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# Did Large Institutional Investors Flock Into the Technology Herd? An Empirical Investigation Using a Vector Markov-switching Model

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# Did Large Institutional Investors Flock into the Technology Herd?

## *New Evidence from a Vector Markov-Switching Regression Exercise*

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**Running title:**

Did Large Institutional Investors Flock into the Technology Herd?

**Abstract**

This paper investigates whether large non-bank institutional investors herded during the dot-com bubble of the 1990s. We use the vector Markov-switching model of Hamilton and Lin (1996) to analyze the technology stock holdings of 115 large institutional investors from 1980 to 2012. By imposing different restrictions on the elements of the transition probability matrix, we are able to test for various lead/lag scenarios that might have existed between the technology stock holding of each investor and that of the residual market. We find that only 17.4% of the investors in our sample herded during the dot-com bubble. Thus, during the dot-com bubble, herding among large institutional investors was not an especially widespread phenomenon. Among those investors that herded, 80% herded during the run-up, 10% during the collapse, and 10% during both phases of the dot-com bubble. About 23% of all investors in our sample exited from the technology sector before the bubble collapsed. These results seem to support Abbreu and Brunnermeier's (2003) theory of bubbles and crashes.

**Keywords:** herding in financial markets; vector Markov-switching models; institutional investors; dot-com bubble.
**JEL Classifications:** C34; C58; G11; G14; G23.

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**Did Large Institutional Investors Flock into the Technology Herd?**

***An Empirical Investigation Using a Vector Markov-Switching Model***

## I. Introduction

Herding in financial markets is often defined as the behavioral tendency of an investor to follow the actions and investment strategies of others.[1] In this paper we look for traces of one particular type of herding that Choi and Sias (2009) define as industry herding, the tendency of investors to follow others into or out of a given industry's stocks over some period of time. Herding can lead to persistent deviations of asset prices from their fundamental values, inefficient distribution of capital, excess volatility,[2] asset bubbles, and crashes. Since herding distorts the risk-return distribution in asset markets, it also has important implications for asset pricing models. There is a vast amount of literature that documents at least some evidence of herding in financial markets.[3] If herding is pervasive among large institutional investors,[4] then we posit that all of the above problems would be exacerbated because the proportion of the stock market capitalization managed by institutional investors has steadily increased from around 7% in the 1950s to nearly 67% in 2010.[5] It is not surprising that this growing importance of institutional investors has led to a recent upsurge in the literature that investigates herding behavior among them. Lakonishok *et al.* (1992), proposed a (LCV) metric for gauging herding and positive feedback trading practices among investors. Using this metric, they examined herding behavior among US pension funds between 1985 and 1989 and found that during this period pension funds herded relatively little. Recognizing that the original LCV metric may suffer from few shortcomings, Wylie (2005), Andreu *et al.* (2009), and

[1] Bikhchandani and Sharma (2000).

[2] See, for example, Blasco *et al.* (2012).

[3] See, for example, Andronikidi and Kallinterakis (2010), Ben-David *et al.* (2012), Billio *et al.* (2012), Choi and Sias (2009), Guo and Shih (2008), Khandani and Lo (2011). Haiss (2005) offers an overview of the related literature.

[4] Institutional investors include but are not limited to pension funds, endowment funds, insurance companies, commercial banks, mutual funds, and hedge funds. These investors exhibit industry herding when the money managers who operate under the umbrella of a larger institution collectively tilt their portfolios toward a particular industry. See Frazzini and Lamont (2008)

[5] Blume and Keim (2012).

Huang *et al.* (2010) modified the metric and analyzed the herd behavior among pension and mutual fund managers in different international markets. All three studies found that investors tend to herd in their respective markets. Wermers (1999) analyzed the trading activity of the mutual fund industry from 1975 through 1994 and found little evidence of herding in the average stock and much higher levels in trades of small stocks and in trading by growth-oriented funds. Nofsinger and Sias (1999) found that institutional investors herd more than individual investors. Sias (2004) and Choi and Sias (2009) examined the dynamics of institutional portfolio holdings and found strong evidence of herding. Finally, a study by Reca *et al.* (2012) concluded that hedge fund managers herd much less than other types of institutional investors.

As the above synopsis of the related literature suggests, evidence on institutional herding is inconclusive and context specific. One branch of the literature examines investor herding behavior during the technology (dot-com) bubble 1998–2000. Brunnermeier and Nagel (2004), for example, examined the trading behavior of hedge funds during this period and found that hedge funds actively purchased technology stocks during the run-up of the bubble and quickly reversed the course shortly before March 2000 when the bubble collapsed. Griffin *et al.* (2011) reached a similar conclusion for a broader group of institutional investors. Both studies found evidence that before the market peaked in March 2000, institutional investors engaged in feedback trading and followed the trades of other sophisticated market participants.

The notion of herding in financial markets is closely related to and goes against the Efficient Market Hypothesis (EMH) of Friedman (1953) and Fama (1965). According to the EMH, rational arbitrageurs would normally bet against overpriced market segments and by doing so drive asset prices back to their fundamentals. The EMH implies that bubbles in asset markets form only when rational investors remain persistently agnostic about overly inflated asset prices. On the other hand, if markets are in fact inefficient, bubbles may form due to market frictions, such as shortsell constraints,[6] agency problems,[7] or other frictions, that prevent investors from betting against overinflated assets. Abreu and Brunnermeier (2003) propose that because of capital constraints, individual rational investors may be unable to drive market prices down even when they are aware of the bubble. Furthermore, they have an incentive to herd and continue investing in overvalued assets (ride on the bubble) as long as there is a common belief that positive-feedback trades will continue pushing the prices of those assets up. Thus, Abreu and Brunnermeier (2003) view asset bubbles as a coordination problem. Bubbles eventually collapse when common knowledge among arbitrageurs about overvalued assets reaches critical mass and the trend reverses to a coordinated sell-off of these assets. Both, Brunnermeier and Nagel (2004) and Griffin *et al.* (2011) provide evidence that institutional investors were well aware of the bubble around the implosion of the technology stock prices and many of them exited this sector before the bubble collapsed. This finding is in line with and supports the hypothesis of Abreu and Brunnermeier (2003).

Our study is another empirical inquiry into the hypothesis that Abreu and Brunnermeier (2003) propose. We investigate whether and to what extent large institutional investors herded during the buildup and collapse of the dot-com bubble of the 1990s. We consider a unique sample of 115 large US institutional investors and the evolution of each investor's technology stock portfolio prior to, during, and after the bubble. Using a vector Markov-switching model of Hamilton and Lin (1996), we formally test whether technology investment regimes of each investor in our sample led or lagged the technology investment regimes of all other investors in the sample. Thus, one of the important goals of this study is to demonstrate that during an asset bubble, certain transition probabilities in a vector Markov-switching model can be conveniently used to gauge investor herding behavior. Our results indicate that while overall institutional herding was not an especially pervasive phenomenon, herding was much more prevalent during the run-up of the bubble than during the collapse. Only 20 out of 115 investors in our sample (or 17.4%) herded during the

[6]See, for example, Scheinkman and Xiong (2003).
[7]See, for example, Shleifer and Vishny (1997).

bubble. Within these 20, 16 (13.9% of the sample) herded during the buildup, 2 (1.7% of the sample) after the collapse, and 2 during both phases of the bubble. 27 (or 23%) investors exited from the technology sector before the bubble collapsed. These results indicate that many sophisticated rational speculators were probably well aware of the bubble even though they rode on it during the buildup. Our results are in strong agreement with those obtained by Brunnermeier and Nagel (2004) and Griffin *et al.* (2011) and also support Abreu and Brunnermeier's (2003) hypothesis of rational asset bubbles.

This study contributes to the literature from at least two different dimensions. First, we propose a new formal empirical test for detecting herding behavior among investors during an asset bubble. As we mentioned above, certain estimated transition probabilities in our vector Markov-switching model may be reflective of investor herding behavior. Using this particular feature of the model, we manage to formally test whether the portfolio regimes of a given investor led, lagged, or coincided with the portfolio regimes of all other sample investors during the dot-com bubble. One attractive feature of our approach is that unlike most other existing methods, our methodology allows for disaggregated (investor-level) analysis of herding behavior. Using our methodology, one can test whether any given investor in the sample exhibited any signs of herding behavior. Subsequently, after considering every investor in the sample, it is straightforward to aggregate the results and use them for the analysis of market-wide herding trends. Our approach to detecting investor herding is novel and, to the best of our knowledge, has not yet been explored in the related literature. The second contribution of our study is related to the uniqueness of the sample of investors that we consider. Our sample consists of 115 largest institutional investors. These are perhaps some of the most sophisticated and rational investors. Thus, our results provide additional empirical evidence regarding herding behavior among some of the most sophisticated and rational investors.

The rest of this paper is organized as follows: Section II explains our data and methodology. Section III describes the empirical results. Section IV concludes.

## II. Data and Methodology

Since 1978, all financial institutions and managers with \$100 million or more under management are required to file quarterly SEC 13(f) reports of their large long positions in exchange-traded or NASDAQ-quoted equity. We retrieved all the reports filed between January 1980 and September 2012 (130 quarters) from the Thomson Reuters database[8] that contained about 218,000 filings by 6,212 distinct investors.[9] Since our goal is to investigate herding behavior among large institutional investors, we concentrated on large investors whose equity portfolio in September 2012 was at least \$1 billion and who by September 2012 had at least 80 quarters of continuous data. By focusing on this particular group of investors, we hope to take advantage of the possible survivorship bias. Since investors in our sample turned out to be the largest at the end, prevalence of herding among them indirectly implies that herding in general may be a successful investment strategy.

The Thomson Reuters database classifies each 13(f) investor into one of the following five categories: banks, insurance companies, investment companies and their managers, independent investment advisors, and all others. In this study, we limited our attention to the latter two.[10,11] Hence, our sample consists of large independent investment advisors and other uncategorized investment companies that by September 2012 had at least 80 quarters of continuous data and at least \$1 billion under

[8]This database is in turn available from Wharton Research Data Services (WRDS).

[9]Investors in the Thomson Reuters database may over time change their reporting status. This may happen when the nature of their operations changes or when new information becomes available. Because of this, there are more distinct manager numbers in the database than reporting institutions. Here we report the number of unique manager numbers.

[10]The ‘independent investment advisors’ category includes mostly asset management companies, investment banks, brokers, and private wealth management companies. The category ‘all others’ includes mostly pension funds, endowment funds, most of the hedge funds, and financial arms of corporations.

[11]Reca *et al.* (2012) identify at least four limitations of using this database that may be relevant to the present study. First, it represents only the long side of investors’ portfolios These authors claim that this limitation may not be very severe. Second, only large positions in excess of 10,000 shares or \$200,000 are required to be disclosed in 13(f) fillings. Third, since investors are required to file these reports only once a quarter, short-term trades may not be reflected in these filings. Finally, institutional investors may exhibit signs of industry herding when individual money managers within a larger institution collectively tilt their portfolio toward a particular industry. Thus, these data are not much helpful in investigating herding behavior among individual money managers.

discretionary management. The Thomson Reuters database has 115 of such investors.

