in holdings coupled with some stock return momentum.

To distinguish active and passive allocation changes, we calculate the passive price/sales ratio, for each fund and quarter. It is the hypothetical price/sales ratio that the fund would have at date t, if it had not traded at all between t and t-1. In this case relative portfolio weights would change from t to t-1 only because of price changes, but not through trading. Table 4 presents the results from panel regressions of fund log price/sales ratios on the passive log price/sales ratio, lagged technology returns (defined as in Section II.C), and lagged technology returns interacted with dummy variables corresponding to the age of the manager at the end of 1997. The sample period runs from the fourth quarter of 1997 to the fourth quarter of 2002.

$$\begin{aligned} Log(P/S_{it}) = a + bLog(P/S)_{it}^{Passive} + cAge_i \\ + R_{Tech,t-1}[d_1(25 \le Age \le 30) + \ldots + d_6(66 \le Age \le 90)] + u_{it} \end{aligned} \quad (3)$$

The table shows, not surprisingly, that the passive price/sales ratio explains a large fraction of the variation in current price/sales ratios. The coefficients of interest are d_1-d_6, the sensitivity of fund managers' active re-allocation choices to past returns of technology stocks, conditional on age categories. A positive coefficient suggests trend chasing, while a negative coefficient indicates contrarian behavior. The coefficient estimates show that younger managers have a tendency to be trend chasers, in contrast with investors older than 55, who tend to shift away from technology stocks following high tech returns. As an alternative test, we estimate the interaction between age and past tech returns,

$$Log(P/S_{it}) = a + bELog(P/S)_{it}^{Passive} + cR_{Tech,t-1} + dAge + eAge \cdot R_{Tech,t-1} + u_{it}. \quad (4)$$

These results confirm the findings above, with the interaction between age and past returns entering significantly negative.

The second set of tests, shown in the right-hand columns of Table 4, replace the lagged return on the technology portfolio with its market-adjusted return, measured as the difference between the technology portfolio return and the return on the CRSP value-weighted portfolio. The motivation for these tests is that trend chasing may be done on a relative basis, with managers favoring stocks that have performed well relative to other stocks. The results (specifications (5) to (8)) are similar for value-weighted regressions, but somewhat weaker in the equal-weighted regressions.

We also experimented with regressions with multiple lags. Adding a second lag of the technology return to the regression results in negative coefficients of similar magnitude on the age interactions with the first and second lag, but we lose statistical precision (which is not surprising given our short sample) and the significance levels are reduced.

Figure 4 provides additional perspective on this trend-chasing behavior. We regress, each quarter, the difference between the actual log price/sales ratio and the passive log price/sales ratio on age. Hence, if the coefficient on age is positive, it indicates that young managers actively decrease the price/sales ratios of their portfolios relative to old managers, if the coefficient on age is negative, it indicates that young managers actively increase price/sales ratios relative to old managers. We then plot the quarterly age coefficients against our technology return index, measured over one quarter in Panel A, and measured over the past year in Panel B. The figures show that in times of rising technology stock prices, the age coefficient tends to be negative, which means that young managers actively increased their technology stock exposure, whereas in times of falling technology stock prices, the age coefficient tends to be negative and thus young managers actively decreased their technology stock exposure, consistent with trend-chasing behavior.

C. Flows into young and old manager funds

The results so far demonstrate substantial variation in exposure to technology stocks across age groups of mutual fund managers. However, these differences could be economically unimportant if young managers control only the smallest mutual funds. Indeed, Figure 5 reveals that in December 1997, young managers start out controlling significantly smaller funds than older managers. Until the peak in technology stock prices in March 2000, however, the distribution shifts, and assets under management for the average young manager fund more than quadruple during a 2-year period. Eventually, they even surpass the average fund size of all other age groups. The share of total assets under management controlled by managers of age 35 and younger grows from approximately 10% in December 1997 to about 20% in March 2000.[4] Thus, the effects of young managers' investment choices are amplified by the growth of assets.

[4] Consistent with our other calculations, these percentage shares are based only on funds that were in existence at the end of 1997. Conditioning on existence in March 2000 yields a greater share controlled by younger managers, because new funds, many of which had holdings concentrated in high tech stocks, tended to be run by younger managers.

The growth in assets under management by young fund managers comes from high returns combined with substantial inflows of new capital. We calculate flows as the difference between total net assets and lagged total net assets, grossed up by the monthly return

$$Flow_{ijt} = TNA_{ijt} - TNA_{ijt-1}(1 + R_{ijt}), \tag{5}$$

where *i* denotes the fund, *j* denotes the category, and *t* denotes the month. To compute abnormal flows, we first sum the dollar flows within each category, scale by lagged total assets within the category, to get the category-specific percentage flow:

$$Category\%Flow_{jt} = \frac{\sum_i \$Flow_{ijt}}{\sum_i TNA_{ijt-1}}. \tag{6}$$

Then, the abnormal dollar flow for a fund *i* in category *j* and month *t* is the dollar flow minus the flow that the fund would obtain if its percentage flow were equal to the percentage flows of its matched category:

$$AbnormalFlow_{ijt} = \$Flow_{ijt} - Category\%Flow_{jt} \cdot TNA_{ijt-1} \tag{7}$$

Panel B shows cumulative abnormal flows, summed up within each age group and over time. The figure shows that funds managed by young managers (up to 35 years) are overwhelming recipients of new funds, receiving roughly $30 billion in cumulative abnormal inflows.

Panel C shows monthly abnormal flows, expressed as a fraction of total net assets for each age group. Funds run by managers between 25 and 35 experience large percentage inflows through April 2000, and continue to receive smaller amounts in the last two quarters of that year. Flows appear sticky: while younger manager funds experience abnormal inflows when technology stocks (and young managers' portfolios) perform well, they do not experience abnormal outflows when these stocks underperform.

Table 5 shows the statistical significance of the flow results. Funds run by managers between the ages of 25 and 30 each receive abnormal inflows of $20 million per month during the course of the bubble, and continue to attract new funds thereafter, possibly because of lags in the performance-flow relationship. Among managers between the ages of 31 and 35, there are substantial inflows during the bubble, followed by nothing in the period that follows.

D. Alternate theories

Our results are consistent with the inexperience hypothesis and they conform closely to the experimental evidence on the behavior of inexperienced traders in laboratory asset markets. In this section, we ask whether our results could also be consistent with other theories.

i. Technology-sector specific human capital

Could technology-specific human capital of young managers explain our results? According to this alternate theory, younger managers overweight tech because they are more skilled at selecting new economy stocks, perhaps because they have a comparative advantage in understanding the business models of high-technology firms. There are many reasons this could be true. First, university education might be biased towards newer technologies, giving recent graduates an edge in the analysis of these firms. Second, younger managers may be more familiar with the products produced by these firms.

The human capital theory predicts that younger managers disproportionately invest in technology stocks, our primary result. However, in some other ways, the theory does not fit well with our results. First, the human capital theory is silent about the dynamics of young managers' technology holdings. It does not predict our finding that young managers initially *underweighted* technology stocks, relative to their benchmarks, but then increased their tech exposure as these stocks performed well. Second, the human capital theory would suggest that should have superior stock selection skills within the universe of tech stocks — both during the rise and fall of tech stock prices. Figure 6 takes a look at this hypothesis. Panel A plots cumulative value-weighted raw returns, net of the value-weighted Morningstar benchmark average. Panel B plots the corresponding holdings-based returns, computed using the CRSP returns of the stocks listed on funds' quarterly holdings reports. Both figures show that young managers significantly outperform through March 2000, but then significantly underperform. The holdings-based returns show less of an outperformance of young managers leading up to the peak, which indicates that the quarterly and sometimes semiannual holdings reports miss some successful (or lucky) stock picks—initial public offerings, perhaps—made by young managers. Panel A looks quite similar to the time series of cumulative technology returns in Figure 1, suggesting that young mangers did not do much more than simply overweight technology stocks, without being able to pick above-average performers within the sector.

