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ABSTRACT

We use mutual fund manager data from the technology bubble to examine the hypothesis that inexperienced investors play a role in the formation of asset price bubbles. Using age as a proxy for managers' investment experience, we find that around the peak of the technology bubble, mutual funds run by younger managers are more heavily invested in technology stocks, relative to their style benchmarks, than their older colleagues. Furthermore, young managers, but not old managers, exhibit trend-chasing behavior in their technology stock investments. As a result, young managers increase their technology holdings during the run-up, and decrease them during the downturn. Both results are in line with the behavior of inexperienced investors in experimental asset markets. The economic significance of young managers' actions is amplified by large inflows into their funds prior to the peak in technology stock prices.

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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." Brooks' (1973) depiction the stock market boom of the late 1960s is that "Youth had taken over Wall Street." More recently, Brennan (2004) proposes that increased stock market 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] Using manager age as a proxy for experience, we start by examining 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 benchmark adjustments rule out simple compositional explanations, such as the possibility that younger managers are more concentrated among growth funds. We also show that younger managers actively rebalance their portfolios in favor of technology stocks – hence the results are not driven simply by price changes of existing positions.

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,

[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, 2007; 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 one believes that prices could perhaps be justified by fundamentals (e.g., as argued by Pastor and Veronesi, 2005).

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 effects of inexperience are not limited to participants in laboratory experiments, or to retail investors. Having gone through professional training, the money managers in our sample are, *a priori*, perhaps least likely to be affected by inexperience, but our evidence shows that inexperience significantly affects their trading behavior too.

Experimental findings provide cues about the channel through which inexperience may affect portfolio decisions. The study by Smith et al. shows that inexperienced traders have adaptive expectations. Similarly, Haruvy, Lahav, and Noussair (2007) find that inexperienced subjects extrapolate recent price movements. To see whether adaptive learning also plays a role for the fund managers in our sample, we study how younger and older managers tilt their holdings in response to past returns of technology stocks. We find that 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. 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. We show that these portfolio shifts are not simply the result of younger managers following mechanical stock- or industry-level momentum strategies.

To assess the economic significance of these results, we examine the total net assets and the flows into funds of young and old managers. 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 abnormal inflows. Thus, retail investors reinforced young managers' shift towards technology stocks. A consequence is that a significant fraction of institutional money is controlled by young managers around the peak of the market. 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. Retail investors, however, achieved extremely low dollar-weighted returns due the poor timing of their inflows.

Our results fit well with models of adaptive learning. According to our 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, 2007). More broadly, our results are consistent with evidence that people learn how to solve decision problems primarily through learning-by-doing (Camerer and Hogarth 1999; List 2003; Agarwal et al. 2007) and that prior experiences influence investor behavior (Feng and Seasholes 2005; Kaustia and Knüpfer 2007; Malmendier and Nagel 2007; Seru, Shumway, and Stoffman 2007). 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 may be less of a role for inexperience in decisions related to 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. A natural place to look is in the set of 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, young managers may be incentivized 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 is not predicted by herding models.

We also consider the possibility that young managers possess specific human capital that allows them to analyze new technologies better than old managers. According to this explanation, 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 (2007). In their model, young managers 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.

Our paper shares with existing work the objective of understanding 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 significantly outperform benchmarks, suggesting an ability to anticipate price movements during the bubble and subsequent decline. Griffin, Harris, and Topaloglu (2005) examine the trading behavior of various investor groups at daily frequency and find suggestive evidence that institutional investors drove and burst the technology bubble. Dass, Massa, and Patgiri (2008) show that mutual funds with high-incentive contracts had relatively lower exposure to technology stocks.

One limitation of our approach is that the time dimension of the data is quite short. Ideally, we would study additional episodes of potential stock price bubbles, but this is not possible given the availability of the Morningstar data. On the other hand, our dataset actually covers more years than in typical studies on the effects of mutual fund manager characteristics on trading behavior. For example, in their analysis of mutual fund manager risk taking, Chevalier and Ellison (1999a) use data from 1992 through 1995. Thus, despite the limitations, our evidence should help advance the understanding of the link between investor characteristics and trading behavior.

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 start by defining the segment of the stock market that comprised the technology stock bubble of the late 1990s. As described in Ofek and Richardson (2003), the stocks affected by the bubble tended to be in the internet and technology sectors. We follow Brunnermeier and Nagel (2004) and use the price/sales ratio to identify the segment of the market most affected by the technology bubble. This simple measure captures the technology segment well. In March 2000, the (3-digit SIC) industries 737 (Computer and Data Processing Services, 33%), 367 (Electronic components and accessories, 21%), and 357 (Computer and Office Equipment, 21%) account for the biggest shares of market capitalization in the highest price/sales quintile of Nasdaq stocks (i.e, among the top-ranked 20% of stocks by price/sales). These three industries also account for the biggest shares in March 1998.

Using SIC codes to identify the stocks affected by the technology bubble, instead of valuation-based metrics like the price/sales ratio, could be problematic. While the SIC code 737 captures many of the stocks that were subject to the technology and internet stock price boom in the late 90s (the internet retailer Amazon.com, for example, is part of this category), this broad group also contains many stocks that were not affected by investors' enthusiasm for technology stocks. Moreover, some stocks that were viewed as part of the technology and internet sector do not have SIC codes that identify them as such. For example, the internet stock Ebay has SIC code 738 which places it into the "Business Services" industry together with many other firms with no connection to the internet sector. However, its price/sales ratio of 484 in the first quarter of 2000 clearly places it in the group of high price/sales stocks. The same is true for most internet stocks: Lewellen (2003) reports that almost all internet stocks in March 2000 had extremely high prices/sales ratios, compared with other stocks. To summarize, since our objective is to identify stocks whose valuations were affected by the technology bubble, rather than identifying technology industry membership per se, we focus on the price/sales ratio in our main analysis, but also conduct some robustness checks using SIC-codes. In terms of semantics, we use the labels "high price/sales stocks" and "technology stocks" interchangeably in the rest of the paper.

Figure 1 illustrates the extreme price movements of stocks in the high price/sales segment of the market 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 1,000 from the end of 1997 to March 2000. The 40% gain in the CRSP value-weighted index over this time period pales in comparison, even though price/sales and price/earnings ratios for the market index also 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 domestic equity 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 because the managers of these portfolios are unlikely to have any discretion over their allocation to 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 the number of managers running the fund and the characteristics of the median manager of the fund. The characteristic we are most interested in is the age of the manager, our proxy for inexperience. Ideally, we would like to have the number of years on the job, but since Morningstar does not have reliable personal data on managers 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 younger and older managers over time. But if we were to update age of the manger year-by-year, a finding that young managers hold more technology stocks could be driven by a tendency of fund management companies to hire younger managers in order to implement a shift towards technology stocks (for example, because fund management companies believe that younger managers better understand internet companies). In any case, untabulated robustness checks show that our main results are quantitatively similar, in fact somewhat stronger, 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 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 means of the CFA and SAT variables for the team. We also calculate the number of female managers.

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 a manager's allocation to technology stocks at the end of

[2] We obtain nearly identical 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. Another possibility, which yields similar results, is to use the age of the most senior member of the team, who may command more power over investment decisions.

each quarter. For about two-thirds of the funds, the data are available quarterly, and for 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) are unchanged until June 30. For funds that report holdings at a semi-annual frequency, we substitute in the holdings from the previous quarter for the missing data. As a result, there is some staleness in our holdings data, which is useful to keep in mind when interpreting the holdings-based results. Each fund's stock holdings are matched with 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.

Finally, we 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 additionally use data on portfolio turnover and fees from the CRSP mutual funds database. Throughout we aggregate the CRSP and Morningstar data for different share classes into fund-level observations.

While the data contain information on dead funds, Morningstar drops identifying information (fund tickers) once the fund has been delisted, or the fund class discontinued. Thus, if one were to mechanically match the data with fund returns from the CRSP mutual funds database, the resulting data would exhibit survivor bias. To counter this, we look up all missing tickers manually before attempting to match to other sources. We perform extensive checks to ensure that there is no survivor bias introduced in the process of matching the Morningstar data with CRSP and Thomson Mutual funds data.

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 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}.

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

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 -0.69 (Sequoia) to 1.93 (ProFunds Ultra). Empirically, we find a cross-sectional correlation of 0.68 between γ_{Tech} and the log price/sales ratio of a fund at the peak of the bubble (March 2000). We also calculate the fraction of the portfolio invested in Nasdaq stocks with 3-digit SIC code 737: this final measure of technology exposure has a correlation of 0.66 with the log price/sales ratio in March 2000.