Figure 1 exhibits the total 13(f) value held by all and these 115 investors. As the figure demonstrates, at the peak of the dot-com bubble in mid-2007 the joint portfolio of all 13(f) filers was worth \$15.4 trillion. At the same time, the size of the joint portfolio of the 115 investors was about \$3.9 trillion, or 25% of the total 13(f) portfolio. During the sample period between 1980 and 2012, investors in our sample held between 14.3% and 29% of the cumulative 13(f) portfolio.

Figure 2 exhibits the total 13(f) value held by the investors in our sample and the size and share of their collective long portfolio held in technology stocks.[12]As the graph also shows, starting in 1997, the share of the collective portfolio held by the 115 investors in technology stocks started diverging from its long-run trend and then, as the dot-com bubble collapsed in the early 2000s, reversed back toward the trend. This unusual behavior of the portfolio share invested in technology stocks is perhaps one of the most obvious manifestations of the dot-com bubble in our data.

The current study examines the temporal relationship between the aggregate and individual investor portfolio shares invested in technology stocks. The share of the aggregate portfolio that the 115 large investors had collectively invested over time in technology stocks appears as a solid line on Figure 2. As it can be seen from the figure, this variable can be modeled as a trend-stationary process with a single temporary shift in the intercept regime that occurred between 1997 and 2002. To demonstrate this point, we detrend this variable[13] and estimate the parameters in the following univariate Markov-switching model with no autoregressive dynamics:

$$y_{M,t} = \mu_t^r + \varepsilon_{M,t} \tag{1}$$

[12]The Thomson Reuters database provides industry classifications for each portfolio stock holding in the 13(f) database. We consider all common stocks with industry codes in Computer Hardware, Software & Services, and Telecommunications as technology stocks.

[13]We obtain detrended series by first estimating the following regression equation $x_{M,t} = \alpha + \beta t + \gamma_{M,t}$, where $x_{M,t}$ is the share of the market portfolio invested in technology stocks, $t$ is a time index, and $\gamma_{M,t}$ is the residual term. We then obtain the estimated residuals $y_{M,t} = x_{M,t} - \widehat{\alpha} - \widehat{\beta} t$ that represent the detrended share of the market portfolio held in technology stocks.

Here $y_M$ is the detrended share of the collective market portfolio invested by the 115 investors in technology stocks. The intercept term, $\mu_t^r$, can be interpreted as the detrended mean share of portfolio invested in these stocks. The model allows this mean to be in one of the two regimes, low ($l$) and high ($h$). Thus $r = \{l, h\}$. We assume that the innovation term is an i.i.d., zero-mean process with Markov-switching heteroscedasticity. The standard deviation of $\varepsilon_M$, $\sigma_M^r$, may also assume two regimes ($l$) and high ($h$).[14] We estimate equation (1) and the smoothed regime probabilities using the procedures outlined in Hamilton (1994) and Kim and Nelson (1999). Our estimates of the intercepts are $\mu^l = -1.40$ and $\mu^h = 10.36$. Using these intercepts and the regime smoothed probabilities, we also obtained the conditional detrended mean portfolio share invested in technology stocks.[15] Figure 3 exhibits this fitted mean and the share of the collective portfolio invested in the technology sector. The graph suggests that the estimated conditional mean does a decent job in tracking the rise and fall of the actual collective investment in the technology sector.

To establish whether the investment in technology stocks of each investor in our sample followed that of others, we would like to determine whether the portfolio share that each investor held in technology stocks also experienced regime shifts during the dot-com bubble and if so, whether the shifts led, coincided, or lagged the shift in the market portfolio of the remaining 114 investors. If the shifts in a given investor's portfolio occurred after the shift in the market portfolio, then we can conclude that the investor followed the market and therefore herded into and/or out of the bubble. This simple idea is closely related to one important aspect of our methodology, offering a justification for why it is acceptable for us to rely on the portfolio share as a metric of an investor's involvement in technology sector investment. Even if the investor did not purchase any additional technology

[14]We allow for Markov-switching heteroscedasticity in the model because our preliminary analysis of the residuals from the homoscedastic model indicated significant deviations from normality. The problem is greatly remedied when Markov-switching heteroscedasticity is allowed.

[15]More specifically, we obtain the conditional mean for any period $t$ by applying the following formula: $\mu^l \times \mathrm{P}(r_t = l|\Im_T) + \mu^h \times \mathrm{P}(r_t = h|\Im_T)$ where $\mathrm{P}(r_t = l|\Im_T)$ and $\mathrm{P}(r_t = h|\Im_T)$ are the smoothed probabilities that $y_{M,t}$ is in the low and high regime respectively.

stocks as the bubble matured, the portfolio share invested in these stocks would have automatically shifted upward as technology stocks appreciated. This upward shift, however, would have occurred simultaneously with the rest of the market and we would not classify this investor as having herded. Thus, whether the investor shifted the portfolio simultaneously with the market or did not shift it at all, we are likely to conclude that the investor did not herd. Only when the shift in the investor's portfolio occurred after that of the residual market, can we conclude that the investor herded. The same logic can be applied when there is a downshift in the market and when the investor leads the market.

We will examine the interplay between a given investor's technology-stock holdings and that of the remaining market of 114 investors by using a version of the vector Markov-switching model employed by Hamilton and Lin (1996), Smith *et al.* (2000), and Balagyozyan *et al.* (2015). This model allows for structural shifts in both variables and is capable of revealing the lead and lag relationships between them. For each investor in our sample, we estimate the following two-regime vector Markov-switching model with no autoregressive dynamics:

$$\begin{aligned} y_{i,t} &= \delta_t^s + \varepsilon_{i,t} \\ y_{M,t} &= \mu_t^r + \varepsilon_{M,t} \end{aligned} \tag{2}$$

Here $y_{i,t}$ and $y_{M,t}$ are the shares of the portfolio that $i$-th investor and the remaining market, consisting of 114 investors, invested at time $t$ in technology stocks. Intercepts $\delta_t^s$ and $\mu_t^r$ are allowed to vary with time and subject to discrete Markov-switches between two regimes: low ($l$) and high ($h$), hence $r, s = \{l, h\}$. We assume that the innovation terms $\varepsilon_{M,t}$ and $\varepsilon_{i,t}$ are correlated processes with zero mean, time-varying Markov-switching heteroscedasticity, and the correlation coefficient $\rho$. Hence, the variance-covariance matrix of the innovation terms is given by:

$$\Sigma_t = \begin{bmatrix} (\sigma_i^s)^2 & \rho\sigma_i^s\sigma_M^r \\ \rho\sigma_i^s\sigma_M^r & (\sigma_M^r)^2 \end{bmatrix} \tag{3}$$

Superscripts $s$ and $r$ in (3) represent heteroscedasticity regimes that can again assume low ($l$) and high ($h$) values.

There are at least two reasons why we do not include any autoregressive or moving-average dynamics in our model specified above. The first reason is uniformity. Estimating the same model for every investor allows us to freely compare the estimated parameters and test results across different investors. If we have to estimate the same model for all investors, then the most parsimonious alternative is likely to be a suitable choice. The second reason is interpretabilty. When the model has no AR or MA components, the intercept terms in the model can be easily interpreted as the mean portfolio shares invested in technology stocks. Interpretation of these coefficients becomes more cumbersome when AR and MA components are introduced. Because one of the goals of this study is to introduce a novel approach of gauging herding, rather than to provide the reader with carefully crafted forecasts, we feel that the most parsimonious model is our best alternative.

Since both $\delta^s$ and $\mu^r$ can be in one of the two regimes, low ($l$) or high ($h$), they can jointly assume one of the following four regimes:

$$\begin{aligned} R^1 &= \{\delta^l, \mu^l\} \\ R^2 &= \{\delta^l, \mu^h\} \\ R^3 &= \{\delta^h, \mu^l\} \\ R^4 &= \{\delta^h, \mu^h\} \end{aligned} \tag{4}$$

Regimes in (4) are not directly observable.[16] However, if we assume that they follow a Markov process, inferences about regimes, their probabilities,[17] and transition probabilities can be made using the procedures described in Hamilton (1994), Kim and Nelson (1999), and Krolzig (1997).

[16]We restrict the shifts in variance regimes to occur only concurrently with the shifts in intercept regimes. This in turn implies that we are able to describe the universe of all regimes by the intercept terms alone.

[17]Smoothed, predicted, and filtered

Shifts between the four regimes in (4) are described by a 4×4 transition probability matrix that we estimate along with the other parameters of model (2)-(3). The matrix is:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{21} & p_{31} & p_{41} \\ p_{12} & p_{22} & p_{32} & p_{42} \\ p_{13} & p_{23} & p_{33} & p_{43} \\ p_{14} & p_{24} & p_{34} & p_{44} \end{bmatrix} \quad (5)$$

where $p_{qk} = \Pr(R_t^q | R_{t-1}^k)$, $q, k = 1...4$ is the transition probability that the regime $R^k$ is followed by regime $R^q$. Because the transition probability matrix (5) already incorporates the temporal interdependency that may exist between the technology stock holding of an investor and that of the market, we assume that the transition probabilities are time invariant. Since each column of the transition probability matrix must add to unity, we need to estimate only twelve probabilities of the matrix.

Hamilton (1990) offers an appealing interpretation of the estimates of transition probabilities: the estimated transition probability $\widehat{p}_{qk}$ is the number of times regime $q$ was followed by regime $k$, expressed as a percentage of the times when the process was in regime $q$. For example, $\widehat{p}_{24}$ can be interpreted as the relative frequency that regime $R^2$ with a low amount of technology stocks held by a given investor and a high amount of these stocks held by the market ($\delta^l$, $\mu^h$) was followed by regime $R^4$ with high amount of technology stocks held by both the investor and market ($\delta^h$, $\mu^h$). If the estimate of this probability is significant, then we can infer that it is likely that the investor followed the market, shifting technology stock holdings from low to high, and therefore herded as the dot-com bubble matured.