More formal statistical inference in Table 6 confirms the impressions from the figures. We report mean value-weighted returns net of the Morningstar benchmark for the bubble and post-bubble periods. In both panels, young managers significantly outperform their benchmarks between 1998Q1 and 2000Q1, but significantly underperform in the following seven quarters. Over the complete sample, there is no significant difference in performance between young and old managers. If anything, the results suggest that young managers performed worse overall than old managers.

Although Morningstar benchmark adjusted returns are revealing, there is a possibility that the Morningstar benchmark does not fully capture differences in style. For example, a small-cap manager who purchases only stocks in the highest price/sales quintile could underperform in the 2000Q2-2002Q4 period because her tilt towards high price/sales stocks is more extreme than that of a typical small growth fund, even if her stock picks perform slightly less poorly than the average stock in the highest price/sales quintile. An alternative adjustment is to adjust returns at the security level using the quarterly data on fund holdings and a finer set of benchmark portfolios. We modify the technique of Daniel-Grinblatt-Titman-Wermers (1997) and form benchmark portfolios based on lagged P/S, Size, 6-month momentum, and exchange (NYSE/AMEX vs. Nasdaq), and we rebalance these portfolios each month (see, also, Brunnermeier and Nagel 2004). The abnormal return of each stock in a fund's portfolio in a given month is the difference between the raw return of the stock and the return on the benchmark portfolio. The abnormal return for the fund is then the value-weighted average of individual stocks' abnormal returns. Panel C of Figure 6 shows these results, sorted by age group. Younger managers exhibit little outperformance until the bubble reaches its peak, and they underperform in the 7 quarters that follow.

To summarize, the additional predictions of the human-capital theory do not receive support in our data. Young fund managers don't appear to have better skill in picking technology stocks than old managers. More broadly, it is also worth contrasting the results on young managers' performance with the returns of hedge funds reported in Brunnermeier and Nagel (2004). While the hedge funds in their sample also had high exposure to technology stocks prior to the market peak, they reduced their exposure as the bubble collapsed and managed to avoid the worst performing stocks during the downturn. As a result, and unlike the young fund managers in our sample, hedge funds significantly outperformed in the last three quarters of 2000.

ii. Herding

The fact that young managers titled their portfolios away from their category benchmark towards technology stocks contrasts with previous results on career concerns of investment professionals. Scharfstein and Stein (1990) and Zwiebel (1995) predict that career concerns can induce herding. Because career concerns are likely to be strongest among young managers, it suggests that funds run by younger managers should have lower tracking error, a fact confirmed by Chevalier and Ellison (1999). In our data, however, young managers show the greatest tendency to deviate from their benchmarks in favor of tech investments. More generally, if we compute monthly returns-based measures of tracking error, we find that young managers are, if anything, more likely to deviate more from their benchmarks during our sample period. Therefore, herding does not appear to explain our findings (although herding could, of course, still be relevant for explaining other aspects of fund managers' decisions that are beyond our focus).

iii. Window dressing

The large inflows into young manager funds suggest a final alternative. Perhaps mutual funds were catering to retail demand for funds with aggressive technology investments by "dressing" up their portfolios with high price/sales ratio stocks to convince clients that the manager chose well-performing stocks. Related evidence in Cooper, Gulen, and Rau (2004) shows that mutual funds changed their names during the bubble to attract inflows from retail investors. Lakonishok, Shleifer, Thaler, and Vishny (1991) document window dressing behavior among pension fund managers. The high returns experienced by technology stocks during 1999 and early 2000 suggest that the incentives to engage in this behavior could have been high.

While it is possible that mutual funds had incentives to engage in window dressing, we see no reason that this should be concentrated in funds with younger managers. Moreover, the tendency of window dressing to increase inflows appears to be modest, if anything at all. Specifically, monthly cross-sectional regressions (untabulated) of percentage inflows on lagged returns and lagged price/sales ratios yield significant coefficients on returns only. Moreover, Cooper et al. show that the effect of name changes on inflows is similar for funds that change their holdings to be consistent with the style suggested their new name and those that do not. It seems that a costly re-allocation of the portfolio is not required to attract flows. Thus, insofar as the young mutual fund managers in our sample chose tech stocks to attract inflows, this must have been done only because they believed these stocks would generate abnormal returns which would then, subsequently, generate inflows. Finally, pure window dressing, in the sense of changing holdings around reporting dates, can be ruled out, because our results also hold when technology exposure is measured using factor loadings estimated from fund returns data.

V. Conclusions

We emphasize four basic findings. First, mutual fund managers run by younger managers disproportionately bet on technology stocks, particularly at the peak of the bubble. Second, young managers exhibit trend-chasing behavior. They increase their holdings in technology stocks after quarters with high technology stock returns. Third, as a result of large abnormal inflows, coupled with the high returns experienced by technology stocks, young managers end up controlling a significant fraction of total mutual fund assets at the peak of the bubble. Fourth, young managers did not exhibit any better skill at picking well-performing technology stocks than older managers. Taken together, the facts are consistent with the popular view that inexperienced investors are susceptible to buy assets with inflated prices during times of bubbles. Our evidence also fits well with findings on the effect of trader inexperience in the experimental asset markets literature. Other possible explanations receive little support in our data.

On a more speculative note, our results may also shed light on the puzzling periodicity of bubbles in financial markets. Bubbles, or bubble-like patterns in stock prices, are relatively rare phenomena. It is unlikely that any single explanation can fully account for them, but it is plausible that investor experience could play a role. Perhaps it takes a new generation of inexperienced investors for a bubble to be possible.

This would be consistent with Galbraith's (1990) claim that "the financial memory should be assumed to last, at a maximum, no more than 20 years. This is normally the time it takes for the recollection of one disaster to be erased."

Appendix: Survivor Bias in the Morningstar Data

The matching process works as follows. We start with the complete database of funds covered by Morningstar that were in existence in December 1997. This yields 4,564 funds (for the analysis in this appendix, and only here, we don't aggregate multiple share classes of a fund). Out of this sample, approximately 53.3% provide data on the age of the managers at the end of 1997, as we report in Table A.1, column NAge/N. There does not appear to be survivor bias in the funds that report age data; if anything, surviving funds are less likely to have data on the age of the managers. We take this subsample of 2,433 funds with available age data and match it to the CRSP data by ticker. Morningstar does not report tickers for funds no longer in existence, and therefore these must be identified manually (a total of 807 funds, mostly consisting of funds that died between 1999 and 2001). Since we don't attempt to match dead funds for which we don't have age data, the CRSP coverage of surviving funds after our linking process is, of course, much higher than of the dead funds. However, what matters is only the combined coverage, i.e., the size of the sample for which we have both Morningstar and CRSP data, shown in column NBoth/N. The numbers show that there is no apparent difference in coverage between surviving and dead funds. Using the CRSP identifiers, we then match to portfolio holdings data reported in the Thomson Financial database. Note that portfolio holdings data may be mapped to more than one CRSP mutual fund share class (e.g., A, B, C, Y, etc). Our final sample includes 2,109 funds, of which 1,573 survive during the entire sample. Combined data coverage from all three data sources (column NAlldata/N) of funds that die in 1998 is poor, but on average the coverage rate for dead funds is very close to the coverage rate of surviving funds. Overall, we see no reason to expect survivor bias in our results.

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Figure 1. Technology stock returns during the technology bubble

Buy-and-hold returns of a value-weighted portfolio of stocks in the highest Nasdaq price/sales quintile, starting in December 1997. The thin line denotes the buy-and-hold return on the CRSP value weighted index. A dashed line marks March 2000, which we refer to as the "peak of the bubble".