D. Summary Statistics

Table 1, Panel A, reports some basic summary statistics on our fund manager data. A couple of points are noteworthy. First, the number of observations varies depending on data requirements. For our basic sample, we require Morningstar and CRSP data, which we have for 1,042 funds (after aggregating 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 835 funds.

Second, the distribution of total net assets is highly skewed (mean \$916 million; median \$165 million). In our analyses, we want to avoid that results are driven by the smallest funds, which are economically less important. For this reason, we also report tests in which we weight observations by the lagged total net assets of the fund, in addition to equal-weighted results.

Third, the mean and median fund manger is close to 45 years old. Panel A, Figure 2, 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 2, 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 about 13, a minimum greater than zero, and a standard deviation of 131. This raises the concern that averages of the price/sales ratio across funds may be susceptible to excessive influence by outliers. For this reason, we focus on 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 3.52. 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 large share of the variation. This large between-style variation, and the fact that young managers tend to be somewhat concentrated in growth funds, as shown in Panel C of Table 1, highlights the need to control for style benchmarks.

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, young mutual fund managers start out neutral, slightly 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, young 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 in 1999, after technology stocks had strongly outperformed the market for several quarters. Looking across the other age categories in March 2000 reveals an almost monotonic relationship between age and adjusted log price/sales at the peak of the bubble. Only the 41-45 and 56+ age categories breaks the monotonicity.

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. 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), a dummy variable indicating whether the fund was managed by more than person (*Team*), and the log of total net assets of the fund in December 1997 (*Fund Size*). 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 SAT 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 about 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 2.53 (Table 1, Panel A), and about 70% of the typical benchmark-adjusted cross-sectional 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 the regressions are simply picking up a composition effect. We do this in two 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 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 similar coefficients on manager age. The R^2 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, reported in column (4), 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.

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 require data from the Thomson holdings database. As the table shows, we also obtain a negative age effect with this alternative measure of technology stock exposure. In this case, the value-weighted results are stronger than the equal-weighted results. Looking across all specifications in the table, it is also apparent that none of the control variables has a consistently significant effect on technology exposure.

Robustness

A number of variations of the basic specification confirm our main result. For each set of tests listed below, we repeat both equal-weighted and value-weighted regressions, with category-level fixed effects included in each case. The results of these robustness checks are reported in Table 3.

i. Alternative measures of technology exposure: We first experiment with different measures of technology stock 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 (with Nasdaq-based quintile breakpoints) of stocks in the fund portfolio as the dependent variable (Specifications (3) and (4)). Finally, we use the percentage of the portfolio in Nasdaq stocks with a 3-digit SIC code of 737 (Computer and Data Processing Services) as dependent variable. This definition of the technology segment follows Cochrane (2003). As can be seen in specifications (5) and (6), we obtain similar results.

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, but specifications (7) to (10) show that the results are roughly similar for single-manager funds and team-managed funds.

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 (11) and (12) show that the point estimate of the slope on age is about twice as big among the group of managers of age 40 and younger (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, 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 variations: We experiment with some additional control variables, including (untabulated) (a) mutual fund fees (expense ratio and 12b-1 fees), (b) tracking error (standard deviation of fund return minus Morningstar benchmark return), (c) fund turnover, and (d) funds' technology exposure at the end of 1997. None of these controls alter our basic result. Fund fees are unrelated to manager age and unrelated to price/sales ratios. Tracking error is weakly positively correlated with manager age, as in Chevalier and Ellison (1999a), and tracking error is also positively correlated with allocation to high price-sales ratio stocks. However, controlling for tracking error, the log price/sales ratio is still strongly negatively related to fund manager age. A similar result holds with portfolio turnover: younger managers trade more, and turnover is positively related to the price/sales ratio at the peak of the bubble. However, controlling for turnover, younger managers still have higher allocations to high price-sales ratio stocks. We also repeat our basic tests with quantile-based age measures; and with the sample restricted to large funds only. Similar results are obtained in both cases.

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 driving this change.

Smith, Suchanek, and Williams (1988) find that traders' price forecasts in experimental asset market experiments tend to be adaptive—forecast changes are correlated with forecast errors in the previous period. Using a similar experimental set-up, Haruvy, Lahav, and Noussair (2007) investigate adaptive expectations formation in more detail, finding that inexperienced individuals form their beliefs about future price changes by extrapolating past price trends from limited data. Applied to our setting with mutual fund managers, the hypothesis 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 conjecture is confirmed in 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 even without doing any trading, 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 changes 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 (assuming that inflows are allocated proportional to existing portfolio weights). In this case relative portfolio weights would change from t to t-1 only because of price changes, but not through trading. By subtracting the passive log price/sales ratio from the actual log price/sales ratio we then obtain the *active* allocation to technology stocks.

Table 4 presents the results from panel regressions of this active allocation measure on lagged technology returns (defined as in Section II.C), and lagged technology returns interacted with age,

$$Log(P/S)_{it} - Log(P/S)_{it}^{Passive} = b_{0j} + b_1 Log(P/S)_{it}^{Passive} + b_2 Age_i + b_3 R_{Tech,t-1} + b_4 \left(R_{Tech,t-1} \times Age_i \right) + u_{it}, \quad (2)$$

where b_{0j} is a style-category fixed effect. To control for possible mean-reversion, we also include the lagged passive log price/sales ratio. The coefficient of interest in these regressions is b_4, the coefficient on the interaction of lagged technology returns and age. As specifications (1) and (2) show, b_4 is negative and statistically significant. This means that as age increases, managers shift from trend-chasing towards more "contrarian" behavior.

The second set of tests, shown in the two 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. Compared with the first set of tests, the results are somewhat weaker both in terms of magnitudes and t-statistics, suggesting that the total return of technology stocks matters more than the market-adjusted return.

We also experiment 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. Controlling for mechanical effects and momentum trading

We can use the measure of active allocation to technology stocks from the previous subsection to address the concern that young managers' allocation to technology stocks in March 2000 could be the simple result of price increases of their existing holdings (without active re-allocation towards technology stocks.)[3] While this is indirectly ruled out by the fact that young managers start with slightly below average exposure to technology stocks in the beginning of 1998, we can directly reject the hypothesis as follows: We repeat the cross-sectional regression from Table 2, replacing the dependent variable with a measure of a fund's *active* allocation to technology stocks, calculated as in Table 4, but now summed up over all quarters from the beginning of 1998 to March 2000. This new dependent variable measures the component of the log price/sales ratio in March 2000 that is due to active rebalancing towards technology stocks during the pre-peak period.

Columns (1) to (4) in Table 5 reports the regression results. Consistent with our previous findings, age is negatively related to active technology allocation. Thus, the results in Table 2 cannot be driven simply by price increases of technology stocks coupled with passive portfolio policies.[4]

Our earlier finding that young managers exhibit trend-chasing behavior with respect to technology stock returns raises the question whether allocation to technology stocks around the peak of the bubble is a simple consequence of having followed a momentum strategy more generally across all stocks or industries. Such a strategy could be motivated by the empirical evidence on the good performance of momentum strategies (Jegadeesh and Titman 1993). In the pre-peak period, a momentum strategy, would have loaded up on high price/sales stocks. While a tendency of young managers to be momentum traders more generally would be an interesting empirical fact, its interpretation would differ from the inexperience effect supported by the other evidence.

We add controls for momentum trading to the regressions in Table 5. Specifically, we calculate, for each fund and quarter, the *active* allocation to momentum (industry momentum) strategies. We first rank stocks (or industries, in the case of industry momentum) by the returns during the six months of quarter t and

[3] Notwithstanding our finding that the results are driven by active rebalancing of younger managers toward technology stocks, passive allocation changes could be just as important as active rebalancing. Mean annual turnover for the funds in our sample was 91 percent, and 95 percent for managers under the age of 45. Thus, given that fund managers were trading heavily, it is hard to argue that even a passive allocation to technology stocks was accidental.

[4] Note that due to the nature of the dependent variable as a sum over the pre-peak period, the regressions in Table 5 condition on survival of the fund (not the manager—recall that we assign the age of the manager at the end of 1997 to each fund). To rule out that survivorship issues are driving the results, we re-estimate all regressions in Table 5 with the dependent variable re-defined as the *average* active allocation to technology stocks over the part of the pre-peak period during which the fund was alive. Thus, in this case we don't condition on survival, but we obtain similar results.

t-1 and form five quintile groups, assigning ranks from 1 to 5. We then calculate the value-weighted average momentum (industry momentum) rank of stocks in each funds' portfolio at the end of quarter t. We also calculate the passive momentum (industry momentum) rank, in similar fashion as we did for the log price/sales ratio. The active allocation is the difference between actual and passive momentum (industry momentum). Our active momentum (industry momentum) control variables are then the accumulation of these differences from the first quarter 1998 to the end of the first quarter 2000.