The elements of the transition probability matrix (5) can capture all the possible variations of the joint dynamics between the technology stock holdings of the market and investor. We need to be careful in interpreting various transition probability terms; for example consider the more explicit version of the transition probability matrix (5):

$$
\mathbf{P} = \begin{bmatrix}
P(\delta_t^l, \mu_t^l | \delta_{t-1}^l, \mu_{t-1}^l) & P(\delta_t^l, \mu_t^l | \delta_{t-1}^l, \mu_{t-1}^h) & P(\delta_t^l, \mu_t^l | \delta_{t-1}^h, \mu_{t-1}^l) & P(\delta_t^l, \mu_t^l | \delta_{t-1}^h, \mu_{t-1}^h) \\
P(\delta_t^l, \mu_t^h | \delta_{t-1}^l, \mu_{t-1}^l) & P(\delta_t^l, \mu_t^h | \delta_{t-1}^l, \mu_{t-1}^h) & P(\delta_t^l, \mu_t^h | \delta_{t-1}^h, \mu_{t-1}^l) & P(\delta_t^l, \mu_t^h | \delta_{t-1}^h, \mu_{t-1}^h) \\
P(\delta_t^h, \mu_t^l | \delta_{t-1}^l, \mu_{t-1}^l) & P(\delta_t^h, \mu_t^l | \delta_{t-1}^l, \mu_{t-1}^h) & P(\delta_t^h, \mu_t^l | \delta_{t-1}^h, \mu_{t-1}^l) & P(\delta_t^h, \mu_t^l | \delta_{t-1}^h, \mu_{t-1}^h) \\
P(\delta_t^h, \mu_t^h | \delta_{t-1}^l, \mu_{t-1}^l) & P(\delta_t^h, \mu_t^h | \delta_{t-1}^l, \mu_{t-1}^h) & P(\delta_t^h, \mu_t^h | \delta_{t-1}^h, \mu_{t-1}^l) & P(\delta_t^h, \mu_t^h | \delta_{t-1}^h, \mu_{t-1}^h)
\end{bmatrix} \quad (6)
$$

If a given investor followed the market and therefore herded when the dot-com bubble collapsed, then one would expect to estimate significant probability $p_{31} = P(\delta_t^l, \mu_t^l | \delta_{t-1}^h, \mu_{t-1}^l)$. Even though this assertion may be appealing at first, in the context of our data it may be misleading. Similar to the observation presented in Figure 3, the $y_{M,t}$ series for every investor in our sample has a single spike in the late 1990s. In contrast, the $y_{i,t}$ series for several investors has several spikes and consequent downshifts of the regime. For these investors, shifts from regime $R^3 = \{\delta^h, \mu^l\}$ to regime $R^1 = \{\delta^l, \mu^l\}$ occurred more than once, and as a result, we would expect to estimate significant $p_{31} = P(\delta_t^l, \mu_t^l | \delta_{t-1}^h, \mu_{t-1}^l)$ even if the investor did not follow the market when the dot-com bubble collapsed. Figure 4 exhibits one such investor. The top panel of the figure exhibits the share of the portfolio that Investor #3 held in technology stocks,[18] while the bottom panel exhibits this share for the residual market of the remaining 114 investors. As the figure shows, there were several instances when the investor's investment in technology stocks shifted downward when the market holding of these stocks was in a *low* regime. The estimate of $p_{31}$ for this investor in particular is significant, even though the investor did not appear to follow the market when the dot-com bubble collapsed in the early 2000s. To circumvent this problem, we instead examine another transition probability, $p_{43} = P(\delta_t^h, \mu_t^l | \delta_{t-1}^h, \mu_{t-1}^h)$. If the estimate of this probability is significant, then it is likely that the downshift in the market holding of technology stocks occurred before that of the investor. Between 1980 and 2012, the $y_{M,t}$ series for every investor downshifted only once when the dot-com bubble collapsed, therefore,

[18] To maintain anonymity of investors in our sample, we randomly assigned a number to each. Here and in the rest of the paper, we refer to the investors by this number.

the significance of this probability most likely implies that the investor followed the market on the downshift when the technology bubble collapsed in the early 2000s.[19]

The interpretations above suggest that if a given investor shifted her portfolio toward technology stocks only after a similar shift occurred among other market participants, then the investor herded during the buildup of the dot-com bubble and we should be able to reject the hypothesis $A$: $H_0^A : p_{24} = 0$. Similarly, the rejection of the hypothesis $B$, $H_0^B : p_{43} = 0$ implies that the shift in the investor's portfolio away from technology stocks occurred only after a similar shift occurred among market participants. If this is the case, then the investor exhibited herding behavior during the collapse of the dot-come bubble.

Applying similar logic, we analyzed the remaining elements of the the transition probability matrix (6). Two other transition probabilities are of particular interest: $p_{34} = P(\delta_t^h, \mu_t^h | \delta_{t-1}^h, \mu_{t-1}^l)$ and $p_{21} = P(\delta_t^l, \mu_t^l | \delta_{t-1}^l, \mu_{t-1}^h)$. If a given investor led the market and moved toward technology stocks before other market participants did during the dot-com bubble buildup, then we should be able to reject the hypothesis $C$, $H_0^C : p_{34} = 0$. Similarly, the rejection of the hypothesis $D$, $H_0^D : p_{21} = 0$ implies that the investor led the market during the collapse of the the bubble and started divesting technology stocks before other market participants did. Thus, for each investor in our sample we can test each of the hypotheses $A$, $B$ , $C$, and $D$, and based on the outcomes of these four tests place the investor in one of possible sixteen categories. These sixteen categories are summarized in Table 2.

While Table 2 is self-explanatory, two features of the table are noteworthy. First, it may seem that Categories 7, 10, and 12-16 are practically impossible. For example, how can an investor in Category 7 at the same time lead and herd into the market during the boom? In practice, this kind of outcome is possible if the investor led the market during the initial buildup of the bubble, then, while the market bubble was

[19] There is the possibility that even after the dot-com bubble collapsed, the investor never downshifted its technology stock holdings. In those cases, it would be inappropriate to label the investor as having herded during the downshift of the market since the investor did not follow the market after the downshift. However, there are only a few such cases and we manually placed them in the appropriate category. We give more detailed explanation of these cases in the Results section of the paper.

maturing, reduced and then shortly thereafter increased the technology stock holding. This investor at the same time led and followed the market. For this investor, the estimates of both $p_{34} = P(\delta^h_t, \mu^h_t | \delta^h_{t-1}, \mu^l_{t-1})$ and $p_{21} = P(\delta^h_t, \mu^h_t | \delta^l_{t-1}, \mu^h_{t-1})$ must be statistically different than zero, and as a result, we reject both hypotheses $A$ and $C$ and place the investor in Category 7. While these outcomes are possible in reality, we would be unable to unambiguously classify the investors in these seven categories as having herded or not. Thus, if our tests place any of the investors in our sample into one of these seven categories, we will consider those investors as belonging to a separate category that we label as uncategorized.

The second noteworthy feature of Table 2 is that there can be some investors for whom we do not reject either or both pairs of hypothesis, A and C and B or D. These investors will fall into one of the categories 1, 3, 4, 5, 7, and 10. For example, our inability to reject hypotheses A and C for a given investor would mean that during the buildup of the dot-com bubble, the investor neither led nor followed the others. Such outcome is possible if the investor's technology portfolio either coincided or had no statistical resemblance with the market technology portfolio. In either case, we label the investor as not having herded during the buildup of the bubble. Similarly, if for a given investor we are unable to reject both hypotheses B and D, we conclude that the investor did not herd during the collapse of the bubble.

For each investor in our sample, we estimated the 21 parameters[20] of the unrestricted model (2) using MLE. In this process, we enforced the constraints $\delta^l < \delta^h$ and $\mu^l < \mu^h$. We also obtain numerical standard errors of the intercept and correlation coefficients. We used the likelihood ratio test to test each of the hypotheses $A$, $B$, $C$, and $D$ for each investor in the sample. Since each test imposes only one restriction on the transition probability matrix, the likelihood ratio statistics has a $\chi^2$ distribution with one degree of freedom. We tested these hypotheses at 5% significance level.

[20] $\delta^h$, $\delta^l$, $\mu^h$, $\mu^l$, $\sigma^h_i$, $\sigma^l_i$, $\sigma^h_M$ ,$\sigma^l_M$, $\rho$ plus 12 transition probabilities in (5)

## III. Results

For each investor in our sample of 115, we estimated the vector Markov-switching autoregressive model in (2). The model estimates of regression parameters are presented in Table 1. For each investor we also tested each of the hypotheses $A$, $B$, $C$, and $D$, and based on the outcomes of all four tests, placed each investor in one of the sixteen categories summarized in Table 2. As we mentioned in Section II, the model may reject hypothesis $B$ for some investors that at least for a while after the collapse of the bubble did not reduce their technology stock holdings and therefore did not in fact herd during the collapse of the bubble. Figure 5 exhibits the detrended technology stock holding of one such investor and the corresponding market series. If no special care is given to the investors in this group, we may end up erroneously classifying some of them as having herded during the collapse of the bubble. There are 14 investors for whom the model rejected hypothesis $B$. We manually screened the technology stock holdings of these 14 investors and found that 7 of them (similar to Investor #35 in Figure 5) did not reduce their technology stock holdings for at least 5 years after the collapse of the dot-com bubble. For these 7 investors, we manually overrode the Test $B$ results from *reject* (1) to *do not reject* (0). For the remaining 7 investors we retained Test $B$ rejection.

As we also mentioned in Section II, it is impossible for us to unambiguously classify any of the investors who ended up in test categories 7, 10, 12, 13, 14, 15, and 16. Our test results reveal that there were six of such investors: one in each of the categories 7 and 10 and two in each of the categories 14 and 16. Since we are unable to unambiguously identify the herding patterns of these six investors, we labeled them as uncategorized.

Table 3 presents the overall aggregate counts and percentages of investors for whom we rejected each of the hypotheses. As these numbers indicate, the largest group among investors is the one for which we rejected hypothesis D. Twenty-seven out of 115 investors in our sample (or about 24%) shifted away from technology stocks before the remaining market did. At the same time, 18 (or about 16%) of the investors exhibited herding behavior (for whom we rejected hypothesis $A$) during the buildup to the bubble. There were 8 investors or 7% that led the market and moved toward the technology sector before the bubble started maturing (for whom we rejected hypothesis C). Finally, there was only a relatively small group of 4 investors (or about 4%) that herded during the collapse of the bubble (for whom we rejected hypothesis $B$). The primary message that emerges from these results is that investors were significantly more likely to herd during the buildup to the dot-com bubble than during the collapse. The fact that about a quarter of the investors exited the technology sector before the bubble collapsed implies that there was a large group of investors who anticipated the collapse. At the same time, a large group of investors jumped onto and rode on the technology bubble only after it took off in the late 1990s. These results are in strong agreement with the findings of Brunnermeier and Nagel (2004) and Griffin *et al.* (2011) and appear to suggest that a large number of investors were well aware of the bubble and, as Abreu and Brunnermeier's (2009) hypothesis would predict, rode on it before it collapsed.

Table 4 presents a more detailed accounting of the test results. In what follows, we will describe and present particular examples of investors in different categories listed in this table. Category 1 is the modal group, including 63 or 54.8 % of investors. For these investors, the model did not lead to a rejection of either hypotheses. This means that investors in this category did not herd into or out of nor lead the the dot-com bubble. This category consists of two types of investors. The first, predominant group is the investors whose technology investment regimes coincided with that of the residual market.[21] The top panel of Figure 6 exhibits the technology stock holding of one such investor (Investor #1). These investors moved in and out of the technology sector simultaneously with the rest of the market. The second, smaller subgroup consists of a few investors[22] whose technology investment regimes have no

[21]We manually examine the graphs of technology portfolio holdings of all 63 Category 1 investors and find that there are about 54 of such investors.

[22]We count 9 of such investors.

visual commonality with that of the rest of the sample market. Figure 7 demonstrate the technology holding of Investor #97 who is in this group. Regardless of the type, more than one half of the investors in our sample neither herded into or out of nor led the dot-com bubble.