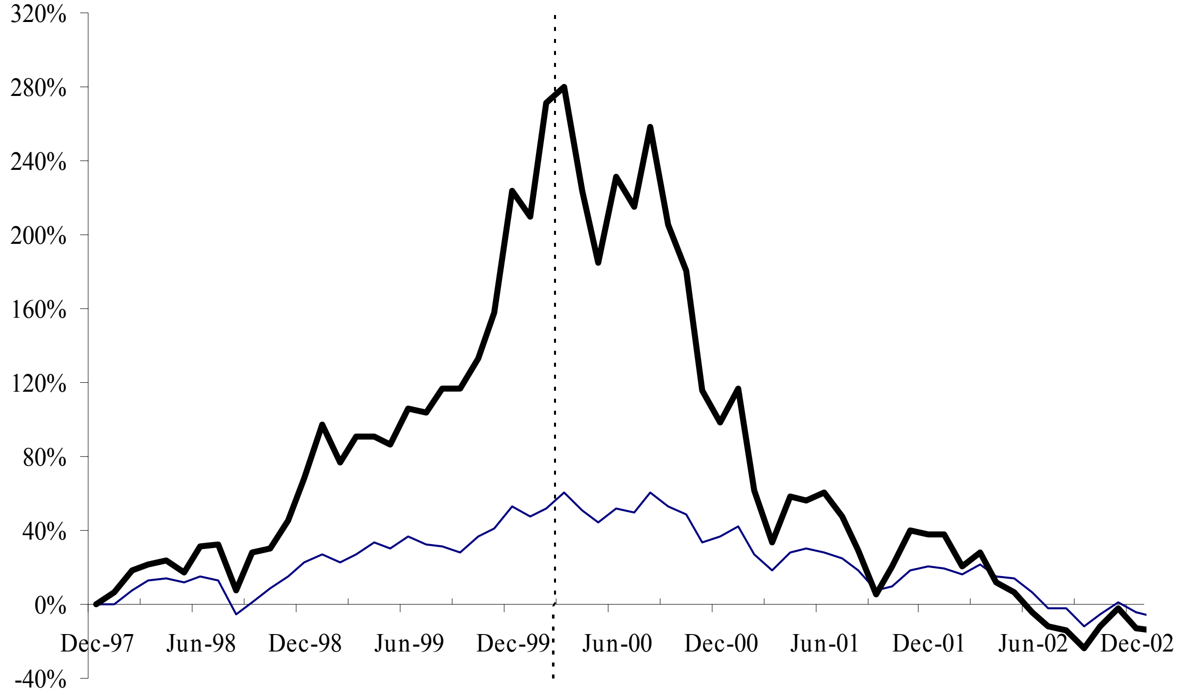
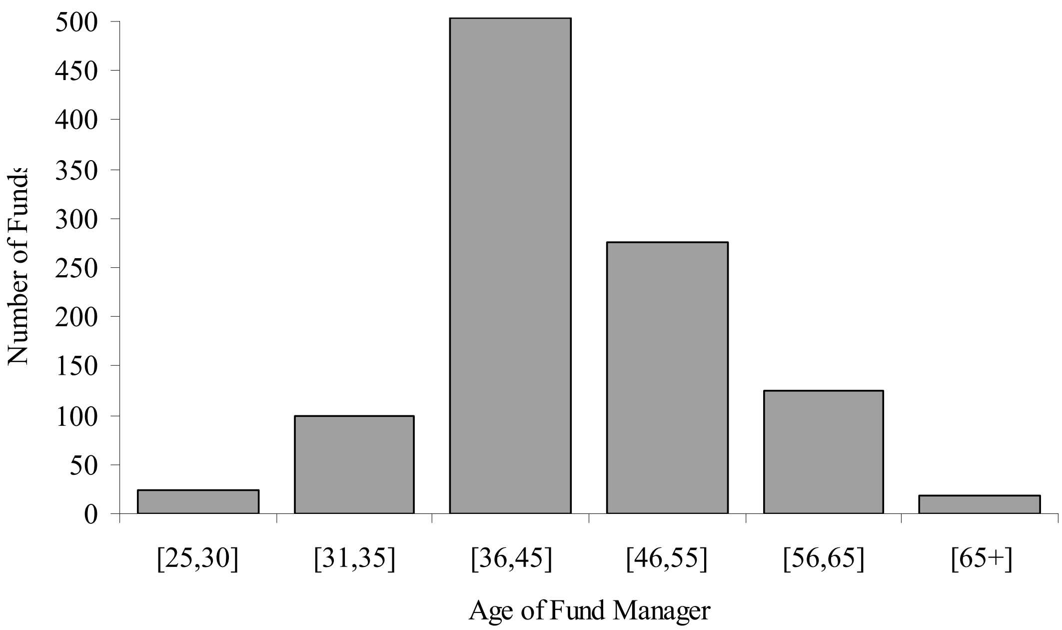


Figure 2. Who managed money during the bubble

Characteristics of managers and teams of managers for all equity mutual funds in existence at the end of 1997. Panel A plots the histogram of manager age. Age is the difference between 1997 and the year of birth, reported by Morningstar. Where the year of birth is not available, the manager is assumed to be 22 years old in the year of college graduation, or 28 in the year in which an MBA is completed. When a fund is managed by more than one person, it is assigned the median age of the members of its team. Panel B plots the histogram of team size. The complete sample includes 2,204 funds, while 1,776 fund report data on age and portfolio holdings at the peak of the bubble.

Panel A. Manager age in December 1997



Panel B. Managing team size

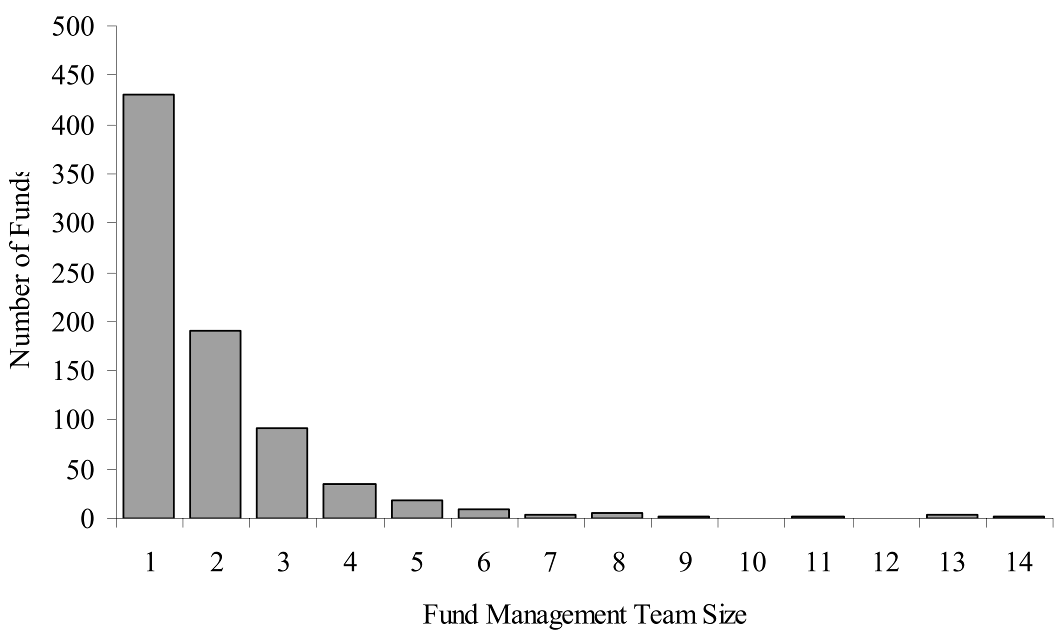
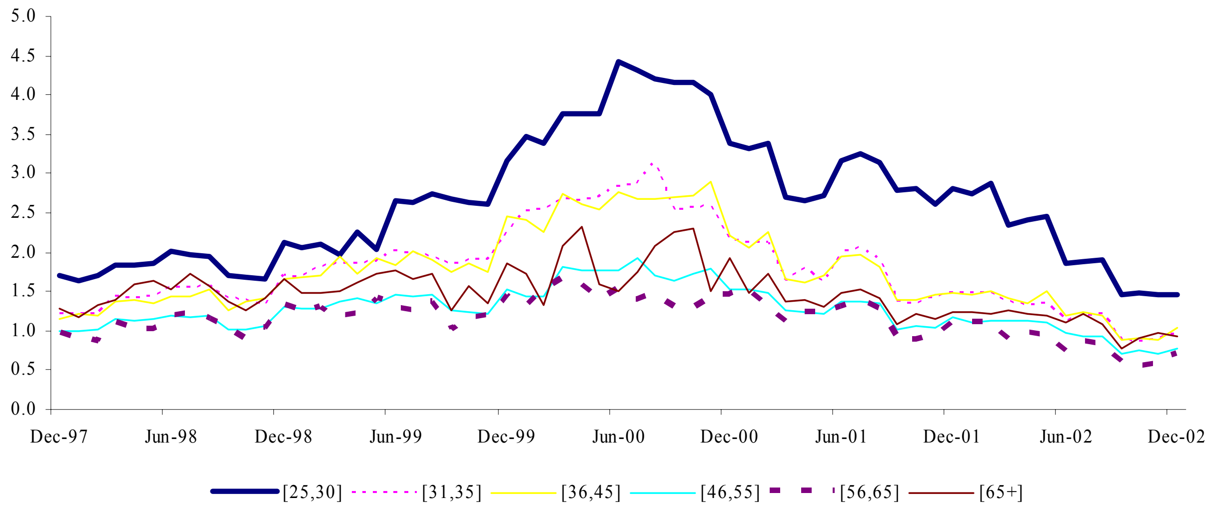