Including momentum controls in the regression effectively asks whether the correlation of age with active technology stock allocation arises simply because younger managers are associated with momentum trading. As columns (5) to (8) in Table 5 report, this alternative hypothesis is not borne out in the data. The momentum controls are indeed strongly positively related with active allocation to high P/S stocks, as one would expect, but their inclusion has little effect on the coefficient on age. Thus, young managers' tendency to actively reallocate towards technology stocks prior to the peak of the bubble is not just the result of momentum trading. Interestingly, we have also experimented with adding controls for the pre-bubble momentum of the portfolio. Again, their inclusion has little effect on the coefficient on age.

D. 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.[5] Thus, the effects of young managers' investment choices are amplified by the growth of assets.

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

$$\$Flow_{ijt} = TNA_{ijt} - TNA_{ijt-1}(1 + R_{ijt}), \tag{3}$$

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:

$$Category\%Flow_{jt} = \frac{\sum_i \$Flow_{ijt}}{\sum_i TNA_{ijt-1}}. \tag{4}$$

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:

$$AbnormalFlow_{ijt} = \$Flow_{ijt} - Category\%Flow_{jt} \cdot TNA_{ijt-1} \tag{5}$$

Panel B 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 until 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 much abnormal outflow when these stocks underperform.

Panel C shows cumulative abnormal flows in millions of dollars, 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. Thus, retail investors amplified the effects of junior managers' inexperience.

[5] 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, were more likely to be run by younger managers.

Given the strong inflows in the pre-peak period, and the lack of strong subsequent outflows, it seems that from the perspective of fund management companies, the behavior of young managers was not that costly. From the perspective of retail investors, however, the picture looks completely different. Their dollar-weighted returns from investing with young managers over the sample period were poor, because in terms of dollars invested, retail investors participated more in the downside than in the upside. But because retail investors are ultimately responsible for allocating inflows to younger managers, they share responsibility for these poor returns.

Table 6 confirms 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. The differences between age groups are clearly statistically significant. Note that we adjust standard errors for persistence of fund flows.

E. Alternate theories

Our results are consistent with the inexperience hypothesis, as well as conforming 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. Mechanical allocations of inflows

One alternative theory is that mutual fund inflows are disproportionately allocated to technology stocks during the pre-peak period, and that as a result, young managers end up holding a disproportionate amount of technology stocks. One problem with this story is that it does not explain *why* managers would disproportionately allocate inflows to technology stocks. In any case, it is straightforward to reject. Under this story, the magnitude of flows received should explain active allocation to high P/S stocks. If we repeat our cross-sectional tests from Table 2, controlling for percentage flows between Q1 1998 and Q1 2000, age retains its negative sign and remains significant.

ii. *Technology-sector specific human capital*

Another alternative explanation is that 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. A version of this theory is espoused in Brooks (1973, p. 212), who describes the widely held belief during the late 1960s that "any man under forty could intuitively understand and foresee the growth of young, fast-moving unconventional companies better than almost anyone over forty."

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.

First, it is silent about the dynamics of young managers' technology holdings. Specifically, it does not predict our finding that young managers initially had neutral exposure to 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 young mangers 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 fund 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 outperform through March 2000, but then 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 7 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 A and B, the youngest managers (ages from 25 to 35) 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 benchmarks do 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 125 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 and Panel C of Table 7 present the results. According to this metric, young 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 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 tilted 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 (1999a) (see, also Hong, Kubik, and Solomon (2000), and Bernhardt, Campello, and Kutsoati (2006) for evidence on herding among security analysts).

In contrast to these earlier papers, in our data, young managers show the greatest tendency to *deviate* from their benchmarks in favor of tech investments. Therefore, herding does not appear to explain our findings. Herding could, of course, still be relevant for explaining other aspects of fund managers' decisions that are beyond our focus. As we report in Section III.A, young managers in our sample have somewhat lower tracking error than older managers, as in Chevalier and Ellison (1999a), even though they deviate more from their benchmarks on the technology stocks dimension.

An interesting feature of career concerns models is that they predict that young managers may be punished for taking risk. If they perform poorly, they may be fired or demoted. With our data, it would seem worthwhile to investigate the subsequent career of managers whose portfolios deviate toward technology stocks. But this turns out to be complicated by the fact that since the late 1990s, a fair number of managers have left the mutual fund data universe completely, going to hedge funds. These typically successful managers cannot be clearly distinguished from those who lose their jobs because of poor performance.

iii. *Anti-herding*

Applications of career concerns models to mutual fund manager behavior typically predict herding, because the payoff function is assumed to be concave in relative performance (due to large negative payoff implied by being fired). However, one could argue that during the Technology Bubble period, the payoff function of young managers might have been convex (e.g., due to the large positive payoffs of being hired by a hedge fund upon outperformance). That could generate incentives for young managers to take on risk and deviate from the benchmark. However, this theory also cannot explain our findings, because young managers in our sample have lower tracking error than older managers. Their technology stock investments are not simply the consequence of loading up on risk. Moreover, anti-herding theories don't make a clear prediction in our case, because there would be many ways in which young managers could take on tracking error if they wanted to—deviating towards technology stocks is only one of many possibilities. For example, they could hold a more concentrated portfolio or they could deviate from the benchmark towards value stocks.

iv. Window dressing

The large inflows into young manager funds suggest a final alternative interpretation. 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. Relatedly, Cooper, Gulen, and Rau (2005) show that many mutual funds changed their names during the bubble to attract inflows. 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 do so were high.

While it is possible that mutual funds had incentives to engage in window dressing, we see no reason why 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 appears unrelated to whether the fund also altered the portfolio holdings consistent with the name change. 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 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 (e.g, Table 2).

IV. Conclusions

We emphasize four main findings. First, mutual funds run by younger managers disproportionately bet on technology stocks, particularly at the peak of the bubble. Our benchmark adjustments and controls rule out simple mechanical explanations based on style category effects, price changes, or inflows. Second, young managers exhibit trend-chasing behavior in the sense that they increase their technology stock holdings particularly after quarters with high technology stock returns. Their high allocation to technology stocks around the peak of the bubble, however, is not simply the consequence of following a general momentum strategy. 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. Thus, retail investors fared poorly at the hands of inexperienced managers. Taken together, the facts are consistent with the popular view that inexperienced investors are susceptible to buy assets with inflated prices during bubble periods. 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.

On a more speculative note, our results may shed light on the puzzling periodicity of bubbles in financial markets. Bubbles, or bubble-like patterns in stock prices, are relatively rare occurrences. It is unlikely that any single explanation can fully account for them, but perhaps there is a role for investor experience. That is, once investors have experienced a bubble and subsequent crash, they are less willing to participate the next time through. The younger fund managers we study in this paper, and perhaps also the retail investors that allocated money to their funds, may have learned from their experiences during the technology bubble. Thus, a bubble can only arise following the arrival of a new generation of investors who are willing to commit their capital to buy overpriced stocks. This would be in the spirit of Galbraith (1990), who claims 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."

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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, rebalanced quarterly, 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".