The second largest group in Table 2 is the investors in Category 5. The 18 investors in this group that constituted nearly 16% of our sample did not follow nor led the technology flock during the buildup but led it before the bubble collapsed; they exited the technology sector before the other market participants did. Figure 8 exhibits Investor #51 that happened to be in this group. This result again suggests that regardless of herding behavior during the formation of the bubble, a significant number of investors probably were aware of and anticipated the end of the bubble.

The 12 investors or 10.4% of the sample that herded during the buildup to the bubble (Category 2) constitute the third largest category. One representative investor from this group is displayed in Figure 9. As the figure makes it clear, Investor #79 shifted toward technology stocks (the upper panel) only after the rest of the market did (the lower panel).

These top three categories make up more than 80% of our sample. By considering these three categories alone, one can already see the take-home message that adds to our previous conclusion: by and large investors did not lead nor lag the technology market during the boom and bust phases of the dot-com bubble (Category 1). Moreover, even if there was some degree of herding, most of it took place during the buildup to the bubble rather than collapse (Categories 2). Finally, a relatively large number of institutional investors in our sample exited from the technology sector before the bubble collapsed (Category 5).

The numbers of investors in the less populous categories 11, 8, 4, 6, 3, and 9 were 5, 4, 3, 2, 2, and 0 respectively. Each of the figures 10-13 shows the technology stock holding regimes of one representative investor in Categories 11, 8, 4, 6.

In order to exhibit a more comprehensive overview of our findings, we combined all our test results into a single classification tree displayed on Figure 14. On the figure, we consider all those investors that herded during the boom or bust or both phases of the bubble as having herded (the top branch of the the tree). Those include investors in Categories 2 and 8 (that herded during the boom), investors in categories 3 and 9 (that herded during the bust), and investors in Category 6 (that herded during both). Thus, there were only 20 investors out of 115 (or 17.5%) that according to our results herded. Again, herding among institutional investors occurred asymmetrically during the boom and bust phases of the dot-com bubble with most of herding occurring during the run-up of the bubble ($16+2=18$ investors) rather than collapse (only $2+2=4$ investors). The graph also highlights that there was not a single investor that has foreseen the buildup of the bubble and later failed to predict the collapse (Category 9).

The middle branch of the tree on Figure 14 represents all those investors who did not herd. Those include investors who either led or did not herd (Categories 1, 4, 5, and 11). Again, the largest sub-group among them is those who did not herd or lead during the boom and bust of the cycle (Category 1). All together, 77.4% of our sample investors did not exhibit any traces of herding.

Finally, for the 6 investors (5.2%) represented by the bottom branch of the tree, we could not unambiguously conclude whether they have herded or not during the dot-com bubble.

In addition to the earlier conclusions that we drew from the numbers in Table 3, the above discussion implies that during the dot-com bubble of the late 1990s, herding among large institutional investors was not an pervasive phenomenon. The investors that did neither led nor followed the market (Category 1) make up the largest category of investors. It is hard to tell whether or not those investors were aware of the bubble. It could very well be the case that they were, yet maybe because of capital constraints, they did not invest against the bubble. This scenario would still be consistent with Abreu and Brunnermeir's (2003) hypothesis. Or it could be the case that those investors simply remained agnostic about the bubble. This would support the Efficient Market Hypothesis. Thus, as far as our data and conclusions are concerned, the fact that the technology stock portfolios of many Category 1 investors coincided with the technology stock portfolio of the the market can be attributed to either hypothesis. At the same time, however, the fact that there was a sizable group of large institutional investors who rode on and then at the right moment jumped off the technology bubble makes a strong case for the Abreu and Brunnermeir's (2003) hypothesis of rational bubbles.

## IV. Summary and Conclusions

This paper used a novel approach to gauge whether large institutional investors herded during the technology bubble of the late 1990s. By imposing various restrictions on the transition probability matrix in a vector Markov-switching model, we were able to test for different lead/lag scenarios that might have existed between technology stock holdings of each investor in our sample and that of the remaining sample during the bubble. Our results indicate that a little more than three quarters of the sample investors did not exhibit any signs of herding behavior. Most of the investors in this group entered and exited the technology sector simultaneously with the rest of the sample. About 23% of the sample investors exited the technology sector before the bubble collapsed; in this phase of the bubble they led rather than followed the technology herd. These results do not mean, however, that we were unable to detect any traces of herding. About 14% of investors followed the rest of the market during the buildup to the bubble, while only 2% herded as the bubble collapsed. Thus, insofar as some traces of herding have been detected, most herding among institutional investors occurred during the buildup rather than the bust of the technology bubble. These results are in line with the results of Brunnermeier and Nagel (2004) and Griffin *et al.* (2011) and seem to support Abreu and Brunnermeier's (2003) hypothesis that asset bubbles are a coordination problem.

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**Table 1. Estimates of the vector Markov-switching regression parameters in (2) for each investor in the sample. *Note*: all intercept and correlation coefficients in boldface are significant at the 5% significance level**

| Investor | $\delta^l$ | $\delta^h$ | $\mu^l$ | $\mu^h$ | $\sigma_\delta^l$ | $\sigma_\delta^h$ | $\sigma_\mu^l$ | $\sigma_\mu^h$ | $\rho$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | **-2.19** | **19.29** | **-1.30** | **11.3** | 3.18 | 7.99 | 1.85 | 4.33 | **0.69** |
| 2 | **-3.34** | **8.99** | **-1.38** | **9.74** | 4.62 | 6.54 | 1.78 | 4.57 | **0.71** |
| 3 | **-2.74** | **3.68** | **-1.61** | **9.82** | 2.07 | 2.57 | 1.63 | 4.85 | **0.26** |
| 4 | **-1.64** | **1.85** | **-1.69** | **9.42** | 0.97 | 1.19 | 1.57 | 4.96 | **-0.14** |
| 5 | **-1.51** | **20.58** | **-1.49** | **11.03** | 6.13 | 8.83 | 1.69 | 4.68 | **0.69** |
| 6 | **-1.09** | **8.89** | **-1.37** | **9.89** | 2.46 | 4.25 | 1.72 | 4.58 | **0.32** |
| 7 | **-1.11** | **3.73** | **-1.48** | **9.94** | 2.74 | 2.33 | 1.67 | 4.66 | **-0.59** |
| 8 | **-2.12** | **2.98** | **-1.36** | **11.2** | 1.65 | 2.17 | 1.76 | 4.58 | **0.30** |
| 9 | **-2.01** | **5.62** | **-1.78** | **9.83** | 2.48 | 1.73 | 1.55 | 5.07 | **-0.39** |
| 10 | **-1.41** | **8.11** | **-1.71** | **9.97** | 2.83 | 2.95 | 1.67 | 4.90 | **0.80** |
| 11 | **-1.47** | **2.49** | **-1.11** | **12.96** | 2.58 | 2.22 | 2.09 | 4.08 | **0.80** |
| 12 | **-3.92** | **11.03** | **-2.21** | **6.05** | 3.52 | 5.90 | 1.69 | 5.29 | **0.80** |
| 13 | **-3.53** | **9.22** | **-1.59** | **6.27** | 3.43 | 7.28 | 1.61 | 4.87 | **0.82** |
| 14 | **-1.12** | **15.16** | **-1.93** | **10.25** | 4.15 | 5.22 | 1.65 | 5.26 | **-0.20** |
| 15 | **-0.69** | **5.26** | **-1.38** | **10.36** | 1.89 | 2.82 | 1.75 | 4.61 | **0.70** |
| 16 | **-1.73** | **29.54** | **-1.37** | **10.14** | 5.62 | 8.81 | 1.70 | 4.58 | **0.14** |
| 17 | **-1.33** | **6.32** | **-1.47** | **8.94** | 2.27 | 4.26 | 1.77 | 4.76 | **0.73** |
| 18 | **-1.55** | **6.30** | **-1.56** | **6.45** | 1.63 | 3.61 | 1.74 | 4.58 | **0.85** |
| 19 | **-3.78** | **1.33** | **-1.67** | **9.27** | 1.39 | 2.04 | 1.57 | 4.93 | **0.64** |
| 20 | **-1.09** | **8.69** | **-1.35** | **10.74** | 2.07 | 3.30 | 1.80 | 4.58 | **0.77** |
| 21 | **-3.42** | **2.13** | **-1.45** | **12.55** | 2.03 | 2.20 | 1.71 | 4.61 | **-0.45** |
| 22 | **-1.94** | **1.46** | **-1.40** | **6.05** | 1.54 | 1.80 | 1.76 | 4.80 | **0.83** |
| 23 | **-2.59** | **3.18** | **-1.34** | **8.67** | 2.65 | 1.60 | 1.73 | 4.63 | **-0.24** |
| 24 | **-1.46** | **9.07** | **-1.63** | **9.94** | 3.23 | 3.84 | 1.65 | 4.87 | **0.74** |

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Table 1 – *Continued from previous page*

| Investor | $\delta^l$ | $\delta^h$ | $\mu^l$ | $\mu^h$ | $\sigma^l_\delta$ | $\sigma^h_\delta$ | $\sigma^l_\mu$ | $\sigma^h_\mu$ | $\rho$ |
|---|---|---|---|---|---|---|---|---|---|
| 25 | **-1.16** | **9.17** | **-1.35** | **10.73** | 1.93 | 3.79 | 1.79 | 4.58 | **0.72** |
| 26 | **-1.29** | **10.27** | **-1.35** | **10.66** | 2.25 | 4.14 | 1.81 | 4.52 | **0.88** |
| 27 | **-1.49** | **11.87** | **-1.35** | **10.63** | 3.10 | 5.46 | 1.80 | 4.57 | **0.74** |
| 28 | **-1.38** | **8.32** | **-1.69** | **10.43** | 2.22 | 4.14 | 1.66 | 5.00 | **0.43** |
| 29 | **-1.90** | **9.68** | **-1.98** | **10.06** | 2.89 | 4.99 | 1.93 | 4.66 | **0.75** |
| 30 | **-1.31** | **2.46** | **-1.67** | **7.71** | 2.38 | 2.95 | 1.59 | 4.83 | **0.74** |
| 31 | **-1.36** | **3.64** | **-1.88** | **7.36** | 2.69 | 1.57 | 1.79 | 4.93 | **0.71** |
| 32 | **-0.97** | **7.92** | **-1.34** | **10.76** | 2.1 | 3.08 | 1.81 | 4.58 | **0.69** |
| 33 | **-1.37** | **10.66** | **-1.36** | **10.51** | 2.08 | 4.20 | 1.73 | 4.58 | **0.80** |
| 34 | **-1.56** | **12.41** | **-1.39** | **9.93** | 3.48 | 4.90 | 1.76 | 4.58 | **0.51** |
| 35 | **-3.66** | **1.54** | **-1.32** | **9.57** | 0.88 | 1.35 | 1.71 | 4.57 | **0.30** |
| 36 | **-1.17** | **6.00** | **-1.36** | **10.20** | 2.12 | 2.8 | 1.70 | 4.58 | **0.29** |
| 37 | **-1.52** | **12.33** | **-1.76** | **10.21** | 3.06 | 3.86 | 1.64 | 5.00 | **0.49** |
| 38 | **-2.30** | **4.51** | **-1.30** | **7.70** | 2.99 | 4.22 | 1.71 | 4.62 | **0.86** |
| 39 | **-1.23** | **21.00** | **-1.54** | **10.75** | 7.23 | 5.12 | 1.70 | 4.8 | **0.11** |
| 40 | **-2.77** | **8.79** | **-1.46** | **7.43** | 2.60 | 5.76 | 1.67 | 4.78 | **0.60** |
| 41 | **-2.39** | **15.54** | **-1.57** | **9.74** | 4.3 | 4.82 | 1.69 | 4.8 | **0.34** |
| 42 | **-2.03** | **11.75** | **-1.70** | **9.79** | 1.88 | 6.87 | 1.52 | 4.76 | **0.68** |
| 43 | **-1.17** | **8.81** | **-1.37** | **10.35** | 1.82 | 4.03 | 1.79 | 4.58 | **0.84** |
| 44 | **-1.68** | **10.43** | **-1.55** | **10.22** | 3.19 | 4.19 | 1.68 | 4.8 | **0.86** |
| 45 | **-3.43** | **2.64** | **-1.32** | **8.58** | 1.72 | 2.68 | 1.76 | 4.59 | **0.54** |
| 46 | **-3.72** | **4.03** | **-1.97** | **10.33** | 1.29 | 3.83 | 1.68 | 5.31 | **0.16** |
| 47 | **-1.87** | **7.61** | **-1.46** | **8.69** | 4.94 | 5.57 | 1.71 | 4.68 | **0.87** |
| 48 | **-5.40** | **5.00** | **-1.69** | **7.38** | 3.39 | 2.44 | 1.61 | 4.59 | **-0.67** |
| 49 | **-1.17** | **9.31** | **-1.33** | **10.92** | 2.02 | 3.99 | 1.81 | 4.58 | **0.63** |
| 50 | **-2.90** | **16.43** | **-2.29** | **9.45** | 7.41 | 6.24 | 1.85 | 5.38 | **0.74** |

