

## Who Drove and Burst the Tech Bubble?

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### ABSTRACT

From 1997 to March 2000, as technology stocks rose more than five-fold, institutions bought more new technology supply than individuals. Among institutions, hedge funds were the most aggressive investors, but independent investment advisors and mutual funds (net of flows) actively invested the most capital in the technology sector. The technology stock reversal in March 2000 was accompanied by a broad sell-off from institutional investors but accelerated buying by individuals, particularly discount brokerage clients. Overall, our evidence supports the bubble model of Abreu and Brunnermeier (2003), in which rational arbitrageurs fail to trade against bubbles until a coordinated selling effort occurs.

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Perceived bubbles, such as the “tech bubble” and the more recent credit and real estate bubbles, pose challenges to efficient market theories and are not well understood. The stock market run-up in the mid to late 1990s was the greatest in the last 140 years of U.S. history in terms of both price appreciation and market-wide valuation multiples.<sup>1</sup> While theoretical models explaining bubbles are plentiful, there is little rigorous empirical work uncovering the complex economic forces responsible for rapid price increases that subsequently collapse. The financial press commonly touted the view that individual investors were largely responsible for the tech bubble.<sup>2</sup> This paper directly examines the relative roles of individual and institutional trading during the rise and fall of technology stocks.

Theoretical modeling of investor interactions has developed along three general paths in the bubble literature.<sup>3</sup> The first path, the rational markets view (e.g., Friedman (1953) and Fama (1965)), recognizes that some agents may trade irrationally but argues that such trading will not significantly affect prices as sophisticated traders (arbitrageurs) quickly trade against irrational agents to eliminate deviations from economic values. The second path invokes frictions. Theories that allow for frictions such as short-sale restrictions (Miller (1977), Harrison and Kreps (1978), and Scheinkman and Xiong (2003)), noise trader risk (DeLong et al. (1990a)), or capital constraints coupled with delegated portfolio management (Shleifer and Vishny (1997)) argue that sophisticated traders may not be able to eliminate a bubble, in which case prices can be driven by noise traders.

The third and more unconventional path predicts that rational speculators may actually drive a bubble. Speculators may initiate or contribute to price movements based on the expectation that positive-feedback traders will purchase the securities later at even higher prices (DeLong et al. (1990b)). Arbitrageurs, knowing that the market is overvalued, maximize profits by riding the bubble (Abreu and Brunnermeier (2002, 2003)). Because of capital constraints, the bubble only bursts when there is a coordinated selling effort among arbitrageurs.

In our empirical analysis, we relate the trading behavior of institutional (sophisticated) investors and individuals (noise traders) to the literature along several dimensions. First, we examine who bought

technology stocks. We find that both institutions and individuals are net technology buyers during the market run-up but institutions are the largest buyers. During the run-up period from January 2, 1997 to March 27, 2000, institutions made 63.6% of active technology purchases while individuals account for the remainder (19.4% via mutual fund flows and 17.0% directly). Even if we are extremely conservative and exclude all purchases from technology-oriented mutual funds (3.6%) and hedge funds (3.7%), institutions still account for 56.3% of total technology purchases. Among institutions, the 688 hedge fund firms in our sample are the most aggressive investors (consistent with Brunnermeier and Nagel (2004)), but the larger set of independent investment advisors and mutual funds (net of flows) actively invest more capital into the technology sector.

Second, we investigate trading patterns around the market peak. If the crash was due to a shift in noise trader sentiment (DeLong et al. (1990a)), then we would expect individual investors to drive the peak and subsequent crash. In contrast, the coordination mechanism of Abreu and Brunnermeier (2002, 2003) suggests that institutional investors drive the fall. We construct a unique database of daily trading activity for institutional and individual investor groups that allows us to focus on short-term trading. Consistent with Abreu and Brunnermeier, we find that institutional investors (except derivatives traders) begin pulling capital out of the market in mid-March 2000, while individuals, particularly discount brokerage clients, accelerate their purchases. We also examine individual stock peaks and find that institutions actively buy until the day before the peak and then rapidly pull out while various individual investor groups continue to increase their holdings. Consistent with Schultz (2008), we find little evidence that new supply of shares through lockup expirations drives price reversals in March 2000 or around individual stock peaks as argued by Ofek and Richardson (2003), Hong, Scheinkman, and Xiong (2006), and Xiong and Yu (2009).

Third, we examine whether institutions trade in the same direction as future fundamentals. For large stocks, pre-peak institutional buying is negatively related to post-peak stock returns. Additionally, institutions are net buyers for six clearly overpriced internet carve-outs identified by Lamont and Thaler

(2003), which provides further evidence that under some circumstances institutions buy in the face of poor economic fundamentals. Lastly, since institutional trading in the same direction as price movements could be a mechanical result of institutions responding more quickly to news on fundamentals, we examine short-term institutional trading patterns around news releases and find that the positive relation between institutional trading and price movements also persists on no-news days and weeks, suggesting the institutional trading pattern is not simply due to their faster response to news.

In addition to being related to the papers cited above, our paper is related to the larger literature that documents the relation between trading by investor groups and stock returns at the cross-sectional (Grinblatt and Keloharju (2000)) or market levels (Choe, Kho, and Stulz (1999)).<sup>4</sup> Brunnermeier and Nagel (2004) find that hedge fund firms generally took larger positions in stocks with high price-to-sales ratios during the 1998 to 2000 NASDAQ run-up. As Brunnermeier and Nagel note, the 53 hedge fund firms in their sample (which own only 0.30% of the aggregate market) are not likely to move market prices. We find that our larger sample of 688 hedge fund firms together with other institutional investors drive the technology run-up and crash.

Although we interpret investor interactions as representing supply and demand forces that influence prices, one might alternatively view this exercise simply as an interesting comparison of investor groups who bought and sold during the rise and fall of technology stocks. We find the former interpretation reasonable, however, in light of growing empirical evidence that institutional demand can affect security prices at short-term (Kraus and Stoll (1972), Scholes (1972), and Shleifer (1986)) and longer-term (Coval and Stafford (2007), Cohen, Diether, and Malloy (2007), and Frazzini and Lamont (2008)) frequencies.<sup>5</sup> We consider institutional and individual purchases as discretionary in the sense that investors (other than index funds) are not obligated to purchase new equity issues. Mechanical purchases of index, technology, and sector funds account for just 3.6% of total technology purchases, suggesting that institutional buying is largely an active practice.

The outline of our paper is as follows. Section I briefly describes the multitude of databases that we use. Section II analyzes aggregate trading in technology stocks by various investor groups and Section III examines investor trading around the market and individual security peaks. Section IV examines whether institutions move prices in the direction of longer-run fundamentals. Our conclusions follow in Section V.

## I. Data

This paper uses several sources of data: proprietary NASDAQ trading data; Thomson Financial for 13f institutional holdings, N-30D mutual fund holdings, and insider trading data; CRSP for mutual fund asset values and returns; weekly mutual fund flows from AMG Data Services; Factiva for news articles; SDC and EDGAR for lockup expirations; Datastream and SDC for float data; and SDC for events that affect the supply of technology stocks such as IPOs, SEOs, mergers and acquisitions, and repurchases.

### *A. Sample*

Our sample consists of NASDAQ technology firms (three-digit SIC code 737, which stands for computer programming, data processing, and other computer-related services) with ordinary common shares (i.e., CRSP share code 10 or 11) trading during the run-up and collapse of the NASDAQ stock market from 1997 to 2002.<sup>6</sup> We define the run-up as the period from January 2, 1997 to March 27, 2000.<sup>7</sup> Over this sample period, an average of 517 NASDAQ technology stocks trade each day. More details are provided in Internet Appendix A.

### *B. Quarterly Holdings of Institutions, Insiders, and Individuals*

For intermediate and long-term analysis, we obtain data on quarterly institutional holdings from the Thomson Financial 13f database (correcting for various issues as described in Internet Appendix B). In addition to the five 13f institution categories (banks, insurance companies, mutual funds, independent investment advisors, and all others), we identify 688 hedge fund firms in the 13f database with valid data

over our sample period predominantly through the use of firms from LionShares and Griffin and Xu (2009). As Brunnermeier and Nagel (2004) discuss, hedge fund firms often operate multiple hedge funds under the same 13f filing.

To study the trading activity of non-institutional investors, we further classify non-institutional shares into insider and individual holdings. We obtain data from SDC on closely held shares for IPOs issued between 1994 and 2002 and adjust insider holdings over time using subsequent insider trades reported by Thomson Financial insider trading data. For firms with IPOs before 1994, we obtain closely held shares from Datastream and adjust over time again using the Thomson Financial insider trading data. We then calculate quarterly individual holdings as the residual shares not held by insiders or 13f institutions. Numerous additional details regarding holdings are provided in Appendix A.