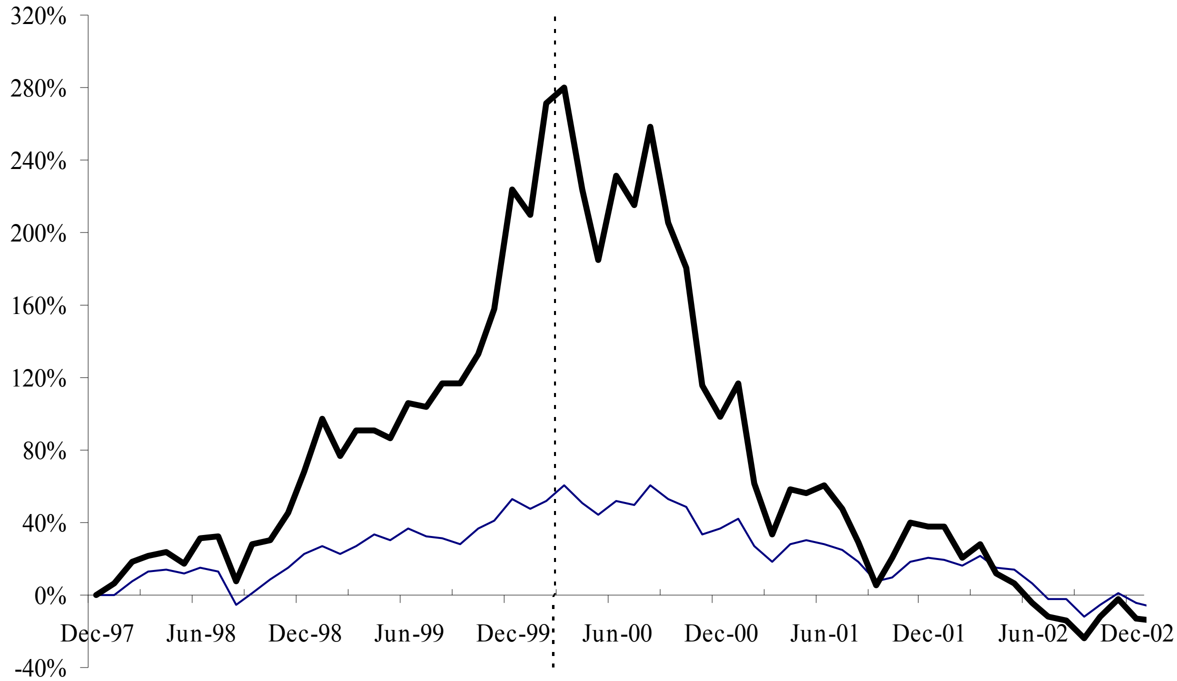
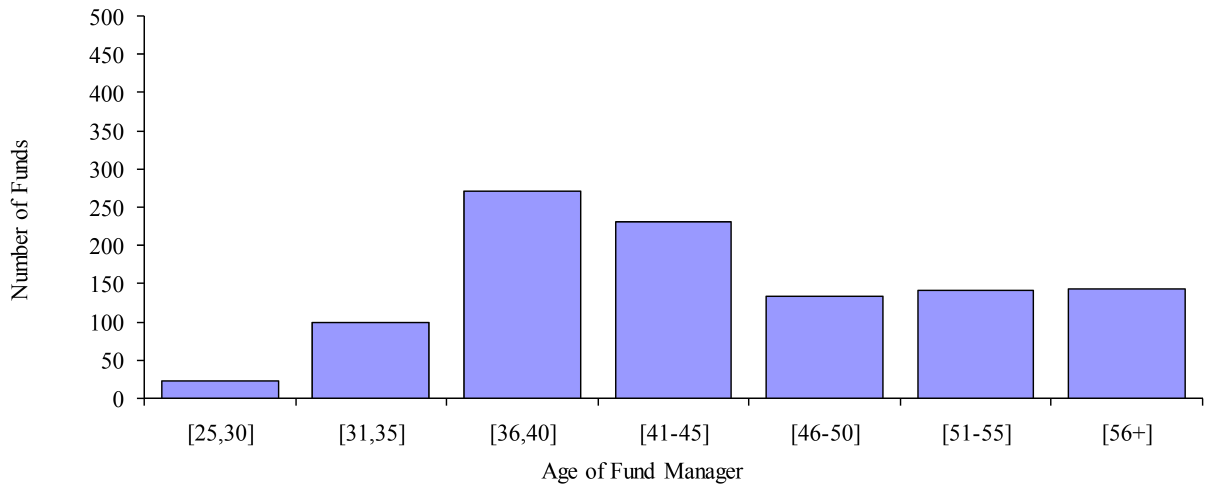


Figure 2. Who managed money during the bubble

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.

Panel A. Manager age in December 1997



Panel B. Managing team size in December 1997

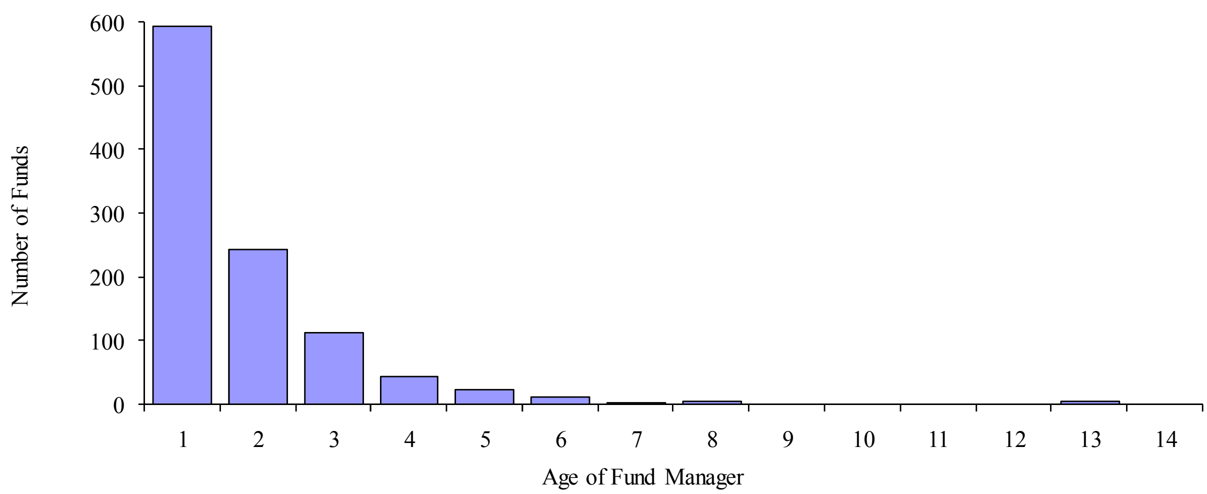
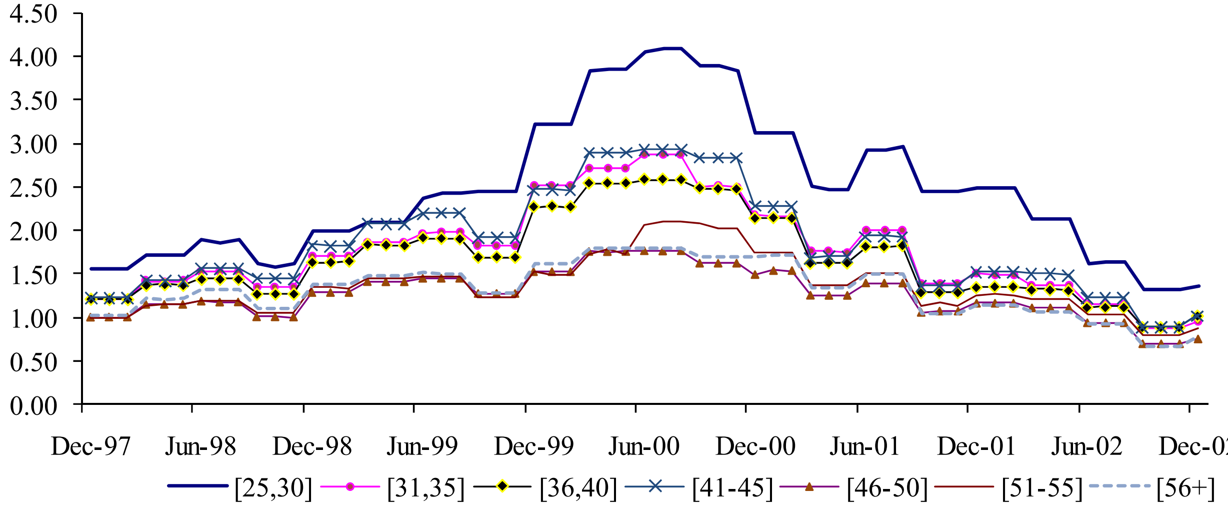


Figure 3. Technology stock exposure, by quarter and age group.

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 average log price/sales ratio, by age group