Figure 3. Technology stock exposure, by quarter and age group.

Time-series of technology stock loadings of domestic equity mutual funds, sorted by age of the mutual fund manager at the end of 1997. Panel A plots value weighted average log price/sales ratios. Panel B plots value weighted log price/sales ratios, demeaned by the benchmark average. Benchmarks are defined as the Morningstar-assigned category for each fund.

Panel A. Value-weighted log price/sales ratio, by age group



Panel B. Value-weighted average log price/sales ratio, by age group, demeaned by Morningstar category

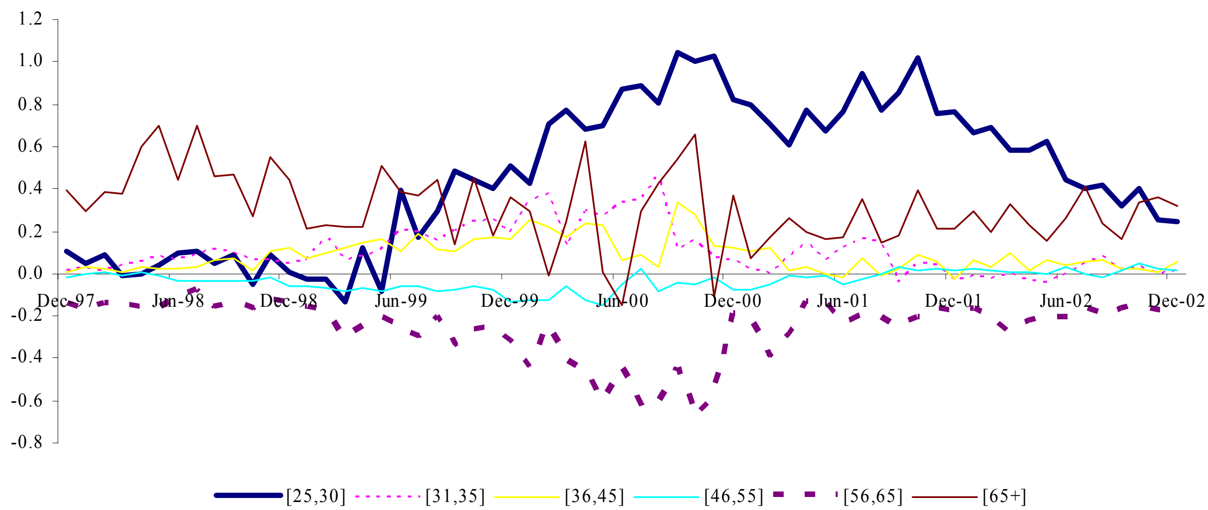


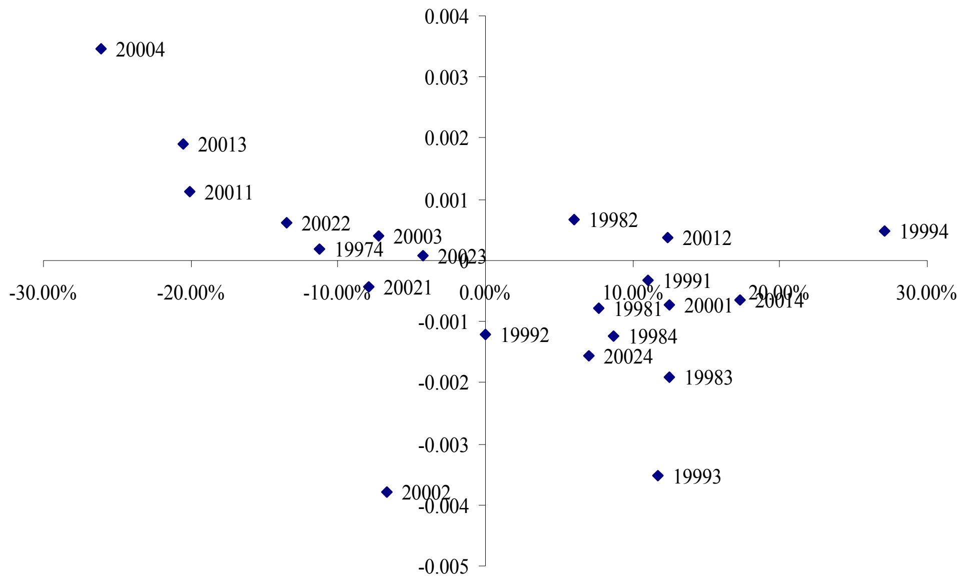
Figure 4. Manager age, past technology stock returns, and active allocation to high price/sales stocks

We estimate quarterly regressions of the change in the allocation to technology stocks on the age of the manager (or median age of group of managers) in December 1997.

$$Log(P/S)_{it} - Log(P/S)_{it}^{Passive} = a_t + b_t Age + u_{it}$$

$Log(P/S)^{Passive}$ denotes the log price/sales ratio that the fund would have if it had not rebalanced its portfolio since the last quarter. Panel A plots b_t, the slope coefficient from this regression, against the return of technology stocks in that quarter. Panel B plots b_t against the one-year return of technology stocks. In both panels, the datapoints are labeled by year-quarter.