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Table 1 – *Continued from previous page*

| Investor | $\delta^l$ | $\delta^h$ | $\mu^l$ | $\mu^h$ | $\sigma^l_\delta$ | $\sigma^h_\delta$ | $\sigma^l_\mu$ | $\sigma^h_\mu$ | $\rho$ |
|---|---|---|---|---|---|---|---|---|---|
| 51 | **-0.43** | **5.87** | **-1.40** | **10.20** | 1.22 | 1.84 | 1.69 | 4.61 | **0.17** |
| 52 | **-1.56** | **9.85** | **-1.66** | **10.50** | 1.62 | 4.05 | 1.70 | 4.69 | **0.93** |
| 53 | **-1.29** | **5.28** | **-1.37** | **10.05** | 3.08 | 3.44 | 1.71 | 4.59 | **0.10** |
| 54 | **-2.48** | **2.62** | **-1.43** | **9.71** | 1.06 | 1.88 | 1.68 | 4.63 | **0.18** |
| 55 | **-5.31** | **9.83** | **-1.43** | **8.55** | 2.94 | 6.84 | 1.78 | 4.68 | **0.63** |
| 56 | **-4.19** | **25.94** | **-1.49** | **8.97** | 5.01 | 8.04 | 1.64 | 4.53 | **0.72** |
| 57 | **-3.45** | **6.28** | **-1.39** | **4.82** | 2.64 | 6.15 | 1.72 | 4.58 | **0.75** |
| 58 | **-1.96** | **6.54** | **-1.62** | **6.46** | 2.15 | 2.93 | 1.74 | 4.78 | **0.75** |
| 59 | **-1.63** | **3.25** | **-1.42** | **11.52** | 1.97 | 1.92 | 1.74 | 4.60 | **0.60** |
| 60 | **-1.43** | **8.51** | **-1.66** | **9.18** | 2.34 | 4.94 | 1.62 | 4.94 | **0.85** |
| 61 | **-0.20** | **0.35** | **-1.35** | **10.83** | 0.15 | 0.31 | 1.76 | 4.57 | **-0.41** |
| 62 | **-1.06** | **5.25** | **-1.28** | **8.65** | 2.46 | 3.05 | 1.71 | 4.58 | **0.85** |
| 63 | **-0.74** | **12.20** | **-1.31** | **10.74** | 2.80 | 4.33 | 1.78 | 4.59 | **0.15** |
| 64 | **-1.00** | **3.40** | **-1.65** | **5.47** | 1.51 | 3.56 | 1.77 | 4.66 | **0.84** |
| 65 | **-1.87** | **10.93** | **-1.78** | **8.07** | 4.09 | 5.32 | 1.69 | 4.96 | **0.78** |
| 66 | **-0.24** | **31.51** | **-1.39** | **10.31** | 5.12 | 0.01 | 1.70 | 4.59 | **-0.39** |
| 67 | **-1.47** | **11.51** | **-1.37** | **10.32** | 3.64 | 3.96 | 1.77 | 4.58 | **0.54** |
| 68 | **-2.05** | **4.78** | **-1.41** | **10.14** | 1.94 | 3.64 | 1.72 | 4.70 | **0.17** |
| 69 | **-3.33** | **13.26** | **-1.49** | **5.87** | 3.77 | 5.88 | 1.82 | 4.48 | **0.83** |
| 70 | **-5.47** | **3.89** | **-1.25** | **5.62** | 2.15 | 6.29 | 1.93 | 4.78 | **0.77** |
| 71 | **-1.35** | **10.40** | **-1.35** | **10.64** | 2.44 | 4.05 | 1.80 | 4.58 | **0.84** |
| 72 | **-1.32** | **1.67** | **-1.48** | **10.09** | 0.73 | 1.32 | 1.84 | 4.20 | **0.65** |
| 73 | **-4.43** | **2.51** | **-1.58** | **8.49** | 2.32 | 3.16 | 1.77 | 4.40 | **0.80** |
| 74 | **-4.06** | **6.19** | **-1.40** | **9.86** | 3.27 | 4.46 | 1.71 | 4.59 | **0.24** |
| 75 | **-1.54** | **12.20** | **-1.37** | **9.98** | 2.77 | 5.73 | 1.79 | 4.57 | **0.77** |
| 76 | **-2.12** | **7.18** | **-1.54** | **9.32** | 2.64 | 4.99 | 1.72 | 4.86 | **0.54** |

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Table 1 – *Continued from previous page*

| Investor | $\delta^l$ | $\delta^h$ | $\mu^l$ | $\mu^h$ | $\sigma^l_\delta$ | $\sigma^h_\delta$ | $\sigma^l_\mu$ | $\sigma^h_\mu$ | $\rho$ |
|---|---|---|---|---|---|---|---|---|---|
| 77 | **-5.55** | **1.42** | **-1.68** | **10.13** | 1.46 | 3.00 | 1.59 | 4.94 | **0.01** |
| 78 | **-1.13** | **8.64** | **-1.37** | **10.45** | 1.6 | 3.57 | 1.78 | 4.59 | **0.76** |
| 79 | **-1.91** | **17.24** | **-1.47** | **8.66** | 2.20 | 6.70 | 1.63 | 4.77 | **0.45** |
| 80 | **-2.82** | **14.08** | **-1.89** | **9.36** | 4.37 | 5.75 | 1.84 | 5.14 | **0.86** |
| 81 | **-1.08** | **8.45** | **-1.35** | **10.72** | 2.47 | 3.83 | 1.79 | 4.59 | **0.54** |
| 82 | **-1.23** | **7.85** | **-1.57** | **9.96** | 1.59 | 3.51 | 1.74 | 4.81 | **0.77** |
| 83 | **-1.34** | **8.24** | **-1.71** | **10.21** | 2.03 | 3.61 | 1.61 | 5.00 | **0.19** |
| 84 | **-1.08** | **8.53** | **-1.36** | **10.51** | 2.56 | 2.70 | 1.79 | 4.58 | **0.70** |
| 85 | **-1.20** | **9.37** | **-1.37** | **10.63** | 2.00 | 4.20 | 1.79 | 4.60 | **0.87** |
| 86 | **-1.51** | **3.46** | **-1.70** | **9.67** | 1.45 | 2.23 | 1.63 | 4.96 | **0.44** |
| 87 | **-2.21** | **11.47** | **-1.35** | **7.69** | 2.39 | 6.14 | 1.76 | 4.44 | **0.75** |
| 88 | **-2.11** | **3.13** | **-1.49** | **10.90** | 1.65 | 1.95 | 1.68 | 4.70 | **-0.23** |
| 89 | **-4.70** | **10.77** | **-1.61** | **8.35** | 4.27 | 4.65 | 1.60 | 4.86 | **-0.45** |
| 90 | **-1.60** | **15.56** | **-1.34** | **2.28** | 7.23 | 5.84 | 1.07 | 5.38 | **0.57** |
| 91 | **-1.07** | **2.18** | **-1.29** | **9.71** | 0.73 | 1.84 | 1.67 | 4.58 | **-0.56** |
| 92 | **-2.66** | **2.35** | **-1.47** | **3.68** | 1.08 | 2.22 | 1.62 | 4.60 | **0.75** |
| 93 | **-6.76** | **9.97** | **-1.38** | **10.29** | 2.24 | 12.83 | 1.70 | 4.58 | **-0.14** |
| 94 | **-2.32** | **14.10** | **-1.68** | **9.78** | 5.33 | 5.98 | 1.63 | 4.94 | **0.64** |
| 95 | **-1.73** | **1.96** | **-1.63** | **8.90** | 1.29 | 1.37 | 1.57 | 4.85 | **-0.34** |
| 96 | **-2.04** | **28.65** | **-1.33** | **10.35** | 4.56 | 10.02 | 1.74 | 4.57 | **0.28** |
| 97 | **-3.34** | **2.10** | **-1.83** | **8.26** | 2.06 | 3.20 | 1.61 | 5.17 | **0.54** |
| 98 | **-7.07** | **9.35** | **-1.58** | **7.74** | 6.39 | 5.82 | 1.61 | 4.91 | **-0.47** |
| 99 | **-3.55** | **6.35** | **-2.09** | **3.03** | 2.62 | 7.34 | 1.31 | 4.91 | **0.85** |
| 100 | **-0.14** | **14.12** | **-1.49** | **10.08** | 3.52 | 0.01 | 1.69 | 4.78 | **-0.12** |
| 101 | **-2.84** | **1.77** | **-1.51** | **7.01** | 1.13 | 2.42 | 1.74 | 4.85 | **0.66** |
| 102 | **-1.27** | **15.64** | **-1.33** | **9.69** | 5.43 | 6.13 | 1.72 | 4.58 | **0.49** |