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

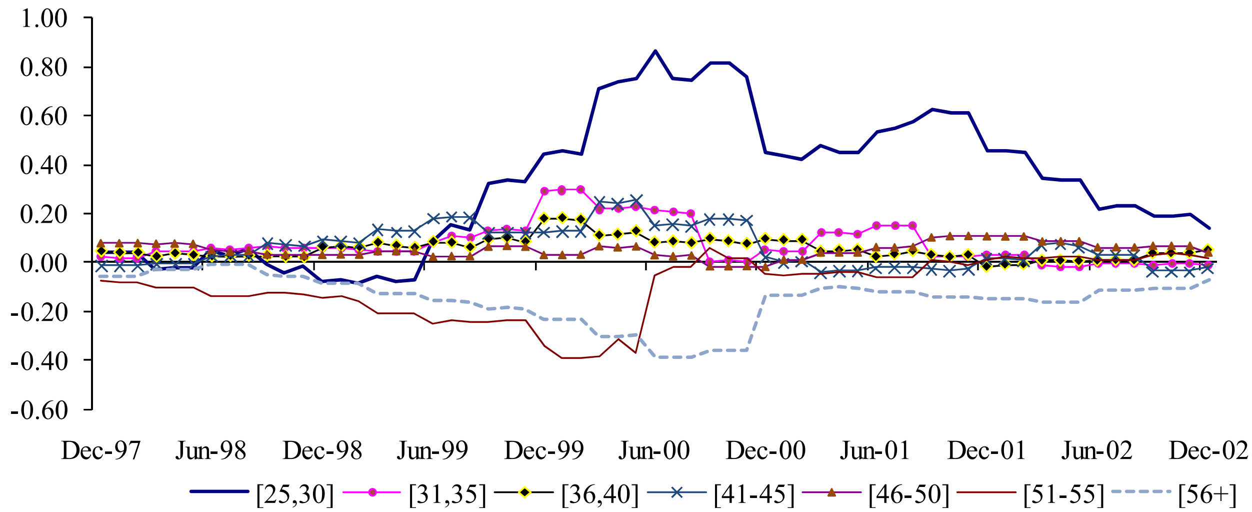


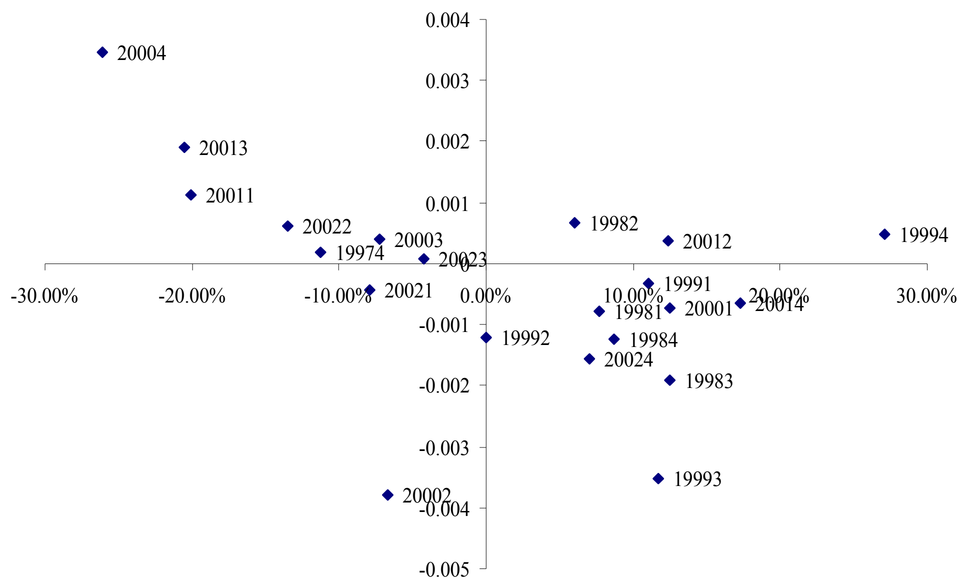
Figure 4. Manager age, past technology stock returns, and active allocation to high price/sales stocks

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 data points are labeled by quarter-year.

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



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

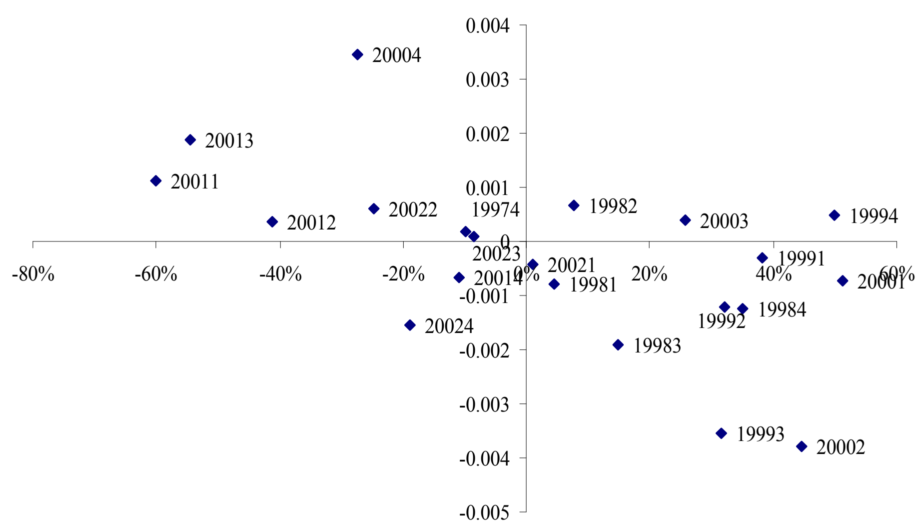
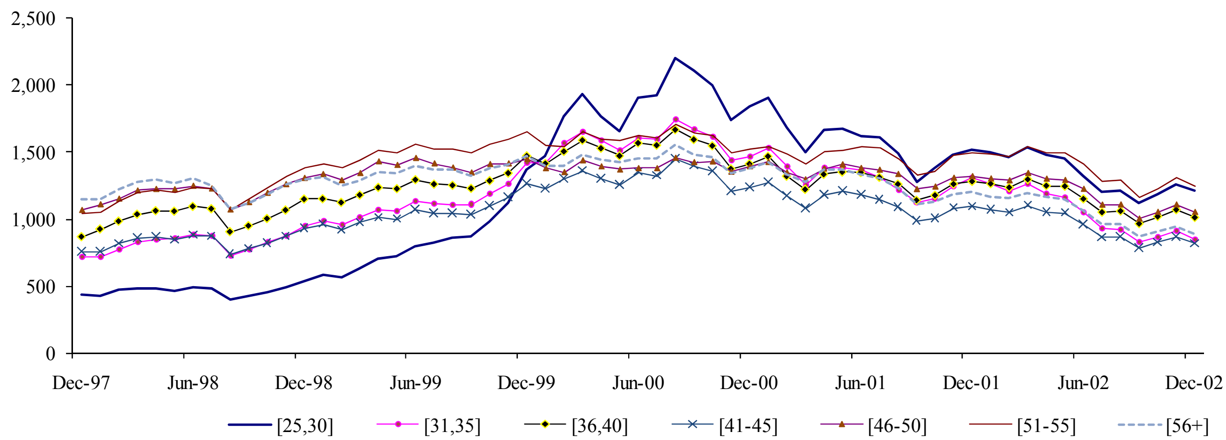


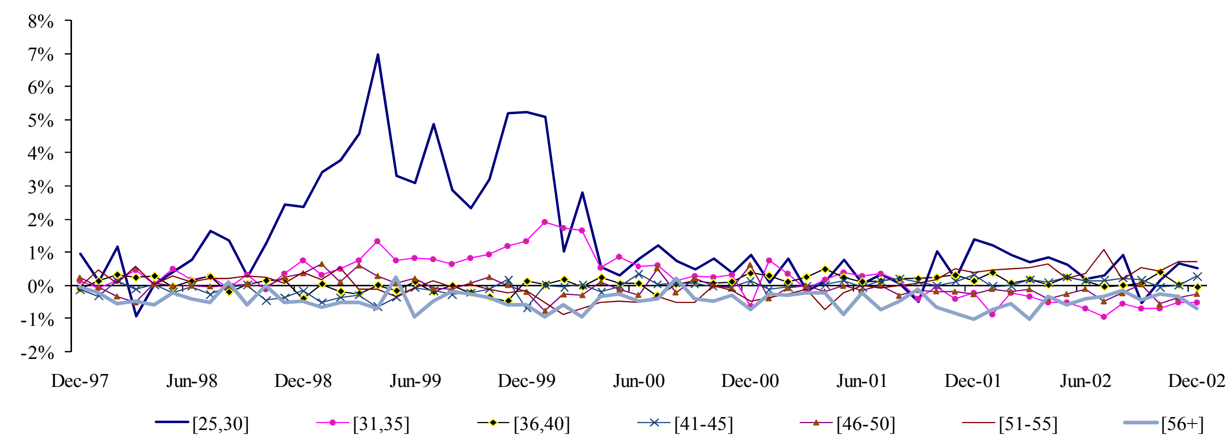
Figure 5. Assets under management and inflows into mutual funds, by age group.

Time-series of total net assets, cumulative abnormal inflows, and percentage 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 monthly abnormal flows as a fraction of total net assets. Panel C plots the sum of cumulative abnormal flows by age group.