Panel A. b_t v. 1-quarter technology stock returns



Panel B. b_t v. 1-year technology stock returns

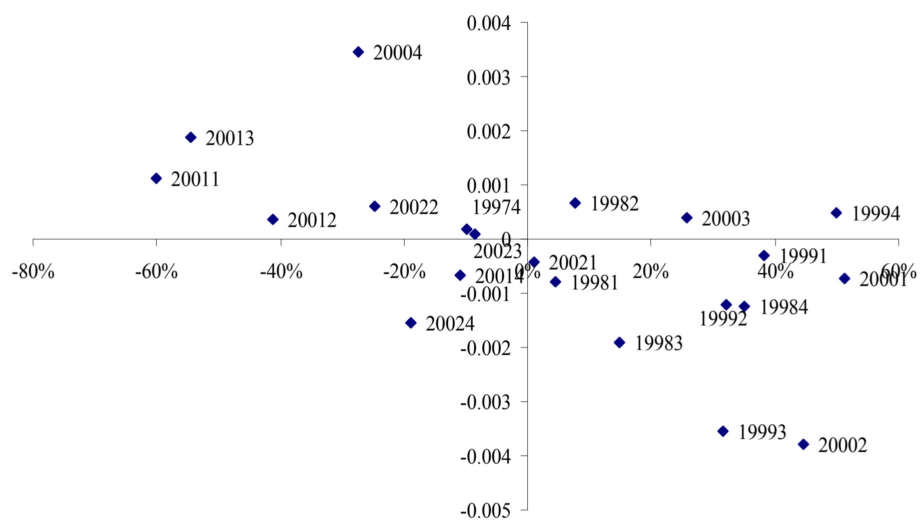
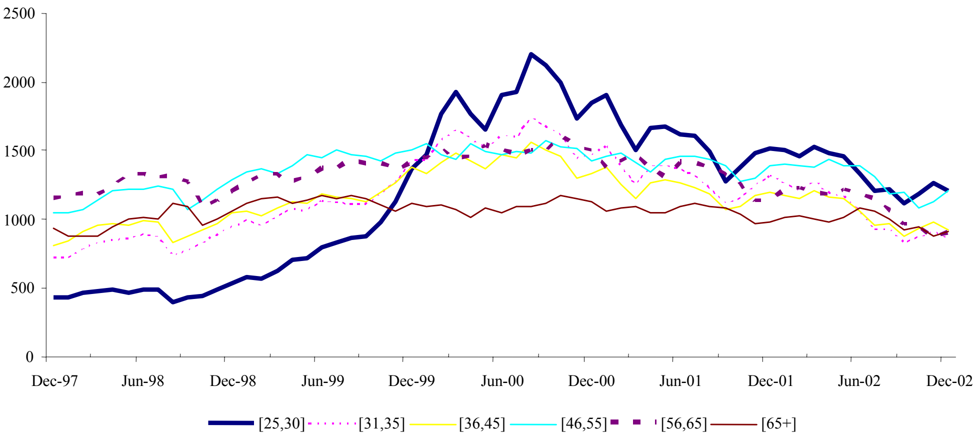


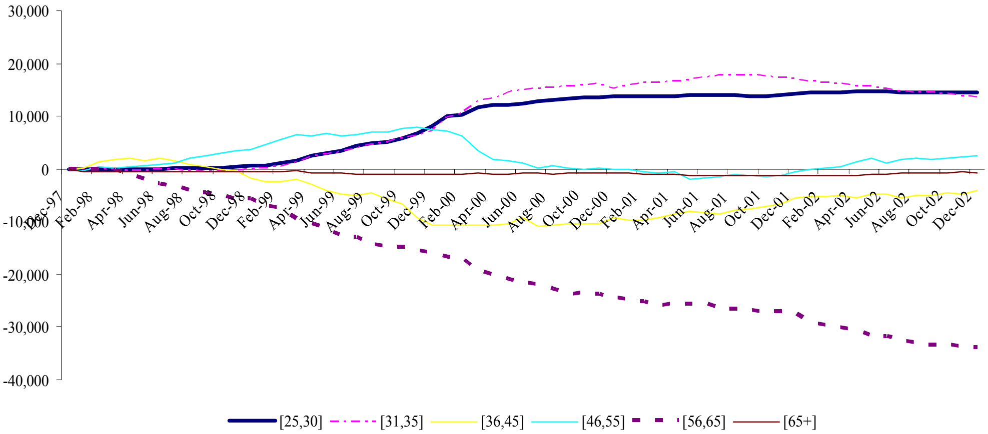
Figure 5. Assets under management and inflows into mutual funds, by age group.

Time-series of total net assets, percentage abnormal inflows, and cumulative abnormal inflows, sorted by the age of the mutual fund manager at the end of 1997. Panel A plots mean total net assets, by age group. The abnormal inflow is the difference between the dollar inflow and the expected dollar inflow calculated using the average percentage inflow for all funds with the same benchmark. Panel B plots the sum of cumulative abnormal flows by age group. Panel C plots monthly abnormal flows as a fraction of total net assets.

Panel A. Total net assets, equal-weighted average for each age group



Panel B. Cumulative abnormal inflows, total for each age group, $millions



Panel C. Abnormal inflows, as a fraction of total net assets, average for each age group

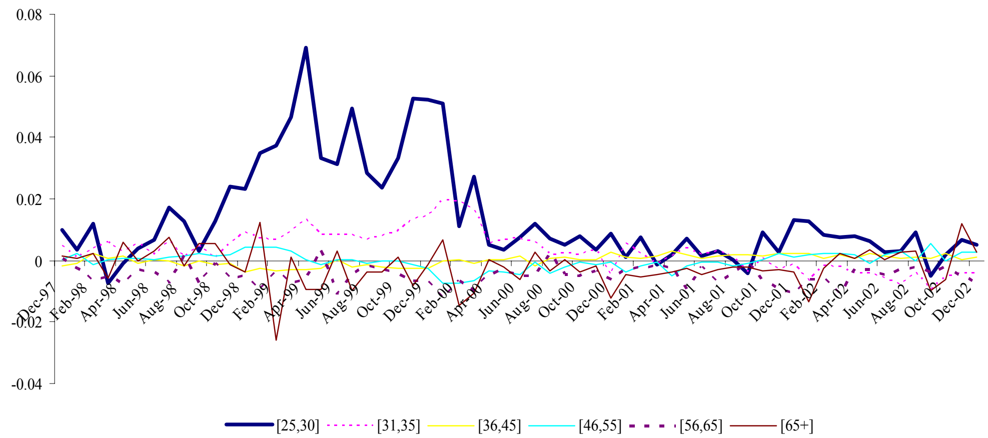
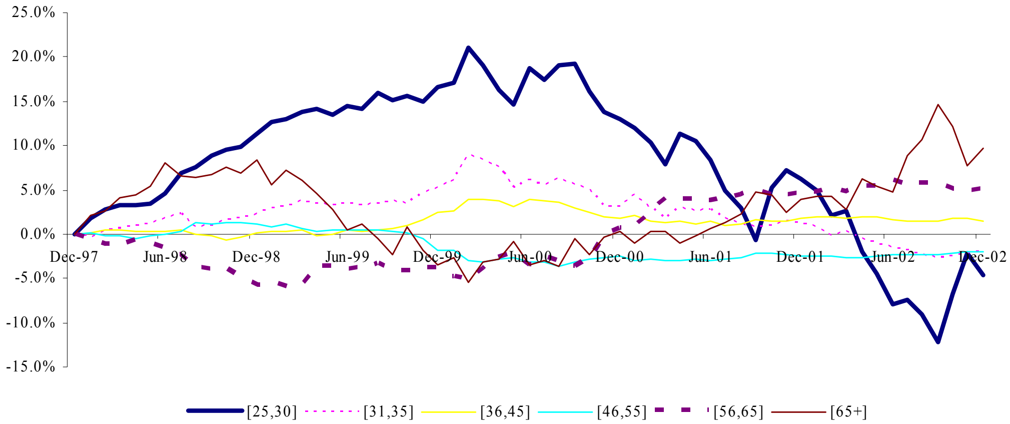


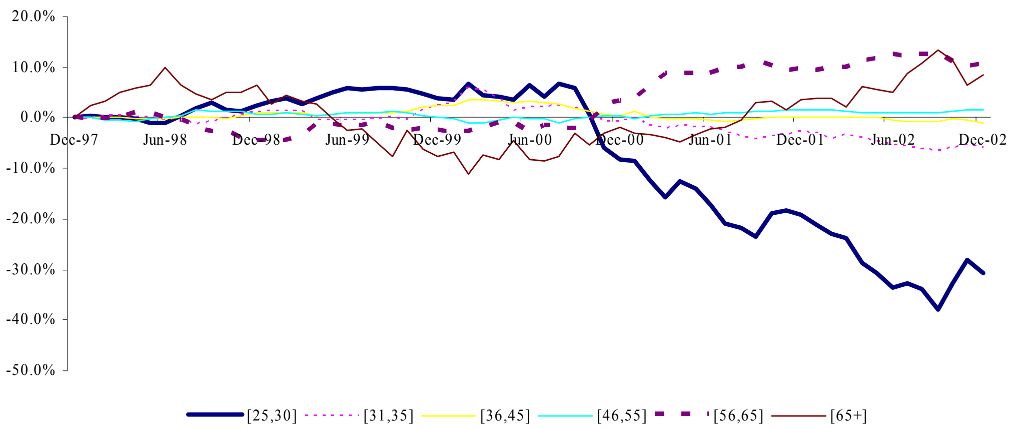
Figure 6. Returns

Cumulative abnormal returns by age group, net of benchmark average, all weighted by total net assets at the end of 1997. Panel A plots cumulative monthly returns net of benchmark average. Panel B plots cumulative monthly returns net of benchmark average, computed from quarterly holdings statements. Panel C plots cumulative Daniel, Titman, Grinblatt, and Wermers (1997) characteristics-adjusted returns, adjusted by benchmark average and computed from quarterly holdings statements.