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Table 1 – *Continued from previous page*

| Investor | $\delta^l$ | $\delta^h$ | $\mu^l$ | $\mu^h$ | $\sigma^l_\delta$ | $\sigma^h_\delta$ | $\sigma^l_\mu$ | $\sigma^h_\mu$ | $\rho$ |
|---|---|---|---|---|---|---|---|---|---|
| 103 | **-2.15** | **16.63** | **-1.36** | **10.49** | 4.98 | 6.23 | 1.77 | 4.56 | **0.71** |
| 104 | **-1.41** | **10.54** | **-1.44** | **10.58** | 2.15 | 4.00 | 1.82 | 4.63 | **0.77** |
| 105 | **-0.87** | **6.29** | **-1.42** | **10.46** | 2.24 | 3.40 | 1.71 | 4.66 | **0.70** |
| 106 | **-5.64** | **7.47** | **-1.52** | **8.70** | 2.29 | 4.18 | 1.63 | 4.91 | **0.39** |
| 107 | **-2.78** | **1.92** | **-1.57** | **9.48** | 0.51 | 2.88 | 1.65 | 4.8 | **-0.38** |
| 108 | **-0.45** | **4.30** | **-1.43** | **10.04** | 2.85 | 1.99 | 1.72 | 4.58 | **0.32** |
| 109 | **-1.68** | **16.09** | **-1.52** | **9.36** | 3.59 | 4.15 | 1.67 | 4.79 | **0.38** |
| 110 | **-2.21** | **5.42** | **-1.60** | **10.29** | 2.42 | 2.98 | 1.63 | 4.83 | **0.10** |
| 111 | **-1.23** | **5.43** | **-1.34** | **8.52** | 2.20 | 3.74 | 1.75 | 4.38 | **0.85** |
| 112 | **-0.82** | **5.06** | **-1.53** | **6.72** | 2.09 | 3.02 | 1.75 | 4.67 | **0.88** |
| 113 | **-2.05** | **13.64** | **-1.54** | **9.58** | 4.52 | 4.55 | 1.70 | 4.77 | **0.71** |
| 114 | **-5.05** | **3.11** | **-1.73** | **9.55** | 1.41 | 2.87 | 1.58 | 5.01 | **0.10** |
| 115 | **-1.52** | **10.46** | **-1.41** | **9.56** | 2.13 | 3.82 | 1.75 | 4.58 | **0.78** |

**Table 2. Depending on the outcome of tests A, B, C, and D (1 = reject and 0 = do not reject), each investor falls into one of the sixteen categories. Each category uniquely describes whether the investor herded or led the market during the buildup or collapse of the dot-com bubble.**

| Category | Reject Hypothesis | | | | Description | | | |
|---|---|---|---|---|---|---|---|---|
| | *A* | *B* | *C* | *D* | *Boom* | | *Bust* | |
| 1 | 0 | 0 | 0 | 0 | did not herd | did not lead | did not herd | did not lead |
| 2 | 1 | 0 | 0 | 0 | herded | did not lead | did not herd | did not lead |
| 3 | 0 | 1 | 0 | 0 | did not herd | did not lead | herded | did not lead |
| 4 | 0 | 0 | 1 | 0 | did not herd | led | did not herd | did not lead |
| 5 | 0 | 0 | 0 | 1 | did not herd | did not lead | did not herd | led |
| 6 | 1 | 1 | 0 | 0 | herded | did not lead | herded | did not lead |
| 7 | 1 | 0 | 1 | 0 | herded | led | did not herd | did not lead |
| 8 | 1 | 0 | 0 | 1 | herded | did not lead | did not herd | led |
| 9 | 0 | 1 | 1 | 0 | did not herd | led | herded | did not lead |
| 10 | 0 | 1 | 0 | 1 | did not herd | did not lead | herded | led |
| 11 | 0 | 0 | 1 | 1 | did not herd | led | did not herd | led |
| 12 | 1 | 1 | 1 | 0 | herded | led | herded | did not lead |
| 13 | 1 | 1 | 0 | 1 | herded | did not lead | herded | led |
| 14 | 1 | 0 | 1 | 1 | herded | led | did not herd | led |
| 15 | 0 | 1 | 1 | 1 | did not herd | led | herded | led |
| 16 | 1 | 1 | 1 | 1 | herded | led | herded | led |

**Table 3. Counts and percentages of the sample (115) investors for whom each of the four hypotheses are rejected. The numbers in the table exclude investors in unclassified Categories 7, 10, 12-16.**

| | Herded during the boom<br>Reject $H_0^A$ | Herded during the bust<br>Reject $H_0^B$ | Led during the boom<br>Reject $H_0^C$ | Led during the bust<br>Reject $H_0^D$ |
|---|---|---|---|---|
| # | 18 | 4 | 8 | 27 |
| % | 15.7% | 3.5% | 7.0% | 23.5% |

**Table 4. Counts and percentages of the sample (115) investors in each test category ranked by the category size. The table excludes unclassified categories 7, 10, 12-16.**

| Category | Description | | Count | Percentage |
|---|---|---|---|---|
| | *Boom* | *Bust* | | |
| 1 | did not herd, did not lead | did not herd, did not lead | 63 | 54.8% |
| 5 | did not herd, did not lead | did not herd, led | 18 | 15.7% |
| 2 | herded, did nor lead | did not herd, did not lead | 12 | 10.4% |
| 11 | did not herd, led | did not herd, led | 5 | 4.3% |
| 8 | herded, did not lead | did not herd, led | 4 | 3.5% |
| 4 | did not herd, led | did not herd, did not lead | 3 | 2.6% |
| 6 | herded, did not lead | herded, did not lead | 2 | 1.7% |
| 3 | did not herd, did not lead | herded, did not lead | 2 | 1.7% |
| 9 | did not herd, led | herded, did not lead | 0 | 0.0% |

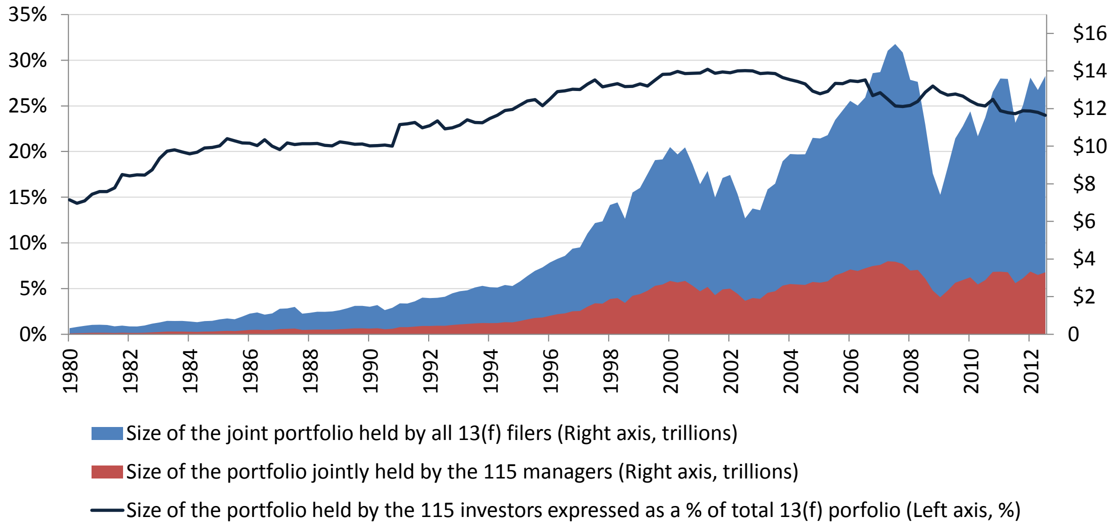


**Figure 1. Total 13(f) value held by all and the 115 managers in our sample (right axis, in trillions) and the percentage of the cumulative portfolio held by the 115 managers in our sample (left axis).**

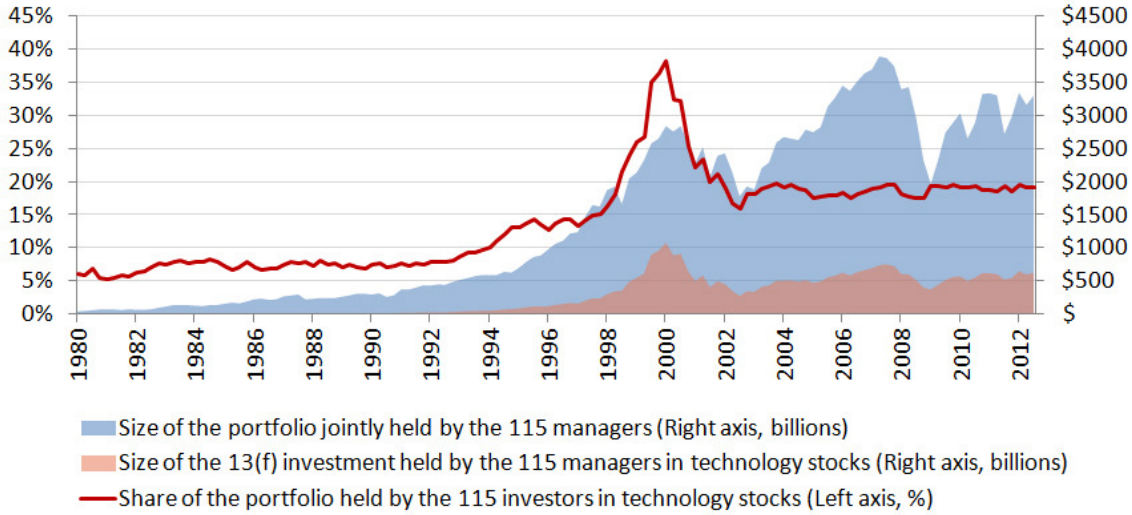


**Figure 2. Value held by the 115 managers in all and technology stocks (right axis, in billions) and the share of the portfolio held by the 115 investors in technology stocks (left axis).**

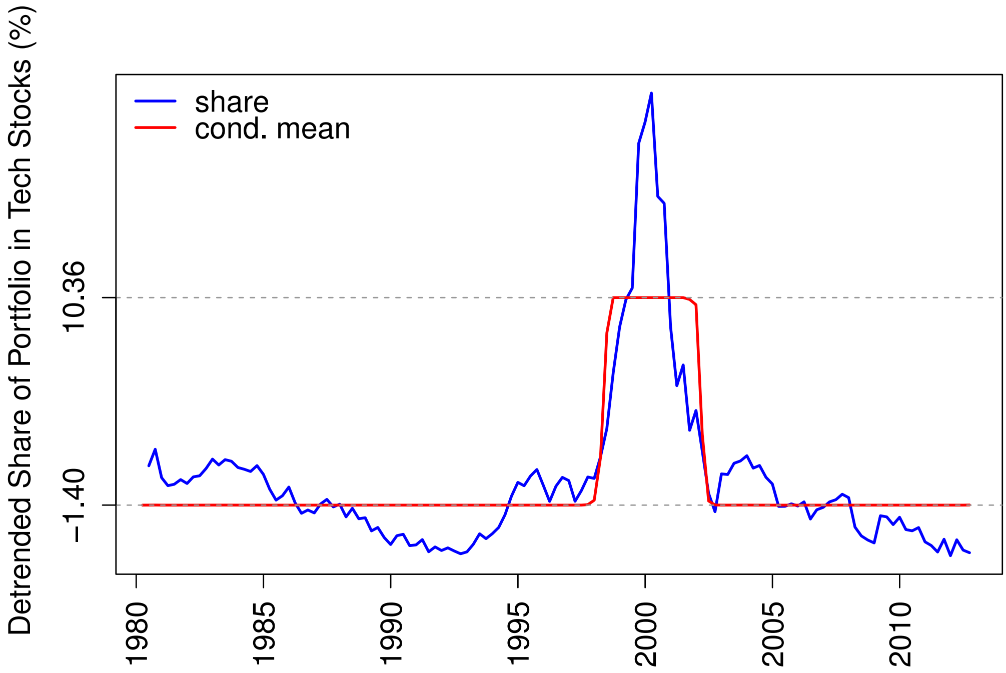


**Figure 3. Share of the collective portfolio held by 115 investors in technology stocks and the Markov-switching conditional detrended mean of the series.**