### *C. NASDAQ Trading Data*

We use proprietary data from NASDAQ clearing records that include the date, time, ticker symbol, trade size, and price of each transaction for each stock. The data also include additional identifying fields about the parties involved in each trade—fields that allow us to assign trading volume to various investor groups. First, each trade is linked to the parties on both sides of the trade. Second, information is provided as to whether the parties are trading for their own account (as a market maker), or whether they are simply handling a trade for a client (agency trading). Third, each trade identifies the buyer and seller. In our analysis, we focus on client trades only. More details are provided in Internet Appendix C.

We directly classify more than 500 brokerage houses through company web pages, news media, the NASD website, and conversations with NASDAQ officials. We confirm these classifications by examining average trade size and re-examining classifications where appropriate. Using this information, we assign trading volume to nine categories: four individual investor groups (general individual, individual full service, individual discount, and individual day trading), four institutional investor groups

(institutional, largest investment banks, 21 hedge funds, and derivatives traders), and one “mixed” group that handles both individual and institutional order flow.<sup>8</sup>

Table I shows several descriptors of trading activity for various investor groups during the NASDAQ run-up. In Panel A, we present percentages of share volume, dollar trading volume, and number of trades accounted for by each group, and average trade size for each group in technology stocks. Institutional traders and mixed-client brokers dominate trading volume. The fraction of daily trading volume accounted for by individual and institutional investor groups did not change markedly over the sample period (see the Internet Appendix). Viewed in isolation, this finding would hardly hint at the dramatic price changes that occurred during this time frame.

[Insert Table I about here]

The average trade size varies between 413 and 615 shares for individual investor groups. Conversely, the average trade for institutional clients exceeds 1,600 shares, and the average trade size for the largest investment bank clients is approximately 2,700 shares. The average trades executed through hedge fund, derivatives, and mixed-client brokers range from 693 to 853 shares—all between the individual and institutional averages.

We explore the trading behavior of investor groups by focusing on daily trading imbalances. For each stock, we compute daily trading imbalances by an investor group as the difference between buy and sell volumes for the investor group, scaled by that day’s shares outstanding, to present a measure of net buying activity relative to the total number of shares. For technology sector-level analysis, we compute value-weighted aggregate imbalances across stocks in the technology index to be consistent with the value-weighted returns. Unclassified trades and omitted market maker trades result in aggregate imbalances being only approximately equal to zero.

We compare quarterly imbalances for institutional and mixed investor groups calculated from our NASDAQ data to quarterly changes in institutional ownership computed using Thomson Financial 13f data. Panel B of Table I presents correlations among these variables for the 1997 to 2002 period. The

average cross-sectional correlation between aggregate institutional imbalances from NASDAQ data and changes in 13f institutional holdings is 0.27. By institutional ownership quartile, correlations are near zero for the lowest institutional ownership stocks but increase monotonically to 0.38 for the highest quartile. The mapping between 13f and NASDAQ data is tightest among stocks that comprise the bulk of market capitalization, an important link since we are interested in the economic forces behind the increase in market capitalization of technology stocks. The mixed imbalances have strong negative correlations with institutional imbalances, indicating that individual trading drives mixed imbalances.<sup>9</sup>

Following Boehmer and Kelley (2009), we obtain an average cross-sectional correlation of 0.72 between NASDAQ and 13f institutional turnover. This number compares favorably to their correlation of 0.44 calculated using NYSE and 13f data. We also benchmark our data to Campbell, Ramadorai, and Schwartz (2009) and find that our data yield a much stronger relation with 13f data in the largest two size quintiles that comprise the bulk of market capitalization (see Appendix B).

#### *D. Flows for Mutual Funds and 13f Institutions*

We construct mutual fund flows data to separate discretionary mutual fund trades from flow-induced trades. We match CRSP mutual fund returns and total net assets with Thomson Financial N-30D mutual fund holdings using Mutual Fund Links provided by Wharton Research Data Services (WRDS). We first follow the literature to calculate fund flows using CRSP fund returns and assets, and then infer flow-induced trading for our merged mutual fund sample and 13f mutual fund families. We also estimate flows for 13f data using quarterly stock returns and holdings. Subsequently, we obtain weekly flows for technology mutual funds and aggressive growth funds from AMG Data Services (who monitor 69% and 65% of technology and aggressive growth fund assets, respectively, during our sample period) and extrapolate these flows to the technology sector as well. Details about the merged mutual fund sample and our methodologies to compute flow-induced trading and to identify index, sector, and technology mutual funds are in Internet Appendices D through G.



### *E. News Articles*

To study how investor reactions to news may influence trading behavior, we manually search the Factiva database and obtain all news articles on firms in the technology sector from January 1, 1997 to December 31, 2002. We follow Tetlock, Saar-Tsechansky, and Macskassy (2008) to collect news articles and carefully account for name changes, mergers, etc. Details are provided in Internet Appendix H.

### *F. SDC Events*

We obtain from SDC various events that affect the supply of shares, including IPOs, SEOs, share repurchases, and mergers and acquisitions. Internet Appendix I provides details on our approach to compute the components of supply. To study the effect of lockup expirations, we obtain IPO and SEO lockup expiration dates and the number of shares subject to lockup from SDC. We manually search prospectuses through the EDGAR database to confirm the expiration dates and fill in missing data on expiration dates and number of shares subject to lockup.

## **II. Which Investor Groups Bought the Technology Sector?**

In this section we examine portfolio weights of individuals and various types of institutions in the technology sector as well as the evolution of demand and supply from a long-run perspective.

### *A. Technology Weights*

We start by analyzing the portfolio weights in technology stocks for institutions and individuals during the 1997 to 2002 period. Panel A of Figure 1 shows that the technology sector (excluding Microsoft) comprises 1.8% of institutional holdings in March 1997, increasing to 6.4% by March 31, 2000. Similarly, technology weights of individuals (net of insiders) increase from 1.0% to 4.3% over the same period.

[Insert Figure 1 about here]

Panel B of Figure 1 shows portfolio weights for six different types of institutional investors. Hedge funds have the largest exposure to technology stocks and are the most aggressive buyers during

the run-up. They decrease their technology exposure through the first two quarters of 1999 followed by aggressive purchases during the second half of 1999. Interestingly, this finding of a failed “attack on the bubble” in early 1999 is nearly identical to Brunnermeier and Nagel (2004) even though our hedge fund sample has 13 times as many hedge fund firms (688 vs. 53). Mutual funds and independent investment advisors have the next largest exposures to the technology sector during the run-up, with banks and insurance companies exposed the least.

### *B. Passive, Active, and Flow-induced Changes in Holdings*

Technology holdings of an investor group could increase because a) previously held technology positions increased in value, b) net flows were received and invested in the technology sector, or c) the investor group actively increased holdings in technology stocks. To isolate the passive change in holdings, we calculate the quarter-end buy-and-hold value of beginning-of-quarter technology positions. Specifically, we calculate passive holdings for an investor group for quarter  $q$  as follows:

$$Passive_q = \sum_i Holdings_{i,q-1} \times (1 + R_{i,q}) , \quad (1)$$

where  $Holdings_{i,q-1}$  is the investor group’s total dollar value of holdings in technology stock  $i$  at the end of quarter  $q-1$  and  $R_{i,q}$  is the buy-and-hold return on stock  $i$  over quarter  $q$ .

We then calculate net active buying as quarter-end technology ownership minus passive holdings and net buying induced by mutual fund flows:

$$Net\ Active\ Buying_q = \sum_i Holdings_{i,q} - Passive_q - NBFloWS_q^{13f} , \quad (2)$$

where  $Net\ Active\ Buying_q$  is total net active buying for the technology sector during quarter  $q$  and  $NBFloWS_q^{13f}$  is the dollar value of flow-induced net buying for 13f mutual fund families.