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



Panel B. Abnormal inflows, as a fraction of total net assets, equal-weighted average for each age group



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

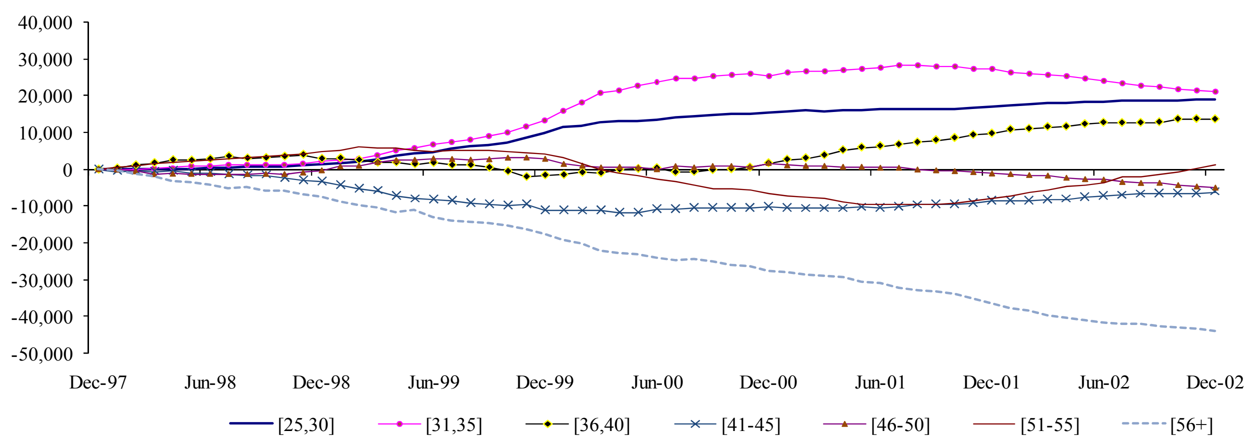
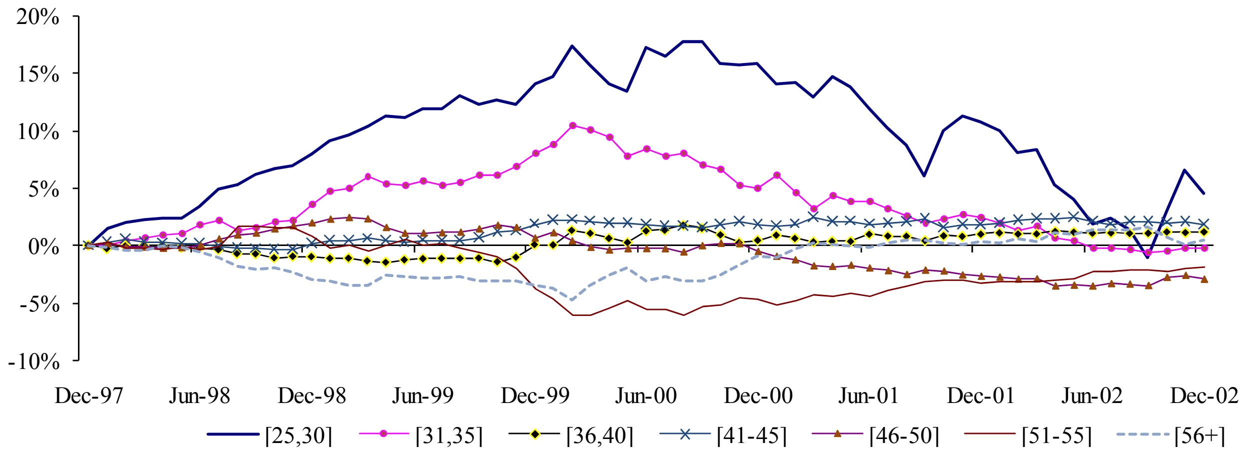


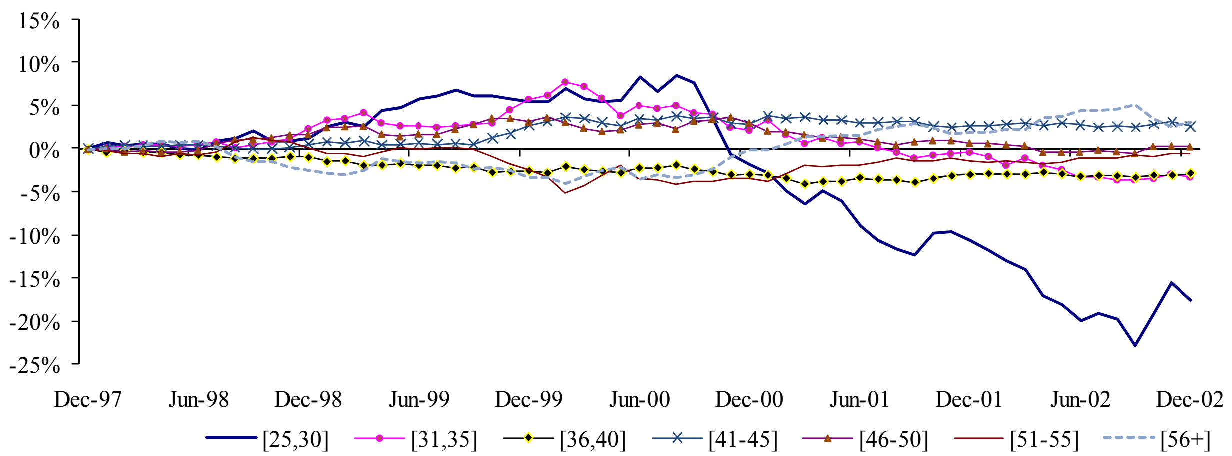
Figure 6. Returns

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, further 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

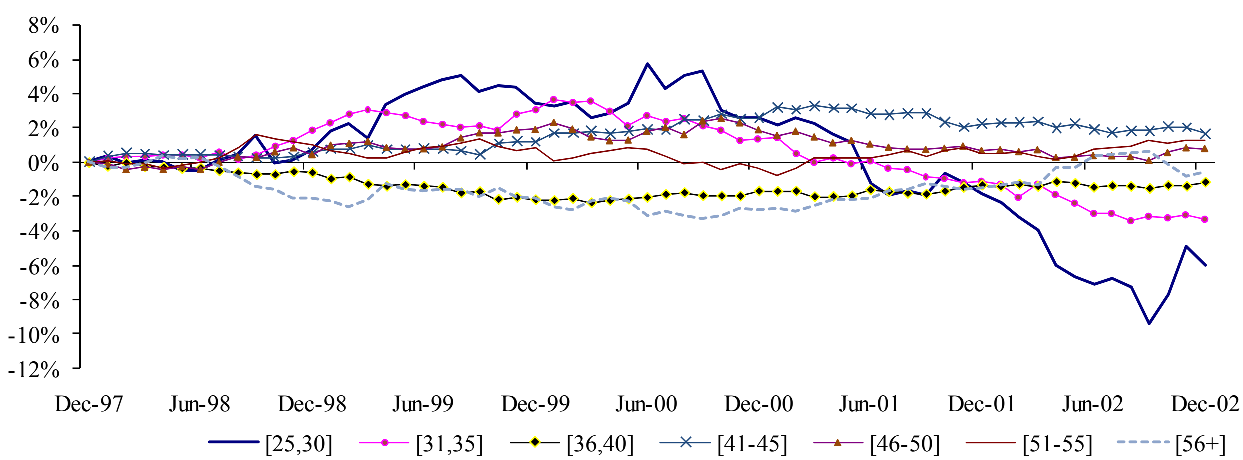


Table 1. Summary statistics

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. The technology share is the ~~fraction~~ percentage of the fund's portfolio in Nasdaq stocks with a 3-digit SIC code of 737. Turnover is measured annually. 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	1,042	915.68	165.49	2796.47	0.01	38245.98
Number of team members	1,042	1.85	1.00	1.48	1.00	14.00
Manager age	1,042	44.89	43.00	8.95	28.00	86.00
Price/sales ratio, March 2000	835	36.86	12.55	131.43	0.46	3138.32
Log price/sales, March 2000	835	2.50	2.53	1.38	-0.78	8.05
Portfolio mean price/sales quintile	835	3.71	3.84	0.64	1.42	5.00
γ^{Tech}	1,042	0.02	-0.04	0.35	-0.69	1.93
γ^{Early}	1,042	0.02	-0.01	0.23	-0.66	1.99
γ^{Late}	1,011	0.03	-0.05	0.44	-0.87	1.90
Technology share, March 2000	835	6.95	6.52	6.11	0.00	48.27
Turnover 1998	930	0.87	0.69	0.70	0.00	4.11
Turnover 1999	966	0.91	0.70	0.85	0.00	7.87

Panel B: Log price/sales ratios in March 2000, by Morningstar benchmark (N=835)

	N	**Mean**	**Median**	**SD**	**Min**	**Max**
Conservative Allocation	24	2.42	2.61	0.77	0.01	3.53
Large Blend	154	2.44	2.50	0.78	0.17	4.64
Large Growth	130	3.45	3.42	0.89	0.41	5.96
Large Value	129	1.24	1.09	0.70	0.15	3.55
Mid-Cap Blend	33	2.09	1.93	1.10	0.54	4.61
Mid-Cap Growth	76	3.83	4.02	0.98	1.18	5.92
Mid-Cap Value	32	1.01	0.75	0.83	-0.78	2.86
Moderate Allocation	97	2.24	2.49	0.97	-0.07	4.48
Small Blend	47	2.24	1.46	1.84	0.28	6.22
Small Growth	88	3.52	3.53	1.43	0.09	8.05
Small Value	25	0.95	0.34	1.61	-0.44	6.79