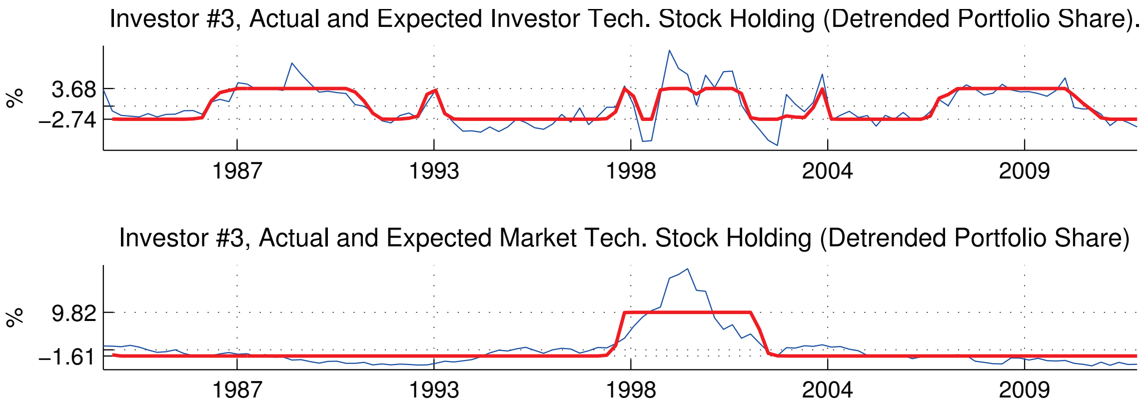


**Figure 4. Technology stock holding of Investor #3 (upper panel) and of the residual market (lower panel). The smooth lines on both graphs are the conditional detrended means of the respective series.**

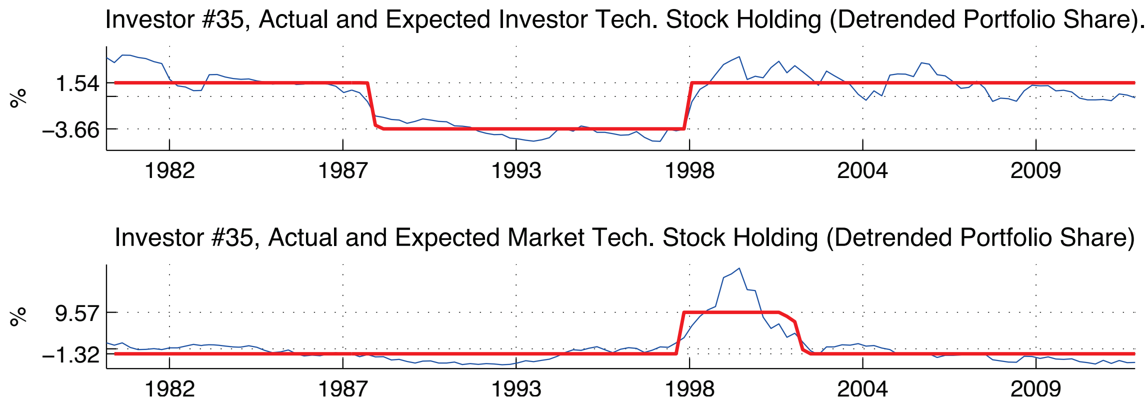


**Figure 5. Technology stock holding of Investor #35 (upper panel) and of the residual market (lower panel). The smooth lines on both graphs are the conditional detrended means of the respective series.**

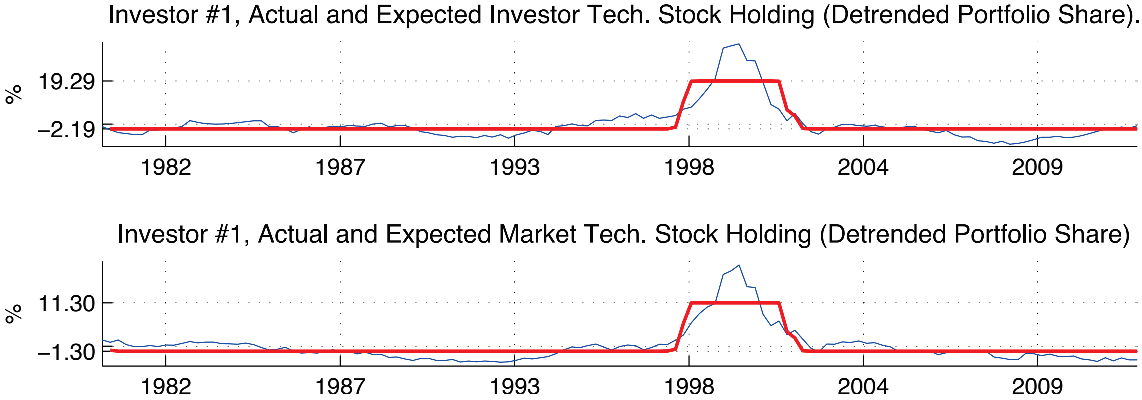


**Figure 6. Technology stock holding of Investor #1 (upper panel) in Category 1 (did not herd & did not lead the market). The lower panel exhibits the technology stock holding of the residual market. The smooth lines on both graphs are the conditional detrended means of the respective series.**

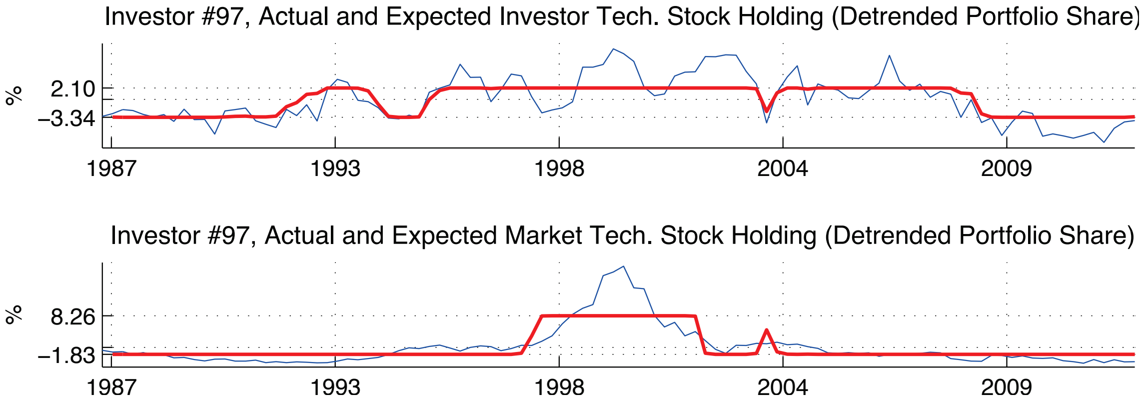


**Figure 7. Technology stock holding of Investor #97 (upper panel) in Category 1 (did not herd & did not lead the market). The lower panel exhibits the technology stock holding of the residual market. The smooth lines on both graphs are the conditional detrended means of the respective series.**

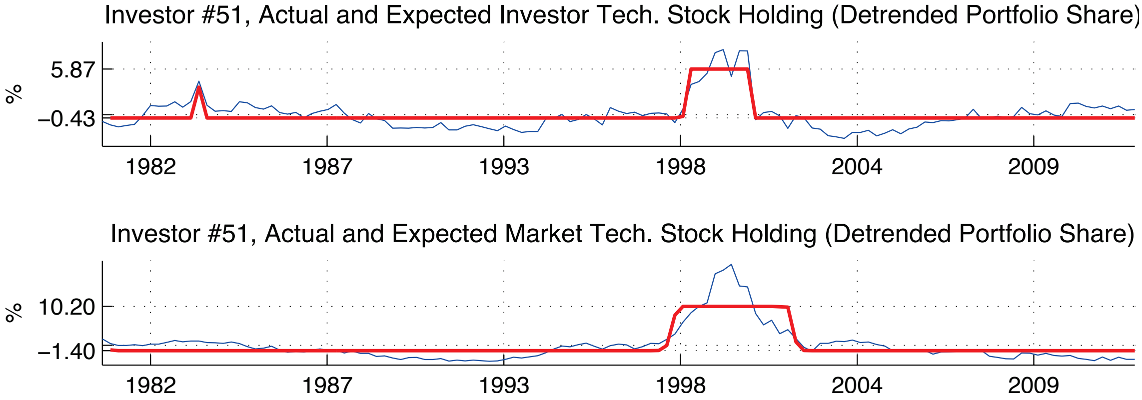


**Figure 8. Technology stock holding of Investor #51 (upper panel) in Category 5 (led the market during the bust). The lower panel exhibits the technology stock holding of the residual market. The smooth lines on both graphs are the conditional detrended means of the respective series.**

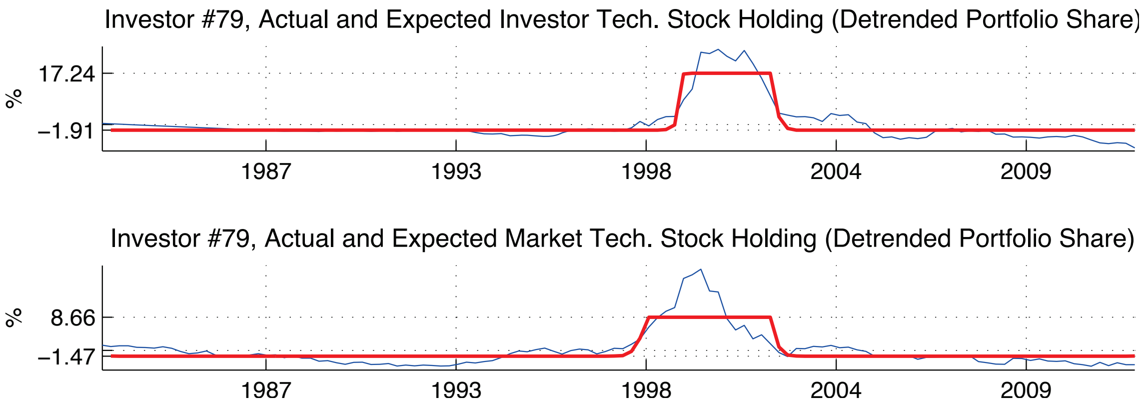


**Figure 9. Technology stock holding of Investor #79 (upper panel) in Category 2 (herded during the boom). The lower panel exhibits the technology stock holding of the residual market. The smooth lines on both graphs are the conditional detrended means of the respective series.**