Although we take great care to calculate individual holdings, we believe individual ownership at the IPO date may be overstated because standard databases do not fully capture the extent of insider holdings.<sup>10</sup> For this reason, we mainly focus on technology stocks that exist at both the start and the end

of a quarter. Technology IPOs are therefore excluded from the analysis in the IPO quarter, but included thereafter. Panel A of Figure 2 shows the cumulative change in demand (net active buying) for technology stocks during the 1997 to 2002 period. Individuals are heavy buyers in 1997 and during the first half of 1999. Conversely, from June 1999 to March 2000 institutions are the main technology buyers. Over the entire run-up period from January 1997 to March 2000, institutions account for 63.6% of technology purchases, mutual fund flows 19.4%, and direct individual purchases 17.0%. Figure 1 also shows that the technology index had lost most of its gains (-72.9%) from March 31, 2000 to March 31, 2001. During this one-year period there were additional purchases worth \$74.6 (233.6 – 159.0) billion, of which 36.4% is due to institutions, 49.0% to individuals directly, and 14.6% to individuals through mutual fund flows.<sup>11</sup>

[Insert Figure 2 about here]

Panel B of Figure 2 presents the cumulative change in demand for technology stocks for the six 13f institution types. On a value-weighted basis, independent investment advisors and mutual funds (net of flows) are responsible for the largest movements of capital into the technology sector, followed by hedge funds and banks. Although hedge funds have the most aggressive technology weights as shown in Figure 1, they only account for 6.2% of technology market capitalization at the peak. Furthermore, technology-oriented hedge funds (257 out of 688 hedge fund firms) only account for 37% of total hedge fund buying during the run-up even with the broadest selection criteria, suggesting that hedge fund buying was not limited to a subset of hedge funds (see the Internet Appendix). Interestingly, independent investment advisors buy large amounts during the two quarters following the March 2000 peak and account for most of the increase in institutional holdings after the peak.

We find that cumulative net buying induced by mutual fund flows up to March 31, 2000 is 4.2% of the technology sector market capitalization (see the Internet Appendix), less than the 7.2% figure for cumulative net active buying by mutual funds after flows. As an alternative check on mutual fund flows, we use AMG weekly flow data, which account for 69% (65%) of total assets of all technology (aggressive

growth) mutual funds on average during our sample period. We then calculate net buying induced by technology fund flows and aggressive growth fund flows by assuming that AMG flows are representative of the sector as a whole. At the end of March 2000, AMG flows account for an increase in ownership of 2.0% of the technology sector, which is 52% lower than the 4.2% increase for flow-induced trading of 13f mutual fund families. These results are consistent with the fact that AMG flows cover the sectors most heavily invested in technology stocks, while flow-induced net buying of 13f mutual fund families covers a broader set of mutual funds.

Index funds raise an interesting issue. If a fund simply invests in a value-weighted index of stocks then the value of its technology holdings will change with movements in market values with no rebalancing needed. As money flows into index funds, we capture these flows using the methodology as previously discussed. However, if funds are initially underinvested in a group of stocks that grew more than others, or if the fund manager does not fully index, fund managers will tinker with technology weights. Additionally, fund managers who invest in technology in proportion to its market capitalization may be forced to invest further in technology stocks if these stocks become a larger part of the market index through new supply being issued. To measure the extent of indexing, we identify all funds that contain keywords that indicate they may be an index, sector, or technology fund. We find that these funds represent 8.58% of mutual fund technology holdings for our sample in March 1997 and 24.21% by March 2000. We estimate that net active demand for this sample is \$5.78 billion for our base sample (as shown in the Internet Appendix), or 5.7% of the \$101.13 billion in total institutional demand from 1997 to March 2000. Hence, if one assumes that all of this index buying was non-discretionary and forced by index funds having to purchase technology shares because of new supply being issued, then this would reduce the net active institutional buying to 60.0% instead of the 63.6% in Panel A of Figure 2. How to treat this buying is not straightforward since it is not possible to ascertain why index and sector funds increase their technology weighting. In the Internet Appendix, we further show that after excluding technology-oriented mutual funds and hedge funds with the broadest definition, the remaining

institutions still account for 56.3% of technology purchases. Although these adjustments tend to reduce the effect of institutional buying, even conservatively assuming all demand from technology-oriented mutual funds and hedge funds is non-discretionary does not alter our inferences.

### *C. Supply of Shares*

Strong demand can be accompanied by an increase in price and/or supply. It is important to note that our measure of change in demand (or net active buying) accounts for price changes. Hence, by construction change in supply will equal change in demand. We examine the possible sources of change in supply including IPOs, SEOs, delistings, insider sales, share repurchases, and stock payments during merger and acquisition activities. Figure 3 shows that the supply of technology shares drifts upward over time as IPOs, stock payments for mergers and acquisitions, and insider sales easily outpace decreases due to technology stock delistings. Overall, out of the \$224.5 billion increase in the net supply of technology shares through March 31, 2000, 33.4% is due to IPOs, 17.0% to insider sales, and 18.4% to stock payments. In the year following the peak (up to March 31, 2001), out of the additional \$82.8 (307.3 – 224.5) billion in capital that came to market, 30.3% is from other changes in shares outstanding such as executive stock compensation, while selling by insiders accounts for 15.2% and IPOs account for another 13.6%.

[Insert Figure 3 about here]

### *D. Technology versus Non-technology Sectors*

We now explore whether trading activity in the technology sector is substantially different than that for non-technology stocks. From January 1997 to March 2000, while the technology sector grew by \$159 billion in new capital (not held by insiders), approximately \$1,060 billion in new capital came into non-technology stocks. This is perhaps not surprising considering that even at its peak the technology sector (excluding Microsoft) was only 6.8% of CRSP market capitalization.

In Table II, we examine if the patterns of individual and institutional trading differ between technology and non-technology stocks. We further divide stocks into two groups of market

capitalization within technology and non-technology sectors. We compare the trading of technology and non-technology stocks in the year prior to the technology peak, when the much of the market run-up occurred. We first focus on large stocks that represent over 99% of the total market capitalization. Consistent with our previous findings in Figure 2, Panel A of Table II shows that institutions are the larger buyer (as a percentage of market capitalization) in large technology stocks in the year prior to the peak, with institutions purchasing 6.7% as compared to 3.7% for individuals. For non-technology stocks, however, individuals purchased 2.5% as compared to 1.5% for institutions. Stated differently, institutional net buying in technology stocks in the year prior to the peak is 1.8 times that of individuals but institutional net buying in non-technology stocks is only 60% of that of individuals. Panel A also presents simple changes in ownership and the level of ownership, which lead to similar inferences. When we examine small stocks we see that here individuals dominate the buying in technology and non-technology stocks. These patterns are interesting in that individuals are probably the marginal buyers in these smaller stocks, but less important for discerning where the majority of market value dislocation is from. Panel B further presents net active buying across institution types. We find that for large stocks, all types of institutional investors are more aggressive in technology stocks than in non-technology stocks except for insurance companies and possibly mutual funds.

[Insert Table II about here]

We compare the demand for technology and non-technology stocks over the period from January 1997 to March 2000 in Panel A of Figure 4. While institutions account for 63.6% of technology purchases up to the market peak, they only account for 31.0% (\$328.9 billion/\$1,060.4 billion) of non-technology purchases during this same period.<sup>12</sup> The fact that institutions account for a significantly higher percentage of technology demand than non-technology demand indicates that the aggressive purchases of technology shares is a discretionary decision made by institutional investors.

[Insert Figure 4 about here]

Panel B of Figure 4 plots the composition of total demand from April 2000 to March 2001, when most of the market value was lost. In the post-peak period, individuals account for the majority of technology purchases while institutions account for the majority of non-technology purchases. This sharp contrast relative to the pre-peak period suggests that individuals have bad timing. We examine this result more thoroughly in the next section.

### **III. Trading around the Technology Sector and Individual Security Peaks**

To distinguish between predictions of bubble theories regarding the burst of the tech bubble, we further examine institutional and individual trading around the March 2000 technology peak as well as individual stock peaks.

#### *A. Technology Peak*

Using NASDAQ clearing data we obtain a high frequency view of whether institutional or individual investors pulled capital out of the technology sector around its peak. Panel A of Figure 5 provides a detailed look at value-weighted imbalances for the technology sector from February 2000 through April 2000, with imbalances cumulated from the beginning of January 2000. The value-weighted technology index excluding Microsoft peaks on March 9 but loses only 8.5% as of March 27, the peak of the broader NASDAQ index. In contrast, from March 27 to April 28, the cumulative return on the technology index is -31.6%.

[Insert Figure 5 about here]

Imbalances of general institutions peaked on March 7. Between March 8 and the end of April, general institutions, the largest investment banks, and hedge fund clients sold 0.87% of the technology sector market capitalization, or 1.34% of the technology sector float. Conversely, all individual investor groups other than the individual full-service group, most dramatically discount brokerage clients, were net buyers throughout March and April 2000 as prices fell precipitously. Our earlier result in Figure 2 Panel B indicates that institutional selling from March 31, 2000 to June 30, 2000 primarily came from mutual funds and hedge funds.