Panel C: Benchmark distribution by fund manager age, for funds reporting holdings in March 2000 (N=835)

	25-30	**31-35**	**36-40**	**41-45**	**46-50**	**51-55**	**56-90**
Conservative Allocation	11%	1%	2%	4%	4%	2%	3%
Large Blend	22%	18%	14%	22%	15%	16%	26%
Large Growth	11%	15%	15%	14%	15%	19%	18%
Large Value	0%	17%	15%	16%	17%	18%	13%
Mid-Cap Blend	0%	3%	5%	4%	1%	5%	4%
Mid-Cap Growth	28%	9%	9%	12%	8%	6%	6%
Mid-Cap Value	11%	2%	4%	4%	4%	4%	4%
Moderate Allocation	6%	8%	11%	9%	20%	15%	10%
Small Blend	0%	10%	8%	2%	7%	6%	3%
Small Growth	11%	15%	12%	12%	8%	7%	8%
Small Value	0%	2%	5%	1%	3%	2%	4%
	100%	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, the log of fund assets at the end of 1997, and other controls. 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. Heteroskedasticity-robust 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	3.422	2.778	3.081	3.810	0.243	0.008	0.129	0.206
	[6.10]	[4.82]	[7.34]	[5.08]	[1.89]	[0.07]	[1.57]	[1.68]
Age in 1997	-0.019	-0.015	-0.015	-0.017	-0.003	-0.002	-0.002	-0.004
	[-3.53]	[-3.22]	[-3.61]	[-2.29]	[-2.58]	[-1.48]	[-1.87]	[-3.56]
Share Female	0.125	0.113	-0.006	-0.005	0.013	0.007	-0.032	0.011
	[0.76]	[0.84]	[-0.05]	[-0.03]	[0.33]	[0.24]	[-1.24]	[0.30]
Share CFA	0.062	0.007	0.114	-0.060	-0.021	-0.027	-0.013	-0.012
	[0.57]	[0.07]	[1.34]	[-0.45]	[-0.77]	[-1.28]	[-0.70]	[-0.48]
SAT	-0.121	-0.063	-0.048	-0.083	0.001	0.037	0.016	-0.036
	[-0.19]	[-0.11]	[-0.10]	[-0.12]	[0.01]	[0.29]	[0.17]	[-0.24]
Team	0.142	0.113	0.168	0.162	0.001	-0.017	0.003	-0.011
	[1.44]	[1.30]	[2.23]	[1.38]	[0.03]	[-0.96]	[0.18]	[-0.49]
Fund Size	-0.015	0.009	-0.001	-0.095	-0.011	-0.003	-0.007	-0.002
	[-0.69]	[0.41]	[-0.08]	[-2.50]	[-2.10]	[-0.43]	[-1.83]	[-0.45]
β_{RMRF}		0.202				0.007		
		[0.99]				[0.14]		
β_{SMB}		0.593				0.408		
		[5.11]				[13.93]		
β_{HML}		-1.255				-0.281		
		[-8.09]				[-6.85]		
Category F.E.	No	No	Yes	Yes	No	No	Yes	Yes
Weighting	EW	EW	EW	VW	EW	EW	EW	VW
Observations	835	821	835	835	955	934	955	955
R-squared	0.02	0.27	0.45	0.64	0.01	0.45	0.59	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, the log of fund assets at the end of 1997, and other controls. Price/sales ratios are measured at the end of March 2000. For each set of robustness tests, both equal-weighted (EW) and value-weighted (VW) regression results are shown. Specifications (1) and (2) replace the dependent variable with the simple price/sales ratio (i.e., without taking the log). Specifications (3) and (4) replace the dependent variable with the average price/sales quintile of stocks in the portfolio; Specifications (5) and (6) replace the dependent variable with the ~~fraction~~ percentage of NASDAQ stocks in the portfolio with 3-digit SIC code 737. In specifications (7) and (8), the sample is restricted to include only funds run by one manager; (9) and (10) show the corresponding results for funds run by teams of two or more managers. Specifications (11) and (12) split the sample by age into 40 and younger (young) and higher than 40 (old). Heteroskedasticity-robust t-statistics are in brackets.

	Simple P/S		Price/sales Quintile		SIC-based share		Single Managers		Manager Teams		Young	Old
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	-1.571	34.452	4.155	4.514	14.017	6.139	3.284	3.696	3.205	3.455	2.626	3.417
	[-0.04]	[1.53]	[23.22]	[12.05]	[7.21]	[1.04]	[5.48]	[2.99]	[5.23]	[3.44]	[2.52]	[6.70]
Age in 1997	-1.189	-0.522	-0.004	-0.006	-0.061	-0.121	-0.010	-0.013	-0.023	-0.021	-0.024	-0.013
	[-2.76]	[-2.04]	[-2.28]	[-1.99]	[-3.16]	[-2.37]	[-1.97]	[-1.78]	[-3.14]	[-1.66]	[-1.23]	[-2.08]
Share Female	-5.007	-2.363	0.025	0.098	-0.783	-1.95	0.083	0.244	-0.441	-1.134	-0.164	-0.024
	[-0.35]	[-0.49]	[0.50]	[1.08]	[-1.54]	[-2.06]	[0.57]	[1.52]	[-1.71]	[-2.73]	[-0.54]	[-0.18]
Share CFA	8.464	7.479	-0.029	-0.098	-0.418	-0.779	0.141	-0.100	0.097	0.184	0.241	0.069
	[1.38]	[1.83]	[-0.80]	[-1.43]	[-0.97]	[-0.81]	[1.40]	[-0.73]	[0.61]	[0.78]	[1.44]	[0.69]
SAT	105.585	28.948	-0.253	-0.392	-5.019	10.625	-0.724	0.091	0.614	0.500	0.657	-0.430
	[1.50]	[1.26]	[-1.25]	[-1.05]	[-2.19]	[1.17]	[-1.02]	[0.07]	[0.90]	[0.57]	[0.69]	[-0.78]
Team	9.809	-0.565	0.052	0.097	0.183	-0.225					0.280	0.120
	[1.02]	[-0.14]	[1.65]	[1.80]	[0.51]	[-0.19]					[1.84]	[1.30]
Fund Size	-0.061	-1.632	-0.013	-0.035	-0.026	-0.32	0.020	-0.118	-0.012	-0.067	0.028	-0.014
	[-0.06]	[-1.29]	[-1.66]	[-1.96]	[-0.25]	[-1.40]	[0.84]	[-2.17]	[-0.49]	[-1.41]	[0.99]	[-0.67]
Category F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighting	EW	VW	EW	EW	EW	VW	EW	VW	EW	VW	EW	EW
Observations	835	835	835	458	835	835	458	458	377	377	316	519
R-squared	0.08	0.16	0.55	0.44	0.37	0.51	0.44	0.67	0.49	0.69	0.47	0.46

Table 4. Trend chasing and manager age

Panel regressions of active allocation to technology stocks on the passive price/sales ratio, lagged technology returns, and lagged technology returns interacted with age. The active allocation to technology stocks in a given quarter is calculated as the difference between the log price/sales ratio at the end of the quarter and the passive log price/sales ratio. The passive log price/sales ratio refers to the log price/sales ratio of a funds' previous quarter's portfolio computed using this quarter's prices. Technology return proxies are alternately the lagged return on the Nasdaq high price/sales quintile portfolio ("tech return"), or the returns on this portfolio net of the CRSP value-weighted return. Regressions are equal-weighted (EW) or value-weighted (VW) by December 1997 total net assets. T-statistics that allow for clustering at the fund level are in brackets.