Panel A. Value-weighted returns net of benchmark



Panel B. Value-weighted holdings-based returns, net of benchmark



Panel C. Value-weighted characteristics adjusted returns, net of benchmark

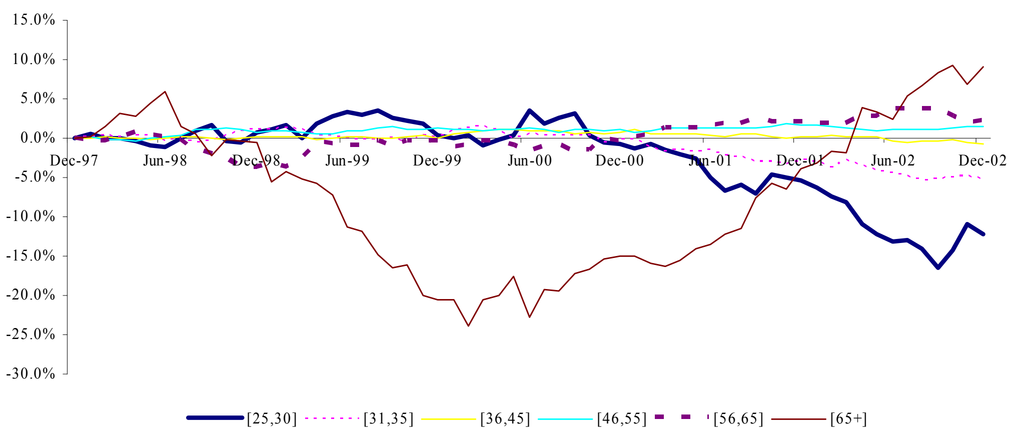


Table 1. Summary statistics

Panel A reports the mean, median, standard deviation, and extreme values of various mutual fund descriptors. The sample includes all domestic non-index equity funds that identify a manager or management team in December 1997. If a fund has multiple share classes, we aggregate across share classes. Total net assets are expressed in millions of dollars. The number of members in the management team is computed as of December 1997. If date of birth is not available, manager age is estimated using college graduation data for each member of the management team. In teams in which there is more than one manager, age is the median age of its members. γ^{Tech} is the coefficient on the technology index from the bivariate regression of monthly fund returns on the CRSP value-weighted market return and a technology index return, where the technology index return is the value-weighted return of all stocks in the highest Nasdaq price/sales quintile (rebalanced monthly) and the time period is January 1998 to March 2000. The table also reports summary statistics on γ^{Early} and γ^{Late}, estimated on the January 1998-December 1998 and January 1999-March 2000 subsamples. Panel B reports summary statistics for technology funds' log price/sales ratios separately for each Morningstar benchmark category. Panel C reports the breakdown of observations by benchmark and fund manager age. Returns and total net asset data are from CRSP; manager data are from Morningstar; price/sales ratios are calculated using portfolio holdings reported by Thomson Financial.

Panel A: Fund descriptors

	N	Mean	Median	SD	Min	Max
Total Net Assets December 1997	1,079	879.64	152.38	2746.48	0.00	38245.98
Number of team members	1,079	1.85	1.00	1.47	1.00	14.00
Manager age	1,079	44.87	43.00	8.91	28.00	86.00
Price/sales ratio, March 2000	855	35.67	12.16	130.00	0.46	3138.32
Log price/sales, March 2000	855	2.47	2.50	1.36	-0.78	8.05
Portfolio mean price/sales quintile	855	3.71	3.83	0.63	1.42	5.00
γ^{Tech}	1,056	0.02	-0.04	0.35	-0.69	1.93
γ^{Early}	1,053	0.02	-0.01	0.23	-0.66	1.99
γ^{Late}	1,025	0.03	-0.06	0.44	-0.87	1.90
Turnover 1998	936	0.87	0.69	0.70	0.00	4.11
Turnover 1999	975	0.90	0.70	0.85	0.00	7.87

Panel B: Log price/sales ratios in March 2000, by Morningstar benchmark

	N	Mean	Median	SD	Min	Max
Conservative Allocation	24	2.38	2.58	0.75	0.01	3.53
Large Blend	158	2.39	2.44	0.76	0.17	4.64
Large Growth	135	3.36	3.34	0.88	0.41	5.82
Large Value	133	1.24	1.10	0.67	0.15	3.38
Mid-Cap Blend	35	2.11	1.93	1.10	0.54	4.64
Mid-Cap Growth	78	3.79	3.90	1.02	1.18	5.92
Mid-Cap Value	32	1.01	0.77	0.83	-0.78	2.86
Moderate Allocation	98	2.22	2.41	0.95	-0.07	4.48
Small Blend	48	2.20	1.46	1.81	0.28	6.17
Small Growth	89	3.51	3.51	1.43	0.04	8.05
Small Value	25	0.99	0.34	1.61	-0.44	6.79

Panel C: Benchmark distribution by fund manager age

	25-30	31-35	36-45	46-55	56-65	66-90
Conservative Allocation	11%	1%	3%	3%	3%	0%
Large Blend	22%	18%	18%	16%	25%	31%
Large Growth	11%	16%	14%	17%	20%	13%
Large Value	0%	17%	16%	18%	12%	19%
Mid-Cap Blend	0%	3%	4%	4%	6%	0%
Mid-Cap Growth	28%	9%	10%	7%	7%	0%
Mid-Cap Value	11%	2%	4%	4%	4%	6%
Moderate Allocation	6%	8%	10%	17%	9%	19%
Small Blend	0%	10%	5%	6%	4%	0%
Small Growth	11%	14%	12%	7%	7%	13%
Small Value	0%	2%	3%	2%	5%	0%
	100%	100%	100%	100%	100%	100%

Table 2. Fund manager age and technology stock holdings at the peak of the bubble.

Cross-sectional regressions of technology stock exposure proxies of domestic equity funds in March 2000 on manager age, a dummy variable indicating whether the manager is female, a dummy variable for whether the manager is a Certified Financial Analyst, an estimate of the average SAT score of the university from which the manager graduated, a dummy variable indicating whether more than one person manages the fund, and other controls:

$$Log(P/S)_i = a + bAge_i + cFemale_i + dCFA_i + eSAT_i + fTeam_i + gZ_i + u_i \,.$$

In the left-hand-side columns, the dependent variable is the log price/sales ratio of the fund. In the right-hand-side columns, the dependent variable is the slope coefficient on the technology index, obtained from a bivariate regression of monthly stock returns on the CRSP value-weighted index return and the return on the technology index. For each fund, this regression is estimated using monthly returns between January 1998 and March 2000. The regressions alternately include category level fixed effects, or controls for Fama-French (1993) factor loadings (β_{RMRF}, β_{SMB}, β_{HML}), estimated using pre-1998 fund returns. White (1980) t-statistics are in brackets. VW denotes value-weighting, EW denotes equal-weighting.