Panel B of Figure 5 shows almost no outflows from mutual funds over this period according to AMG flow data, suggesting that institutional investors actively pulled out of the technology sector rather than responding to flows. Panel B also shows that the magnitudes of insider sales and lockup expirations are slowly decreasing around the market peak. The number and dollar value of lockup expirations rise dramatically as early as August 1999, long before the bubble burst in March 2000 (see the Internet Appendix). Unlike investor demand patterns, these results show no drastic shift in supply that can account for the burst of the bubble. Consistent with non-binding supply constraints, Battalio and Schultz (2006) show that investors could have shorted stocks synthetically with options in early 2000 but Lakonishok et al. (2007) find that sophisticated investors generally did not practice this strategy.

#### *B. Trading around Individual Stock Peaks*

We examine trading patterns around individual stock peaks from January 1997 to December 2000 in the same spirit as Brunnermeier and Nagel's (2004) examination of quarterly hedge fund trading activity. Figure 6 reports equal-weighted cross-sectional averages of cumulative imbalances for investor groups for the two months surrounding individual peaks. In the month before the peak, general institutions buy slightly more than 0.35% of shares outstanding.<sup>13</sup> Conversely, derivatives traders are small net sellers prior to the peak. Purchases by general individual and discount brokerage clients increase markedly the day before and the day of the peak. These groups continue buying after the peak, in dramatic contrast to widespread institutional selling of close to 0.37% for all institutional groups during the 21 trading days following the peak. Full-service brokerage clients also buy as prices fall, albeit to a lesser degree.

[Insert Figure 6 about here]

In supplemental results (see the Internet Appendix), we extend the window on each side of the peak to 60 trading days and find extremely strong institutional buying before the peak from day -60 to day -1 and institutional selling after the peak continuing until day +60. We also examine trading patterns by firm size quartiles (see the Internet Appendix). For the smallest firms, individuals (mostly discount



brokerage customers) are entirely responsible for driving prices up. However, institutional buying prior to peaks is stronger in the largest three size quartiles. In the largest two quartiles, institutions are the main buyers during the run-up and they start pulling out on the day of (quartile 3) or the day after the peak (top quartile). These results highlight the importance of individuals in small stocks and institutions in large stocks, which account for most of the market capitalization of the technology sector.

We further explore institutional trading patterns using 13f institutional holdings data. This approach provides a long-term view of trading at a quarterly frequency. Panel A of Figure 7 plots the average cumulative net buying and flow-adjusted net active buying for institutions in the eight quarters surrounding individual peaks. Aggregate institutional buying coincides with individual peaks. After the peak, institutions sell at a slower rate than they buy during the run-up. Panel B of Figure 7 displays cumulative net active buying (net of flows) by institution type around individual peaks. Although all institution types are net buyers before the peak, independent investment advisors lead all groups in magnitude, increasing holdings by more than 3% in the four quarters before the peak.

[Insert Figure 7 about here]

Coval and Stafford (2007) and Frazzini and Lamont (2008) demonstrate that investor flows can cause predictable mutual fund trading in individual stocks. We directly examine the flow-induced net buying for each institution type around individual stock peaks in Panel C of Figure 7. The impact of flows is relatively small for all institution types except mutual funds, for which the flow-induced change in holdings during the four quarters prior to the peak represents 1.72% of the firm's market capitalization. In comparison, the total net buying of mutual funds including flows is 3.63% for the same period, so flows represent slightly less than half of the buying pressure from mutual funds. Panel C also shows that individuals investing directly in these stocks are actually net sellers in the two quarters prior to the peak but net buyers following the peak. In total, individual investors (through flows and direct investment) are net buyers of 1.41% of an event firm's market capitalization in the four quarters prior to the peak compared to 8.78% for institutions (net of flows).

Since quarterly 13f data limit inferences on the exact timing of institutional trading patterns around our 580 stock peaks, we examine the subset of 95 peaks that occur within five trading days of the end of a quarter (coinciding with 13f report dates). As shown in Panel D of Figure 7, institutional net active buying coincides with price peaks, consistent with NASDAQ trading data (Figure 6). This pattern is most prevalent for mutual funds, investment advisors, and hedge funds. Hedge funds and investment advisors are the most aggressive sellers in the quarter after the peak.

Panel E of Figure 7 examines the change in the supply of shares due to insider selling, SEOs, stock payments to acquire interest in other companies, etc. Although the supply of shares generally increases over time, it appears that stock peaks coincide with acceleration in insider selling and stock payments for acquisitions. The increase in supply through insider selling and stock payments continues after the peak as well.<sup>14</sup>

Shares locked up at issuance do not effectively increase the supply of shares until the lockup expires. Panel F of Figure 7 examines the timing of IPO and SEO lockup expirations relative to individual stock peaks. In contrast to the lockup explanation of Ofek and Richardson (2003) but consistent with Schultz (2008), we find that lockup expirations do not generally coincide with individual stock peaks. For example, 40% of lockups expire more than three months before the peak and another 29% more than three months after the peak. Likewise, the values of lockup expirations, expressed as a percentage of the event firm's market capitalization, show no discernible patterns around individual stock peaks.<sup>15</sup>

#### **IV. Bubble or Fundamental Mechanics?**

Our evidence can be interpreted as institutions either facilitating mispricing or believing rationally in future growth prospects in the technology sector. To help distinguish between these possibilities, we first examine whether institutional and individual net active buying during the run-up is related to post-peak stock price movements. Additionally, we examine whether institutional trading

moves prices toward or away from fair value for a sample of six carve-outs that Lamont and Thaler (2003) associate with clear overpricing. Lastly, we examine whether institutions were just trading based on fundamental values reflected in stock-specific news or reacting to their own signals.

#### *A. Pre-peak Institutional and Individual Trading and Post-peak Returns*

We first investigate whether institutional buying prior to March 31, 2000 is indicative of relatively greater future stock returns (as a proxy for future fundamentals). Because our previous findings in Table II show that buying patterns differ dramatically with firm size, we focus on firms in the top 25% of CRSP market capitalization but later examine results for the next largest quartile. The largest 25% firms represent 95.8% of CRSP total market capitalization as of March 31, 2000. Next, we assign sample firms into terciles according to the difference between one-year institutional buying (excluding flows) and one-year individual buying prior to March 31, 2000.

As an alternative and continuous measure of “bubbly” stocks we first report the price-to-sales (P/S) ratios, as proposed by Brunnermeier and Nagel (2004). Table III shows that compared to stocks bought heavily by individuals, stocks bought heavily by institutions have higher P/S ratios at the market peak, and they experience higher returns in the year prior to the peak. More importantly, Table III shows that stocks heavily bought by institutions experience much more negative one- and two- year returns from the market peak of March 31, 2000 than those heavily bought by individual investors.<sup>16</sup> When we examine P/S-adjusted returns for stocks heavily bought by institutions, we find that the majority of the negative returns in the post-peak periods can be explained by the high P/S ratios (the bubbly nature) of these firms. However, there is weak evidence of negative P/S-adjusted returns in the two-year period after the market peak.

[Insert Table III about here]

We further estimate cross-sectional regressions of one-, two-, and three-year buy-and-hold stock returns after March 31, 2000 on institutional and individual buying in the year prior to March 31, 2000 for the top 25% and 50% CRSP stocks in terms of market capitalization. Panel A of Table IV shows that

both institutional buying (excluding flows) and individual buying (including flows) during the run-up are significantly negatively related to post-peak returns.<sup>17</sup> Coefficients for the two groups are nearly identical with more explanatory power for institutional buying, particularly in the top 25% of market capitalization. Panel B further tests whether the net active buying by institutions in excess of individual buying is negatively related to future returns. Institutional buying relative to individual buying is a negative predictor of future returns in the top 25% of firms but not significantly so in the top 50%. The fact that institutional buying leads to larger post-peak reversals than individual buying for the largest 25% of stocks, which account for most of the CRSP market capitalization, suggests that institutions moved stock markets in what was clearly the wrong direction.<sup>18</sup>

[Insert Table IV about here]

#### *B. Do Institutions Ever Trade in the Direction of Clear Mispricing?*

For more evidence on whether institutions rationally respond to fundamental information or fuel prices that they know to be artificially high, we analyze the six equity carve-outs identified by Lamont and Thaler (2003) to be clearly overpriced.<sup>19</sup> In these cases the market value of the parent firm's ownership in the carve-out exceeds the market value of the parent firm for a considerable amount of time, with the parent firm clearly intending to enforce the carve-out. We examine net buying of investor groups in the 60 days prior to the day when the clear overpricing is corrected. Figure 8 shows that institutions buy on average 1.5% of the market value (2.9% of the float) of these overpriced carve-outs from day -60 to day -12 before they start selling. Conversely, derivatives traders sell about 1.0% from day -30 to day 0. Trading of the four individual groups is close to zero except for discount traders, the least sophisticated individual group, who buy 0.45% from day -36 to day 0. Interestingly, in the last 12 days while institutions are aggressively selling the carve-outs, discount traders (and individuals in aggregate) continue to purchase and lose from their trades. Though limited to only six firms, these results are consistent with institutions fueling prices that they should know to be artificially high.