	R_{t-1}= Tech Return		R_{t-1}= Tech Return – CRSP VW	
Constant	0.156	0.098	0.158	0.095
	[10.46]	[6.75]	[10.44]	[6.45]
Log $(P/S)^{Passive}$	-0.063	-0.028	-0.062	-0.026
	[-11.21]	[-5.91]	[-11.11]	[-5.18]
Age in 1997	-0.001	-0.001	-0.001	-0.001
	[-2.50]	[-1.83]	[-2.66]	[-1.85]
R_{t-1}	0.347	0.344	0.248	0.357
	[3.53]	[3.11]	[1.86]	[2.31]
R_{t-1} × Age in 1997	-0.006	-0.005	-0.003	-0.005
	[-2.84]	[-2.09]	[-1.03]	[-1.66]
Fixed Effects	Yes	Yes	Yes	Yes
Weighting	EW	VW	EW	VW
Observations	16,865	16,855	16,865	16,855
R-squared	0.03	0.02	0.03	0.02

Table 5. Fund manager age and active allocation to technology stock holdings

Cross-sectional regressions of domestic equity managers' active allocation to technology stocks, summed up over the period from the beginning of 1998 to 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, the log of fund assets at the end of 1997, active allocation to momentum, and active allocation to industry momentum. The active allocation to technology stocks in a given quarter is calculated as the difference between the log price/sales ratio at the end of the quarter and the passive log price/sales ratio. The passive log price/sales ratio refers to the log price/sales ratio of a funds' previous quarter's portfolio computed using this quarter's prices. For active allocation to momentum (industry momentum), we rank stocks (3-digit industries) by the returns during the six months of quarter *t* and *t*-1 and form five quintile groups, assigning ranks from 1 to 5. We then calculate the value-weighted average momentum (industry momentum) rank of stocks in each funds' portfolio. We also calculate the passive momentum (industry rank), in similar fashion as for the log price/sales ratio. The active momentum allocation is the difference between actual and passive momentum (industry momentum) rank at the end of quarter *t*. Our active momentum (industry momentum) control variables are then the accumulation of these differences between the end of the first quarter 1998 and the end of the first quarter 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. Heteroskedasticity-robust t-statistics are in brackets. VW denotes value-weighting, EW denotes equal-weighting.

	Y = Active allocation to high price/sales stocks							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.909	1.160	0.968	1.541	0.881	0.887	0.895	1.246
	[2.34]	[2.94]	[2.43]	[2.78]	[2.26]	[2.25]	[2.28]	[2.27]
Age in 1997	-0.012	-0.012	-0.013	-0.010	-0.013	-0.013	-0.013	-0.010
	[-3.51]	[-3.69]	[-3.94]	[-2.15]	[-4.01]	[-4.00]	[-4.04]	[-2.14]
Share Female	0.018	0.027	-0.009	0.016	-0.047	-0.062	-0.061	-0.075
	[0.17]	[0.27]	[-0.08]	[0.12]	[-0.46]	[-0.59]	[-0.58]	[-0.57]
Share CFA	0.001	-0.006	0.008	-0.028	0.025	0.028	0.028	0.003
	[0.01]	[-0.08]	[0.11]	[-0.27]	[0.35]	[0.41]	[0.39]	[0.02]
SAT	-0.274	-0.361	-0.286	-0.938	-0.220	-0.247	-0.257	-0.613
	[-0.60]	[-0.78]	[-0.60]	[-1.65]	[-0.47]	[-0.53]	[-0.56]	[-1.11]
Team	0.002	0.012	0.005	-0.023	-0.018	-0.019	-0.017	-0.057
	[0.03]	[0.18]	[0.08]	[-0.28]	[-0.27]	[-0.29]	[-0.26]	[-0.69]
Fund Size	0.017	0.014	0.016	-0.001	0.019	0.019	0.019	0.003
	[1.19]	[0.94]	[1.04]	[-0.04]	[1.27]	[1.31]	[1.29]	[0.10]
β_{RMRF}		-0.165						
		[-1.37]						
β_{SMB}		-0.141						
		[-1.46]						
β_{HML}		-0.002						
		[-0.02]						
Active MOM					0.155		-0.037	
					[2.87]		[-0.32]	
Active Industry MOM						0.317	0.367	0.295
						[4.29]	[2.16]	[2.83]
Category F.E.	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Weighting	EW	EW	EW	VW	EW	EW	EW	VW
Observations	835	821	835	835	835	835	835	835
R-squared	0.02	0.03	0.04	0.13	0.06	0.07	0.07	0.16

Table 6. 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 normal flow. The abnormal flow is the difference between the actual flow and the normal 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. Autocorrelation-consistent t-statistics, following Newey and West (1987), with three lags, are reported in brackets.

	1998Q1-2000Q1		2000Q2-2002Q4		Full Sample	
	Mean	[t]	Mean	[t]	Mean	[t]
Panel A. Abnormal Monthly Flows ($ millions, equal-weighted average)						
$25 \leq$ Age ≤ 30	20.20	[3.35]	8.66	[5.38]	13.96	[4.34]
$31 \leq$ Age ≤ 35	7.62	[2.99]	-0.20	[-0.11]	3.39	[1.81]
$36 \leq$ Age ≤ 40	-0.20	[-0.37]	1.96	[4.68]	0.97	[2.23]
$41 \leq$ Age ≤ 45	-1.81	[-4.38]	0.85	[3.59]	-0.37	[-0.90]
$46 \leq$ Age ≤ 50	0.21	[0.20]	-1.56	[-2.73]	-0.74	[-1.19]
$51 \leq$ Age ≤ 55	-0.14	[-0.10]	0.66	[0.33]	0.29	[0.22]
$56 \leq$ Age ≤ 90	-5.73	[-6.89]	-5.45	[-8.25]	-5.58	[-10.81]
Panel B. Abnormal Monthly Flows as a fraction of assets under management (percent, value-weighted)						
$25 \leq$ Age ≤ 30	2.49	[4.22]	0.53	[5.82]	1.43	[3.86]
$31 \leq$ Age ≤ 35	0.66	[3.69]	-0.09	[-0.59]	0.25	[1.72]
$36 \leq$ Age ≤ 40	-0.01	[-0.17]	0.15	[4.88]	0.08	[2.27]
$41 \leq$ Age ≤ 45	-0.19	[-4.44]	0.08	[3.72]	-0.04	[-1.04]
$46 \leq$ Age ≤ 50	0.02	[0.23]	-0.13	[-2.76]	-0.06	[-1.24]
$51 \leq$ Age ≤ 55	0.02	[0.20]	0.07	[0.50]	0.05	[0.51]
$56 \leq$ Age ≤ 90	-0.44	[-7.94]	-0.44	[-7.70]	-0.44	[-11.21]

Table 7. Monthly returns

Abnormal returns by age group, net of benchmark value-weighted 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 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, net of category benchmark (% monthly)						
25 ≤ Age ≤ 30	0.56	[3.66]	-0.34	[-1.00]	0.07	[0.37]
31 ≤ Age ≤ 35	0.36	[3.13]	-0.31	[-2.65]	0.00	[-0.05]
36 ≤ Age ≤ 40	0.04	[0.51]	0.00	[0.06]	0.02	[0.41]
41 ≤ Age ≤ 45	0.08	[1.76]	-0.01	[-0.20]	0.03	[0.98]
46 ≤ Age ≤ 50	-0.01	[-0.08]	-0.08	[-1.60]	-0.05	[-1.10]
51 ≤ Age ≤ 55	-0.22	[-1.71]	0.12	[2.10]	-0.03	[-0.46]
56 ≤ Age ≤ 90	-0.13	[-1.46]	0.12	[1.44]	0.01	[0.14]
Panel B. Holdings-based Returns, net of category benchmark (% monthly)						
25 ≤ Age ≤ 30	0.14	[1.02]	-0.68	[-2.01]	-0.30	[-1.52]
31 ≤ Age ≤ 35	0.27	[2.17]	-0.33	[-2.49]	-0.05	[-0.55]
36 ≤ Age ≤ 40	-0.08	[-1.41]	-0.02	[-0.37]	-0.05	[-1.26]
41 ≤ Age ≤ 45	0.13	[2.02]	-0.04	[-0.57]	0.04	[0.85]
46 ≤ Age ≤ 50	0.09	[1.11]	-0.06	[-0.88]	0.01	[0.14]
51 ≤ Age ≤ 55	-0.15	[-1.26]	0.13	[1.43]	0.00	[-0.02]
56 ≤ Age ≤ 90	-0.09	[-0.95]	0.19	[1.64]	0.06	[0.76]
Panel C. Characteristics-adjusted Returns, net of category benchmark (% monthly)						
25 ≤ Age ≤ 30	0.06	[0.43]	-0.25	[-1.21]	-0.11	[-0.84]
31 ≤ Age ≤ 35	0.14	[2.09]	-0.21	[-3.01]	-0.05	[-0.95]
36 ≤ Age ≤ 40	-0.09	[-2.36]	0.03	[1.00]	-0.03	[-1.07]
41 ≤ Age ≤ 45	0.06	[1.55]	-0.02	[-0.36]	0.02	[0.61]
46 ≤ Age ≤ 50	0.05	[0.98]	-0.02	[-0.40]	0.01	[0.38]
51 ≤ Age ≤ 55	0.01	[0.16]	0.04	[0.74]	0.02	[0.61]
56 ≤ Age ≤ 90	-0.07	[-0.95]	0.05	[0.78]	0.00	[-0.06]