	Y = Log Price/Sales, March 2000				Y = Tech γ			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	3.357	2.713	3.052	3.509	0.176	-0.067	0.091	0.219
	[6.16]	[4.80]	[7.50]	[5.03]	[1.45]	[0.61]	[1.09]	[1.83]
Age	-0.02	-0.015	-0.015	-0.02	-0.003	-0.002	-0.002	-0.005
	[-3.83]	[-3.48]	[-3.93]	[-2.73]	[-2.48]	[-1.92]	[-2.23]	[-4.17]
Share Female	0.111	0.12	0.012	0.019	0.009	0.008	-0.018	0.009
	[0.69]	[0.92]	[0.09]	[0.12]	[0.25]	[0.31]	[-0.74]	[0.25]
Share CFA	0.028	-0.004	0.091	-0.015	-0.033	-0.024	-0.003	-0.002
	[0.27]	[-0.05]	[1.10]	[-0.11]	[-1.33]	[-1.22]	[-0.20]	[-0.10]
SAT	-0.099	0.09	-0.014	-0.535	0.005	0.112	0.025	-0.041
	[-0.16]	[0.16]	[-0.03]	[-0.75]	[0.03]	[0.95]	[0.25]	[-0.28]
Team	0.138	0.12	0.175	0.116	-0.007	-0.014	0.013	-0.016
	[1.45]	[1.43]	[2.41]	[0.99]	[-0.29]	[-0.83]	[0.87]	[-0.77]
β_{RMRF}		0.187				0.029		
		[0.92]				[0.63]		
β_{SMB}		0.597				0.363		
		[5.15]				[13.07]		
β_{HML}		-1.183				-0.256		
		[-7.92]				[-7.23]		
Category F.E.	No	No	Yes	Yes	No	No	Yes	Yes
Weighting	EW	EW	EW	VW	EW	EW	EW	VW
Observations	855	839	855	834	1056	1031	1056	1024
R-squared	0.02	0.27	0.45	0.63	0.01	0.40	0.54	0.75

Table 3. Fund manager age and technology stock holdings: robustness

Cross-sectional regressions of technology stock exposure proxies of domestic equity funds in March 2000 on manager age, a dummy variable indicating whether the manager is female, a dummy variable for whether the manager is a Certified Financial Analyst, an estimate of the average SAT score of the university from which the manager graduated, a dummy variable indicating whether more than one person manages the fund, and other controls:

$$Log(P/S)_i = a + bAge_i + cFemale_i + dSAT_i + eTeam_i + fZ_i + u_i \,.$$

Price/sales ratios are measured at the end of March 2000. For each set of robustness tests, both conventional (equal-weighted) and value-weighted regression results are shown. Specifications (1) and (2) replace the dependent variable with the simple price/sales ratio (i.e., not the log). In specifications (3) and (4), the sample is restricted to include only funds run by one manager; (5) and (6) show the corresponding results for funds run by teams of two or more managers. Specifications (7) and (8) replace the dependent variable with the average price/sales quintile of stocks in the portfolio. White (1980) t-statistics are in brackets.

	Simple price/sales		Single mgr funds: Log(P/S)		2+ mgr funds: Log(P/S)		Price/sales Quintile		Young	Old
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	-3.133	34.794	3.245	3.398	3.202	3.177	4.122	4.405	2.771	3.35
	[-0.07]	[1.63]	[5.61]	[3.27]	[5.57]	[3.39]	[24.21]	[12.91]	[2.72]	[6.88]
Age	-1.216	-0.61	-0.01	-0.018	-0.025	-0.023	-0.004	-0.008	-0.027	-0.014
	[-2.88]	[-2.58]	[-2.03]	[-2.48]	[-3.53]	[-1.92]	[-2.53]	[-2.80]	[-1.42]	[-2.35]
Share Female	-3.926	-2.047	0.109	0.252	-0.427	-1.051	0.035	0.098	-0.196	0.031
	[-0.29]	[-0.47]	[0.76]	[2.15]	[-1.68]	[-2.64]	[0.73]	[1.24]	[-0.66]	[0.26]
Share CFA	6.618	7.172	0.136	-0.025	0.049	0.172	-0.031	-0.067	0.21	0.038
	[1.12]	[1.92]	[1.37]	[-0.19]	[0.32]	[0.68]	[-0.86]	[-1.01]	[1.28]	[0.39]
SAT	108.268	16.621	-0.596	-0.509	0.629	0.183	-0.29	-0.515	0.786	-0.411
	[1.58]	[0.76]	[-0.89]	[-0.46]	[0.94]	[0.20]	[-1.46]	[-1.43]	[0.83]	[-0.79]
Team	9.714	-1.428					0.055	0.08	0.302	0.121
	[1.06]	[-0.37]					[1.77]	[1.56]	[2.07]	[1.36]
Category F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighting	EW	VW	EW	VW	EW	VW	EW	VW	EW	EW
Observations	855	834	465	455	390	379	855	834	823	802
R-squared	0.08	0.15	0.43	0.66	0.49	0.68	0.54	0.69	0.37	0.47

Table 4. Trend chasing and manager age

Panel regressions of technology stock exposure on the passive price/sales ratio, lagged technology returns, and lagged technology returns interacted with dummy variables corresponding to the age of the manager at the end of 1997, or, alternatively, an interaction term of lagged technology returns with age:

$$Log(P/S)_{it} = a + bLog(P/S)_{it}^{Passive} + cAge_i + R_{Tech,t-1}[d_1(25 \le Age \le 30) + ... + d_6(66 \le Age \le 90)] + u_{it}$$

$$Log(P/S)_{it} = a + bLog(P/S)_{it}^{Passive} + cAge_i + dR_{Tech,t-1} + eR_{Tech,t-1} \cdot Age_i + u_{it}$$

The passive log price/sales ratio refers to the log price/sales ratio of a funds' previous quarter's portfolio computed using this period's prices. Returns are alternately the lagged return on the high price/sales quintile portfolio, or the returns on this portfolio net of the CRSP value weighted return. Regressions are either equal weighted (EW) or value weighted (VW) by December 1997 total net assets. Autocorrelation- and heteroskedasticity-robust standard t-statistics, allowing for clustering at the fund level, are shown in brackets.

	R_{t-1}= Tech Return				R_{t-1}= Tech Return – CRSP VW			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.109	0.109	0.095	0.096	0.112	0.112	0.093	0.093
	[7.54]	[7.51]	[5.13]	[5.18]	[7.59]	[7.58]	[4.97]	[4.97]
Log $(P/S)^{Passive}$	0.966	0.966	0.995	0.995	0.966	0.966	0.996	0.996
	[245.27]	[245.06]	[220.83]	[218.54]	[245.33]	[245.45]	[211.62]	[210.95]
Age	-0.0006	-0.0006	-0.0013	-0.0013	-0.0006	-0.0006	-0.0013	-0.0013
	[-2.20]	[-2.16]	[-3.54]	[3.59]	[-2.33]	[-2.33]	[-3.49]	[-3.49]
R_{t-1}		0.293		0.418		0.238		0.475
		[2.98]		[3.13]		[1.73]		[2.76]
$R_{t-1} \cdot$ Age		-0.006		-0.006		-0.003		-0.007
		[-2.67]		[2.26]		[-0.97]		[-2.12]
$R_{t-1} \cdot [25 \le Age \le 30]$	0.176		0.053		0.205		0.138	
	[1.42]		[0.24]		[1.30]		[0.64]	
$R_{t-1} \cdot [31 \le Age \le 35]$	0.103		0.079		0.024		0.109	
	[1.30]		[1.02]		[0.24]		[0.76]	
$R_{t-1} \cdot [36 \le Age \le 45]$	0.078		0.208		0.186		0.221	
	[2.78]		[3.23]		[4.24]		[3.84]	
$R_{t-1} \cdot [46 \le Age \le 55]$	0.022		0.140		0.073		0.119	
	[0.63]		[2.05]		[1.86]		[2.85]	
$R_{t-1} \cdot [56 \le Age \le 65]$	-0.110		-0.071		-0.023		-0.005	
	[-2.29]		[-1.30]		[-0.38]		[-0.08]	
$R_{t-1} \cdot [65 \le Age \le 90]$	0.143		-0.011		0.269		-0.057	
	[1.95]		[-0.26]		[1.73]		[-1.14]	
Weighting	EW	EW	VW	VW	EW	EW	VW	VW
Observations	16696	16696	16366	16366	16696	16696	16366	16366
R-squared	0.900	0.900	0.930	0.930	0.900	0.900	0.930	0.930

Table 5. Monthly flows

The monthly flow is the difference between total net assets and the product of lagged total net assets and the fund's gross return. To calculate abnormal flow, we compute the value-weighted percentage inflow by category benchmark. We apply this percentage flow to each fund in each month, yielding a dollar denominated expected flow. The abnormal flow is the difference between the actual flow and the expected flow. Panel A summarizes abnormal flows for the funds in our sample, in millions of dollars. Panel B summarizes abnormal flows as a fraction of assets under management, expressed in percentage terms.