[Insert Figure 8 about here]

### *C. Were Institutions Simply Following the News?*

While our results are supportive of institutional trading moving prices of technology stocks up, one may argue that the positive relation between institutional trading and price movements is due to the fact that the financial press drove stock prices and institutions simply reacted to information in the news more quickly than individuals. To test whether the relation between institutional trading and prices is driven by institutions reacting to news articles, we separately examine trading activity on days with news and no news. In a similar spirit as Section IV.A, we focus on the largest 50% of technology stocks, which account for over 98.6% of technology market capitalization. On each day  $t$ , we assign stocks to portfolios according to whether there are any news articles about the firm in the top 10 newswires during the  $[t-3, t]$  window and whether their returns in excess of the technology index return are negative or positive.

Panel A of Table V shows that for days with or immediately following news articles, general individual group and day traders trade in the same direction as stock returns but discount brokerage clients trade in the opposite direction. Institutions and the largest investment banks, on the other hand, trade in the same direction as returns. For days with no news there is a slightly weaker pattern of institutions and the largest investment banks moving with returns, suggesting that responding to news explains only part of institutional trading. Panel B further shows that the four individual groups taken together trade against lagged returns for both news days and no-news days, while the four institutional groups trade with lagged returns for both news days and no-news days. We also examine the weekly frequency (see the Internet Appendix) with no discernible difference between weeks with and without news. Institutions move in the same direction as contemporaneous weekly returns, while individuals move in the opposite direction.

[Insert Table V about here]

Panel C of Table V presents for the largest 50% of technology stocks daily, weekly, and monthly Fama-MacBeth cross-sectional regressions of individual stock returns on trading imbalances for eight

investor groups during the run-up period. We standardize returns and imbalances in each cross-section. The standardization measures how closely returns and imbalances move together but does not take into account the price impact a large investor group would have relative to a small group. At the daily frequency, institutions exhibit the strongest positive relation with stock returns, where a one-standard deviation change in institutional trading is accompanied by a 0.18 standard deviation (or 1.43%) increase in stock returns. At the weekly and monthly frequency, institutional trading continues to be strongly correlated with returns. We next estimate daily and weekly regressions interacting news dummies with investor imbalances. Consistent with the sorting results in Panel A, the last two columns show that the positive relation between institutional trading and returns remains strong on no-news days.<sup>20</sup>

Overall, the daily and weekly evidence at the cross-sectional level indicates that institutions move with returns. This pattern is prevalent on both news and no-news days and thus inconsistent with the conjecture that institutions are simply reacting to fundamentals in the news.

## **V. Conclusion**

This paper examines the trading behavior of individual and institutional investors during the spectacular rise and fall of the technology sector from January 1997 to December 2002. From January 1997 to March 2000, both institutions and individuals actively purchase technology shares with institutional buying exceeding the sum of direct and indirect (through mutual funds) individual purchases. During March 2000 institutional investors quickly pulled capital out of the market, while individual investors continued to buy. Institutional investors also drive the run-up of individual technology stocks, particularly in large stocks. Individuals, in contrast, purchase large amounts following individual stock peaks and during the year following the market peak in March 2000. Cross-sectional patterns for individual stock peaks are generally consistent with institutions moving with and following returns in all but the smallest stocks. In contrast to the explanation that institutions drove prices higher

with a rational but mistaken belief in future growth opportunities, we find that institutions trade in the direction of clear mispricing in a small sample of equity carve-outs.

Our results directly challenge the view sophisticated investors consistently move against mispricing, a central building block of market efficiency. Nor does the evidence support bubble models in which individuals move prices while smart money (institutions) passively stands aside. We also find evidence inconsistent with share supply restrictions and lockups being the sole cause of the bubble. Overall, our evidence suggests that the most sophisticated market participants actively purchased technology stocks during the run-up and quickly reversed course in March 2000, driving the collapse—a finding consistent with Abreu and Brunnermeier (2003). Individual investors actively bought during both the run-up and particularly the collapse, highlighting their relatively unsophisticated behavior in the stock market. Future research should further explore the stabilizing and destabilizing roles that sophisticated investors play in capital markets.

## Appendix A. Quarterly Holdings of Institutions, Insiders, and Individuals

We construct a comprehensive panel data set of insider holdings using three different approaches. 1) SDC approach: we obtain data from SDC on shares offered (including the overallotment option) for IPOs issued between 1994 and 2002. We define closely held shares on the IPO date as the difference between CRSP shares outstanding and shares offered in the IPO. We then update the shares held by insiders after the IPO date using insider trading data from Thomson Financial. We delete duplicate insider trades for a given firm-date with the same shares held, shares traded, transaction price, and transaction type to avoid double counting a trade reported redundantly by insiders who jointly own the shares transacted. 2) Datastream approach: we obtain annual data on closely held shares from Datastream, and compute the shares held by insiders between two reports by updating the figure from the previous report using insider trading data from Thomson Financial. For IPOs, Datastream closely held shares are only available some time after the IPO date, so we backfill from the first report to the IPO date using Thomson Financial insider trading data as well. 3) Form 3 approach: officers and directors, and any beneficial owners of more than 10% of a class of the company's stock, must initially file a Form 3 statement of ownership with the SEC. We define closely held shares on the IPO date as the sum of all Form 3 holdings filed by officers and directors for the window  $[-365, +10]$ , where day 0 is the IPO date. We update post-IPO closely held shares using Thomson Financial insider trading.

Insiders and institutions can overlap. For example, a venture capital firm can be both a 13f institution and an insider. If that venture capital firm sells 5% of a firm's shares during a quarter to individuals, this trade is likely captured by both Thomson Financial insider trading data and 13f institutional holdings data, resulting in 10% individual buying (since individual ownership is one minus institutional and insider ownership). To avoid this double counting, we screen to exclude institutional trades from Thomson Financial insider trading data. We construct the list of institutional trades within the insider trading data as follows. We first exclude a trade if the insider is a top executive, director, etc. Within the remaining trades we identify institutional trades based on whether the insider's name contains



key words that indicate an institution.<sup>21</sup> Further, we manually screen the remaining names to identify institutions whose names do not contain a key word (for example, Morgan Stanley). If the trade is from a trust or a foundation, we classify it as an institutional trade if the name can be matched to a 13f institution.

Overlaps in holdings of insiders and institutions could occur due to initial IPO allocations as well. We identify potential overlaps when aggregate institutional and insider ownership (after excluding institutional insider trades) exceeds 100% of shares outstanding.<sup>22</sup> For these cases, we take the maximum quarterly overage across the sample period and subtract it from IPO closely held shares. For a small number of firms for which this adjustment makes IPO closely held shares negative, we use the Datastream approach discussed above.

We next compile insider holdings using the SDC approach for 68% of the technology sample and the Datastream approach for the rest.<sup>23</sup> We calculate quarterly individual holdings as 100% minus the sum of 13f institutional holdings and insider holdings. For the analysis involving insiders and individual investors, we exclude firms with missing insider data and firm-quarters for which combined ownership exceeds 100% in either the current or previous quarter.<sup>24</sup> The subsample with complete insider holdings (and therefore individual holdings) contains 91% of firm-quarters.

One issue is that we might underestimate insider ownership and therefore overestimate individual ownership for IPOs. For example, Aggarwal, Prabhala, and Puri (2002) find that only 27.2% of IPO shares are allocated to individual investors between May 1997 and June 1998. However, we find that at the end of the IPO quarter, individuals receive 62.5% of shares allocated in technology IPOs (72.8% for all IPOs). There are two potential reasons for the underestimation of insider ownership at the time of the IPO. First, some IPOs have no valid SDC data or their SDC data are replaced with Datastream data due to the reasons described above. For 54 of our 406 IPOs we use Datastream data, which potentially understates IPO insider ownership. According to Datastream, average closely held shares for these IPOs is 43.97% on the IPO date and 46.09% at the end of the IPO quarter. Since

average institutional ownership is 11.41%, individual ownership equals 42.50% ( $100\% - 46.09\% - 11.41\%$ ) or 75.6% of float at the end of the IPO quarter, significantly higher than both the literature (Aggarwal, Prabhala, and Puri (2002)) and the corresponding percentage from our SDC sample.