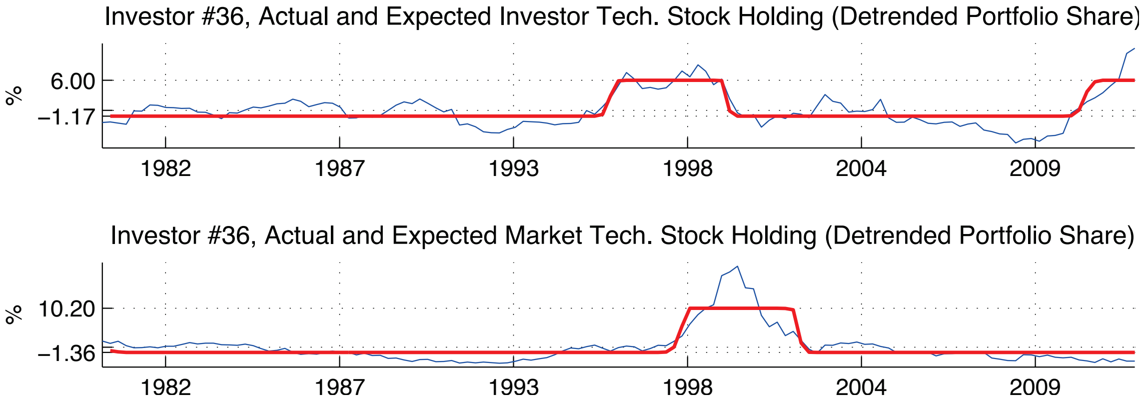


**Figure 10. Technology stock holding of Investor #36 (upper panel) in Category 11 (led the market during the boom and bust). The lower panel exhibits the technology stock holding of the residual market. The smooth lines on both graphs are the conditional detrended means of the respective series.**

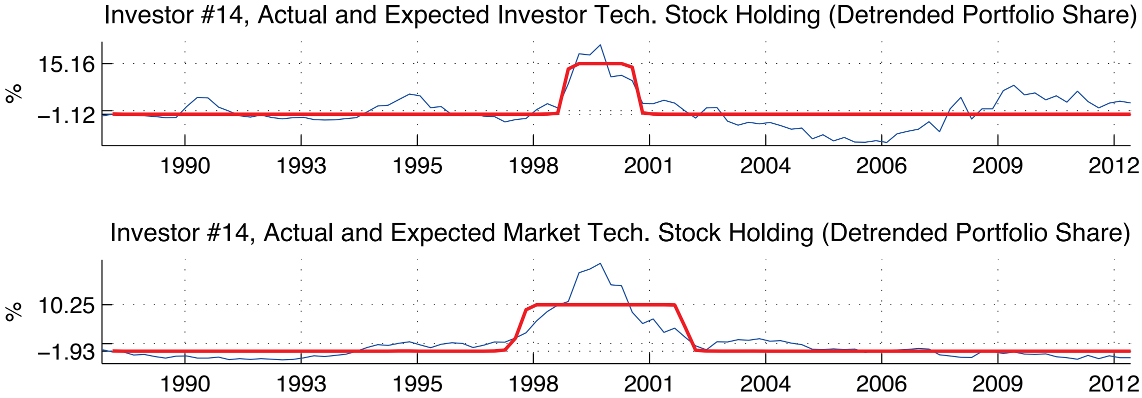


**Figure 11. Technology stock holding of Investor #14 (upper panel) in Category 8 (herded during the boom & led the market during the bust). The lower panel exhibits the technology stock holding of the residual market. The smooth lines on both graphs are the conditional detrended means of the respective series.**

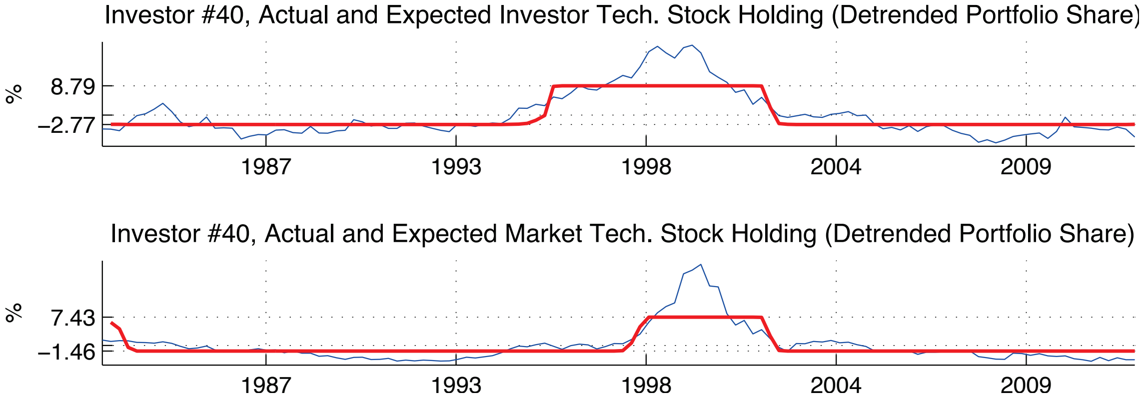


**Figure 12. Technology stock holding of Investor #40 (upper panel) in Category 4 (led the market during the boom). The lower panel exhibits the technology stock holding of the residual market. The smooth lines on both graphs are the conditional detrended means of the respective series.**

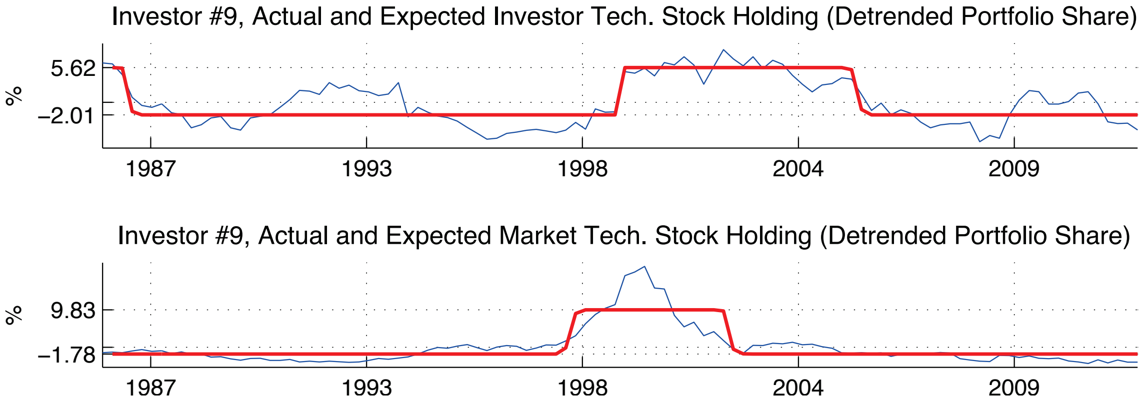


**Figure 13. Technology stock holding of Investor #9 (upper panel) in Category 6 (herded during the boom and bust). The lower panel exhibits the technology stock holding of the residual market. The smooth lines on both graphs are the conditional detrended means of the respective series.**

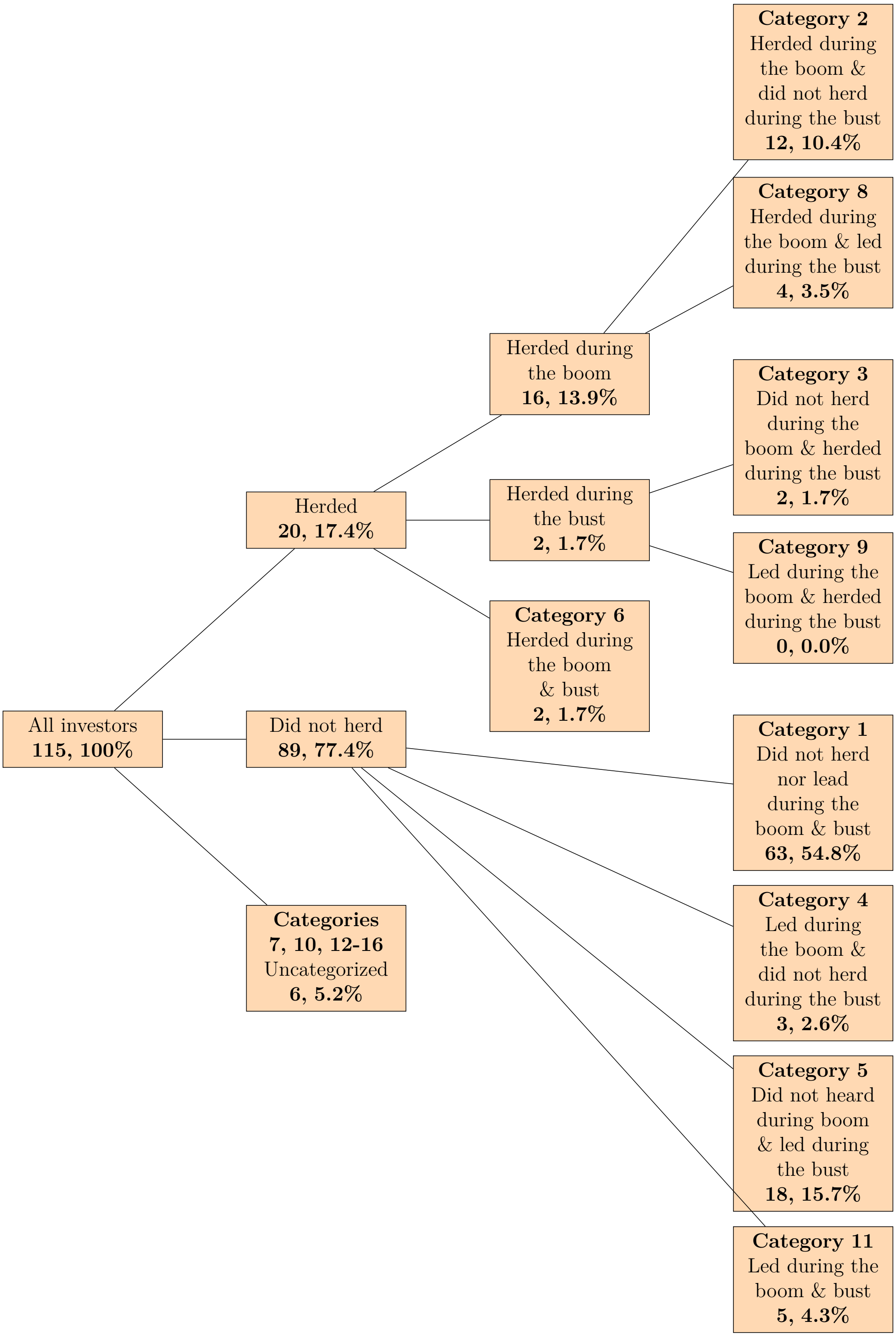


**Figure 14. Breakdown of the sample investors between different test categories and relevant groups. The numbers at the bottom of each box represent the number and percentage of all sample investors within the group.**