	1998Q1-2000Q1		2000Q2-2002Q4		Full Sample	
	Mean	[t]	Mean	[t]	Mean	[t]
Panel A. Abnormal Monthly Flows ($ millions, equal-weighted average)						
25 ≤ Age ≤ 30	20.20	[5.48]	8.66	[6.70]	13.96	[7.12]
31 ≤ Age ≤ 35	7.62	[5.10]	-0.20	[-0.18]	3.39	[3.24]
36 ≤ Age ≤ 45	-0.95	[-3.26]	1.46	[7.11]	0.35	[1.52]
46 ≤ Age ≤ 55	0.04	[0.06]	-0.50	[-1.00]	-0.25	[-0.61]
56 ≤ Age ≤ 65	-6.23	[-6.69]	-5.87	[-8.82]	-6.04	[-10.88]
66 ≤ Age ≤ 90	-2.20	[-1.42]	-2.43	[-2.86]	-2.33	[-2.76]
Panel B. Abnormal Monthly Flows as a fraction of assets under management (percent, value-weighted)						
25 ≤ Age ≤ 30	2.49	[6.85]	0.53	[6.65]	1.43	[6.74]
31 ≤ Age ≤ 35	0.66	[6.22]	-0.09	[-0.98]	0.25	[3.09]
36 ≤ Age ≤ 45	-0.08	[-3.07]	0.12	[7.35]	0.03	[1.34]
46 ≤ Age ≤ 55	0.02	[0.36]	-0.03	[-0.75]	-0.01	[-0.23]
56 ≤ Age ≤ 65	-0.47	[-6.99]	-0.47	[-8.80]	-0.47	[-11.22]
66 ≤ Age ≤ 90	-0.19	[-1.36]	-0.23	[-2.65]	-0.21	[-2.68]

Table 6. Monthly returns

Abnormal returns by age group, net of benchmark average, all weighted by total net assets at the end of 1997. Panel A summarizes average monthly returns net of Morningstar benchmark average. Panel B summarizes average monthly returns net of Morningstar benchmark average, weighted by total net assets at the end of 1997 and computed from quarterly holdings statements. Panel C summarizes cumulative Daniel, Titman, Grinblatt, and Wermers (1997) characteristics-adjusted returns, adjusted by Morningstar benchmark average and computed from quarterly holdings statements. Age, in all cases, refers to the age of the manager of the fund, or median age of the managers within a team, at the end of December 1997.

	1998Q1-2000Q1		2000Q2-2002Q4		Full Sample	
	R	[t]	R	[t]	R	[t]
Panel A. Raw Returns (% monthly)						
25 ≤ Age ≤ 30	0.68	[3.30]	-0.72	[-1.49]	-0.08	[-0.26]
31 ≤ Age ≤ 35	0.30	[2.12]	-0.32	[-2.28]	-0.03	[-0.31]
36 ≤ Age ≤ 45	0.14	[1.93]	-0.07	[-1.27]	0.03	[0.53]
46 ≤ Age ≤ 55	-0.11	[-1.33]	0.03	[0.76]	-0.03	[-0.75]
56 ≤ Age ≤ 65	-0.13	[-1.01]	0.27	[2.14]	0.08	[0.89]
66 ≤ Age ≤ 90	-0.11	[-0.33]	0.39	[1.12]	0.16	[0.66]
Panel B. Holdings-based Returns (% monthly)						
25 ≤ Age ≤ 30	0.16	[0.75]	-1.06	[-2.12]	-0.50	[-1.70]
31 ≤ Age ≤ 35	0.20	[1.27]	-0.35	[-2.41]	-0.10	[-0.87]
36 ≤ Age ≤ 45	0.12	[1.86]	-0.14	[-2.03]	-0.02	[-0.34]
46 ≤ Age ≤ 55	-0.04	[-0.55]	0.08	[1.34]	0.02	[0.50]
56 ≤ Age ≤ 65	-0.06	[-0.43]	0.38	[2.02]	0.18	[1.41]
66 ≤ Age ≤ 90	-0.27	[-0.57]	0.48	[1.23]	0.14	[0.46]
Panel C. Characteristics-adjusted Returns (% monthly)						
25 ≤ Age ≤ 30	-0.03	[-0.18]	-0.35	[-1.28]	-0.20	[-1.20]
31 ≤ Age ≤ 35	0.06	[0.67]	-0.21	[-2.72]	-0.09	[-1.48]
36 ≤ Age ≤ 45	0.03	[0.76]	-0.05	[-1.36]	-0.01	[-0.49]
46 ≤ Age ≤ 55	0.03	[0.62]	0.02	[0.59]	0.02	[0.86]
56 ≤ Age ≤ 65	-0.02	[-0.13]	0.08	[0.94]	0.04	[0.51]
66 ≤ Age ≤ 90	-0.73	[-1.80]	0.90	[2.68]	0.15	[0.53]

Table A1. Measuring survivorship bias in the data matching process

Data is broken down according to the year that Morningstar states the fund dies. From this sample, some fraction (NAge/N) report data on the age of its managers, and a fraction (NCRSP/N) is linked to returns and total net assets data from the CRSP Mutual Funds database. The combined CRSP and Morningstar coverage is shown in column NBoth/N. We match the remaining sample to the Thomson holdings data, using the CRSP identifier. (NHoldings/N) denotes the fraction of the original data for which we have holdings data. An observation is considered to have "all data" if it contains a CRSP identifier as well as reporting data on holdings. We count these observations as a fraction of our starting sample (Nalldata/N) and as a fraction of data for which we have information on manager age (Nalldata/Nage).

Dies in year:	N	Age Data ?	NAge / N	CRSP Data?	NCRSP / N	Both CRSP & Age Data?	NBoth / N	NBoth / NAge	Holdings Data?	NHoldings / N	All Data ?	Nalldata / N	Nalldata/ NAge
Survives	**3,323**	1,761	53.0%	3,142	94.6%	1,757	52.9%	99.8%	2,707	81.5%	**1,573**	47.3%	89.3%
1998	**185**	84	45.4%	81	43.8%	75	40.5%	89.3%	67	36.2%	**61**	33.0%	72.6%
1999	**202**	123	60.9%	124	61.4%	122	60.4%	99.2%	110	54.5%	**108**	53.5%	87.8%
2000	**288**	150	52.1%	139	48.3%	134	46.5%	89.3%	110	38.2%	**106**	36.8%	70.7%
2001	**221**	134	60.6%	131	59.3%	126	57.0%	94.0%	108	48.9%	**103**	46.6%	76.9%
2002	**149**	74	49.7%	76	51.0%	72	48.3%	97.3%	70	47.0%	**67**	45.0%	90.5%
2003	**181**	95	52.5%	108	59.7%	92	50.8%	96.8%	90	49.7%	**81**	44.8%	85.3%
2004	**15**	12	80.0%	10	66.7%	10	66.7%	83.3%	10	66.7%	**10**	66.7%	83.3%
All	**4,564**	2,433	53.3%	3,811	83.5%	2,388	52.3%	98.2%	3,272	71.7%	**2,109**	46.2%	86.7%