Second, our adjustment for overlapping ownership might also understate insider ownership and therefore overstate individual ownership of IPOs. Before adjustment the average closely held shares for 352 IPOs with SDC data is 72.41% on the IPO date and 72.81% at the end of the IPO quarter. As a result, individual ownership is 12.27% at the end of the IPO quarter, accounting for only 45.1% of the float. However, after we subtract overlapping ownership between institutions and insiders (i.e., the maximum amount by which their combined ownership exceeds 100%) from IPO closely held shares, the average closely held shares at the end of the IPO quarter becomes 63.84% while individual ownership is 21.24%, accounting for 58.7% of float, which is also significantly higher than what the literature documents.

Due to the concern of overestimating IPO individual ownership, for our main tests we use the sample containing technology stocks that exist at both the beginning and the end of a quarter (excluding technology IPOs from the analysis in the IPO quarter). We use the full sample for robustness checks.

## **Appendix B. Investor-type Classifications for NASDAQ Trading Data**

We identify the largest 100 NASDAQ market makers each year from 1997 to 2002 and the top 500 market makers from October 1999 to September 2002, according to trading volume. These efforts result in a set of 619 unique market makers handling 98.2% of NASDAQ volume over our sample period. We classify each market maker using their own web pages, news media, conversations with NASDAQ officials, information gathered from the NASD website, and other reliable sources of public information. In many cases classifications are verified through several sources. We classify the remaining smaller market participants according to average market maker trade size. Firms with average trade size of less than 500 are classified as individual general, those with average trade size between 500 and 1,000

are classified as mixed, and those with average trade size above 1,000 are classified as institutional. We also adjust our classifications for mergers on the effective merger date, so that each market maker in the sample is accurately classified on each day.

We describe our nine categories and provide sample firms for each category below:

- Individual General – Brokers in this category focus on retail services to individuals and offer some mix of at least two of full-service, discount, or daytrading brokerage services (e.g., Mayer and Schweitzer, Datek Securities, Ameritrade, J.B. Oxford and Co., and Big J Securities).
- Individual Full Service – This category consists of brokers that primarily provide full-service brokerage to individuals (e.g., Wedbush Morgan Securities, H&R Block Financial Advisors, A.G. Edwards & Sons, and CIBC Wood Gundy Securities).
- Individual Discount – Brokers in this category primarily provide discount brokerage services to individuals (e.g., Charles Schwab, TD Waterhouse, Brown & Co. Securities, and Scottrade).
- Individual Day Trading – Brokers in this category specialize in providing daytrading services to active individual traders (e.g., Momentum Securities, Assent, Heartland Securities, Landmark Securities, and Broadway Trading).
- Institutional – This category consists primarily of firms that broker only for institutional clients. We classify firms that offer individual brokerage exclusively to high net worth individuals and institutional brokers as institutional brokers (e.g., UBS Warburg, J.P. Morgan Chase, Credit Suisse First Boston, NDB Capital Markets, and Robertson Stephens). Also included in the institutional category are strictly proprietary trading firms (e.g., Swift Trade and Domestic Securities).
- Largest I-banks – This classification consists of three of the largest investment banks in our sample, the largest participants in the business of prime brokerage for hedge funds, which accounts for approximately 60% of that market.

- Hedge Fund – This category consists of 21 registered market participants whose primary trading activity is on behalf of hedge funds or families of hedge funds (e.g., Nova Fund, Sierra Trading Group, Ramius Securities, Peters Securities, and Millenco). Given that these hedge funds have their own market making desks, it is likely that they engage in high frequency trading strategies.
- Derivatives – This category consists of firms that specialize in the trading of options, futures, and other derivative financial instruments (e.g., Timber Hill, First Options of Chicago, Susquehanna Capital Group, Lit America, and Hull Trading).
- Mixed – This category consists of brokers who conduct a large number of trades on behalf of both individuals and institutions (e.g., Citigroup, Deutsche Bank Alex Brown, Herzog Heine Geduld, Merrill Lynch, National Financial Services, and Paine Webber Jackson Curtis).

In addition to the comparison with Boehmer and Kelley (2009) mentioned in the text (at the end of Section I.C), we compare the mapping between our NASDAQ data and 13f data to that of Campbell, Ramadorai, and Schwartz (2009). They infer daily institutional trading activity from the Trade and Quote (TAQ) database by estimating regressions for each size quintile for the 1993 to 2000 period and report adjusted-R<sup>2</sup>s of 0.123, 0.100, 0.142, 0.133, and 0.142, respectively. We estimate a similar regression model except that we replace the TAQ variables with our institutional flows and our institutional flows interacted with lagged 13f holdings. The adjusted-R<sup>2</sup>s are 0.038, 0.107, 0.137, 0.210, and 0.226 from the smallest to the largest quintile. We obtain much higher adjusted-R<sup>2</sup>s for the largest two quintiles, which comprise the bulk of market capitalization.

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## Footnotes

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<sup>1</sup> Using data from 1871 to 2000, Shiller (2000) shows that in real terms the S&P 500 price run-up from 1992 to 2000 is even larger than the 1920s run-up, and the January 2000 P/E multiple (using the prior 10-year earnings) of 44 exceeds the September 1929 P/E ratio of 33.

<sup>2</sup> “Economists and market experts say (individual) investors ... not the so-called ‘smart money’ on Wall Street – are the reasons behind the greatest bull market in history” (“Little guy becomes market’s big mover; professionals lose their lock on Wall St. trading,” *The Washington Post*, February 2, 1999, E01). See also “Market savvy,” *Los Angeles Times*, November 17, 1998, C4, and “Where no investor has gone before: Amateurs steered the ship through a spacey year,” *The Washington Post*, January 3, 1999, H01.

<sup>3</sup> Brunnermeier (2001, 2008) evaluates bubble models and LeRoy (2004) discusses empirical bubble connections. We use the term “bubble” in the spirit of Kindleberger (1978) as “an upward price movement over an extended range that then implodes.” Although Ofek and Richardson (2002) provide compelling evidence that price levels were too high to be explained by reasonable expectations of future cash flows, our paper does not directly relate to this debate.

<sup>4</sup> Grinblatt, Titman, and Wermers (1995), Grinblatt and Keloharju (2001), Griffin, Harris, and Topaloglu (2003), Kaniel, Saar, and Titman (2008), Barber and Odean (2008), and Linnainmaa (2010), among others, examine investor trading with respect to past individual stock returns. At the market level, Shapira and Venezia (2007), Lipson and Puckett (2010), Boyer and Zheng (2009), and Cohen (2003) examine trading activity.

<sup>5</sup> Grinblatt and Han (2005), Han and Wang (2007), Andrade, Chang, and Seasholes (2008), Lou (2010), and Greenwood and Nagel (2009) provide evidence that non-informative demand can cause price dislocations. Chordia, Roll, and Subrahmanyam (2002) note that it is more intuitive to think of aggregate prices as driven by the ‘inventory paradigm’ (supply and demand) rather than asymmetric information.

<sup>6</sup> For our value-weighted results, we exclude Microsoft because Microsoft’s market capitalization is 44.9% (on average, ranging between 21.6% and 58.3%) of the technology sector during our sample period. Including Microsoft generally makes patterns more volatile, but inferences are similar.

<sup>7</sup> Our value-weighted technology index (excluding Microsoft) actually peaked on March 9, 2000 at 5.71 times its value on January 1, 1997, or 5.60 times if we further exclude the IPO quarters to be consistent with our analysis of institutional and individual demand.

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<sup>8</sup> Institutional brokerage houses with private wealth management businesses are counted as institutional. We refer to trades by “institutions” although a more accurate but cumbersome classification would be trades “executed through brokerage houses dealing primarily with institutions.” We provide details of investor-type classifications in Appendix B.

<sup>9</sup> In the Internet Appendix we examine correlations among imbalances for the nine investor groups.

<sup>10</sup> We find that individuals receive 62.5% of shares allocated in technology IPOs (72.8% for all IPOs), which is far above the 27.2% in Aggarwal, Prabhala and Puri (2002) with proprietary SEC allocation data. Since insider ownership at the IPO quarter is likely understated (and individual holdings overstated), we measure insider ownership several ways (see Appendix A) but ultimately think it is best to exclude stocks in the quarter of issuance. Griffin, Harris, and Topaloglu (2007) find that institutions are the dominant driver behind the high “dot-com” IPO pricing through laddering activity.

<sup>11</sup> In the Internet Appendix, we include IPOs and delistings in the calculations. Under this approach, individuals play a slightly greater role but institutions (net of flows) are still the largest buyers with 55.7% of technology purchases during the run-up, even though our lack of complete allocation data likely overestimates individual purchases.

<sup>12</sup> We further document the time series of demand for non-technology stocks in the Internet Appendix. Due to the large number of non-technology stocks, we also repeat the tests by excluding all stocks in the highest quartile of price-to-sales ratios, a measure of bubbly stocks proposed by Brunnermeier and Nagel (2004), to address the concern that non-technology stocks might contain some hidden “new economy” stocks. In this more restrictive “old economy” sample, we find (in the Internet Appendix) that during the run-up period institutions buy 46.4% of non-technology stocks while individuals buy the remaining 53.6% (directly or through mutual fund flows).

<sup>13</sup> In the Internet Appendix, we find similar results using imbalances adjusted for firm size and turnover.

<sup>14</sup> Although individual stock peaks cluster in March 2000 (151 peaks in March 2000 versus 429 peaks in other months), these results are robust to excluding March 2000 peaks (see the Internet Appendix).

<sup>15</sup> In the Internet Appendix, we also examine imbalances in the 60 trading days before and after lockup expirations. Institutions begin selling 49 (seven) trading days before IPO (SEO) lockup expirations. In contrast, individuals consistently buy during this window.

<sup>16</sup> In the Internet Appendix, we repeat the tests using change in ownership, an alternative measure to net active buying, and the second highest quartile of CRSP firms in terms of market capitalization, and find similar patterns with few statistically significant differences.

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<sup>17</sup> A caveat of this regression design is that the residuals can be cross-sectionally correlated due to the potential co-movements of post-peak stock prices, leading to inflated *t*-statistics that should be treated with caution.

<sup>18</sup> In the Internet Appendix, we estimate regressions of post-peak returns on one- or two-year pre-peak institutional net active buying, flow-induced net buying, and individual net buying simultaneously. All three components are negatively related to future returns with institutions and flows generally having the largest coefficients.

<sup>19</sup> We thank Ravi Jagannathan for this suggestion.

<sup>20</sup> We also perform the news analysis with alternative samples of technology firms including the full sample, top 25% largest firms, bottom 50% smallest firms; with alternative news measures; and with panel regression techniques (see the Internet Appendix). We find similar results, consistent with Bhattacharya et al. (2009), who conclude that the media was not a significant factor for internet stocks.

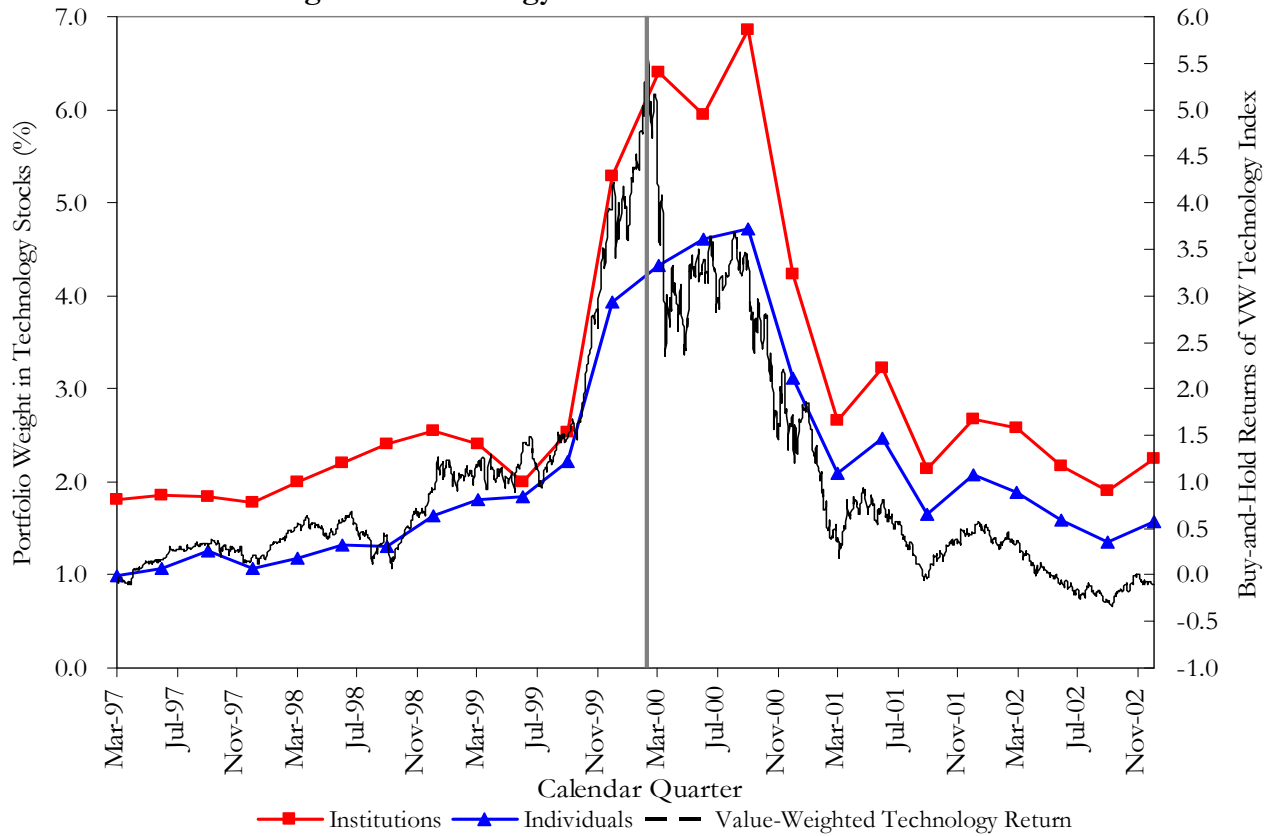
<sup>21</sup> The keywords include the following: “bank,” “venture,” “capital,” “investment,” “inv ,” “invt ,” “invs ,” “lp,” “lp,” “insurance,” “ins ,” “associate,” “assoc,” “pension,” “advisor,” “holding,” “hlds,” “management,” “mgmt,” “mgt,” “fund,” “property,” “buyout,” “financ,” “fin ,” “institution,” “equity,” and “partners.”

<sup>22</sup> For a small number of firm-quarters for which insider holdings are negative or above 100%, we use the most recent insider holdings between zero and 100%.

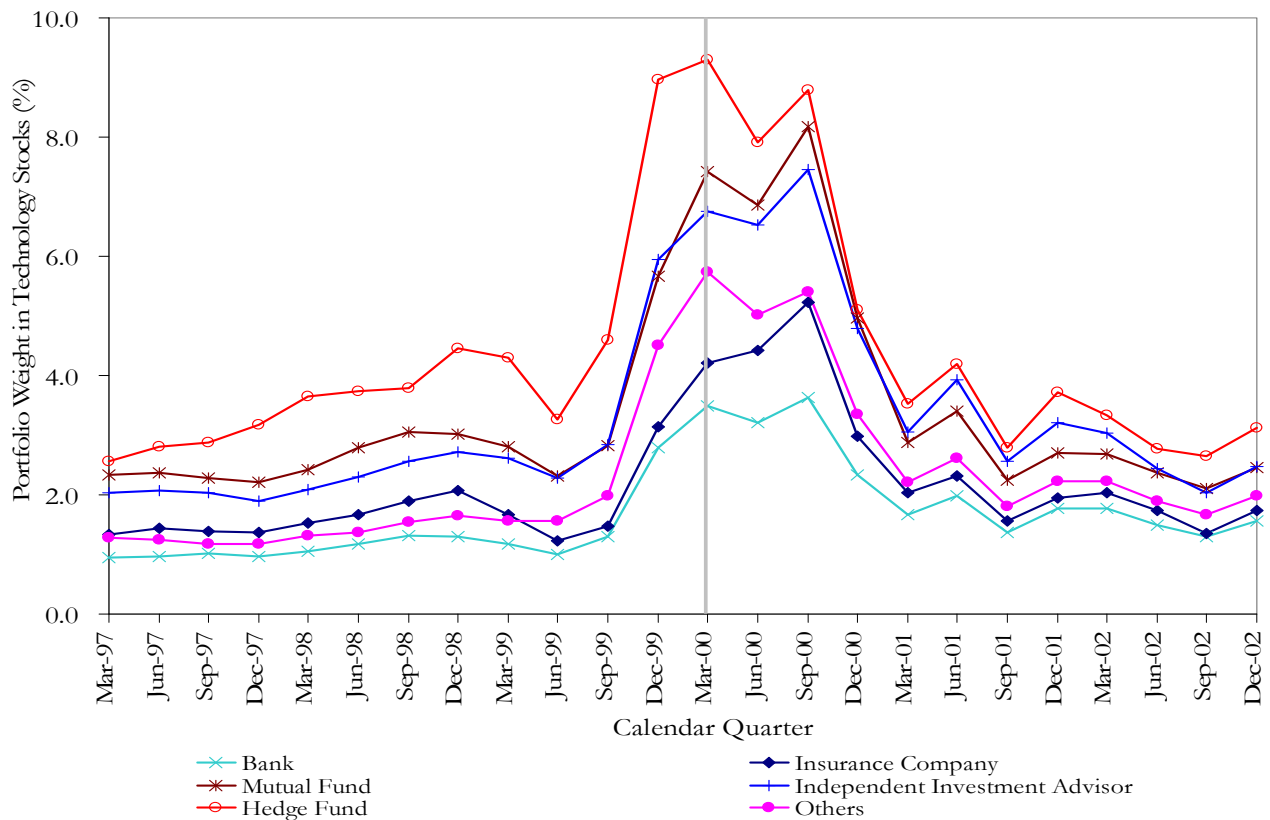
<sup>23</sup> The majority of the firms for which we apply the Datastream approach are those with IPOs prior to 1994. We use the Form 3 approach for four technology firms missing both SDC and Datastream data.

<sup>24</sup> Since we already make adjustments for SDC firms with combined ownership above 100%, these cases of combined ownership exceeding 100% are firms from Datastream.

**Panel A. Portfolio weights in technology stocks: Institutions and individuals**

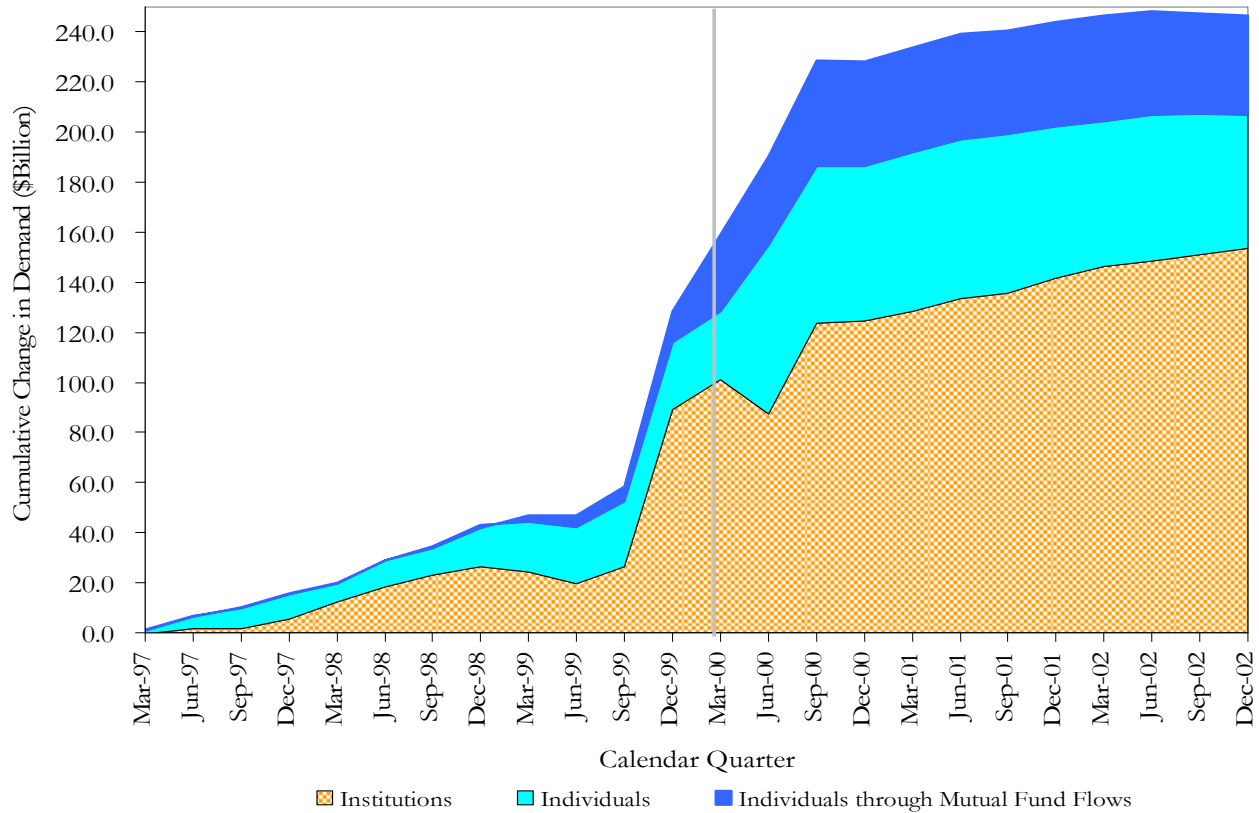


**Panel B. Portfolio weights in technology stocks: 13f institution types**

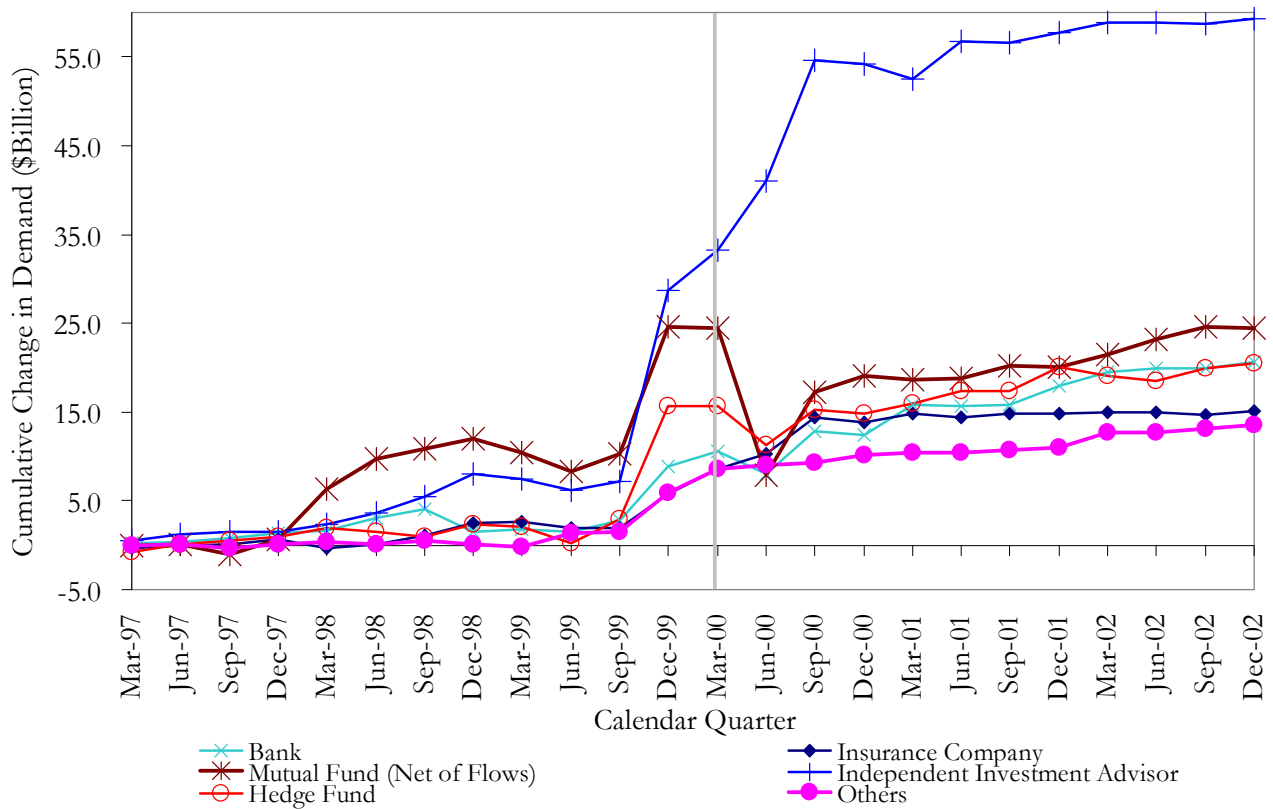


**Figure 1. Portfolio weights in technology stocks.** This figure plots portfolio weights in NASDAQ technology stocks (three-digit SIC code=737 with ordinary common shares, excluding Microsoft) for various investor groups during the 1997 to 2002 period. Panel A plots portfolio weights at the end of each quarter for institutions and individuals (net of insiders), where portfolio weight is the percentage of total dollar holdings accounted for by technology stocks for an investor group. Panel B plots portfolio weights in technology stocks for the six 13f institution categories.

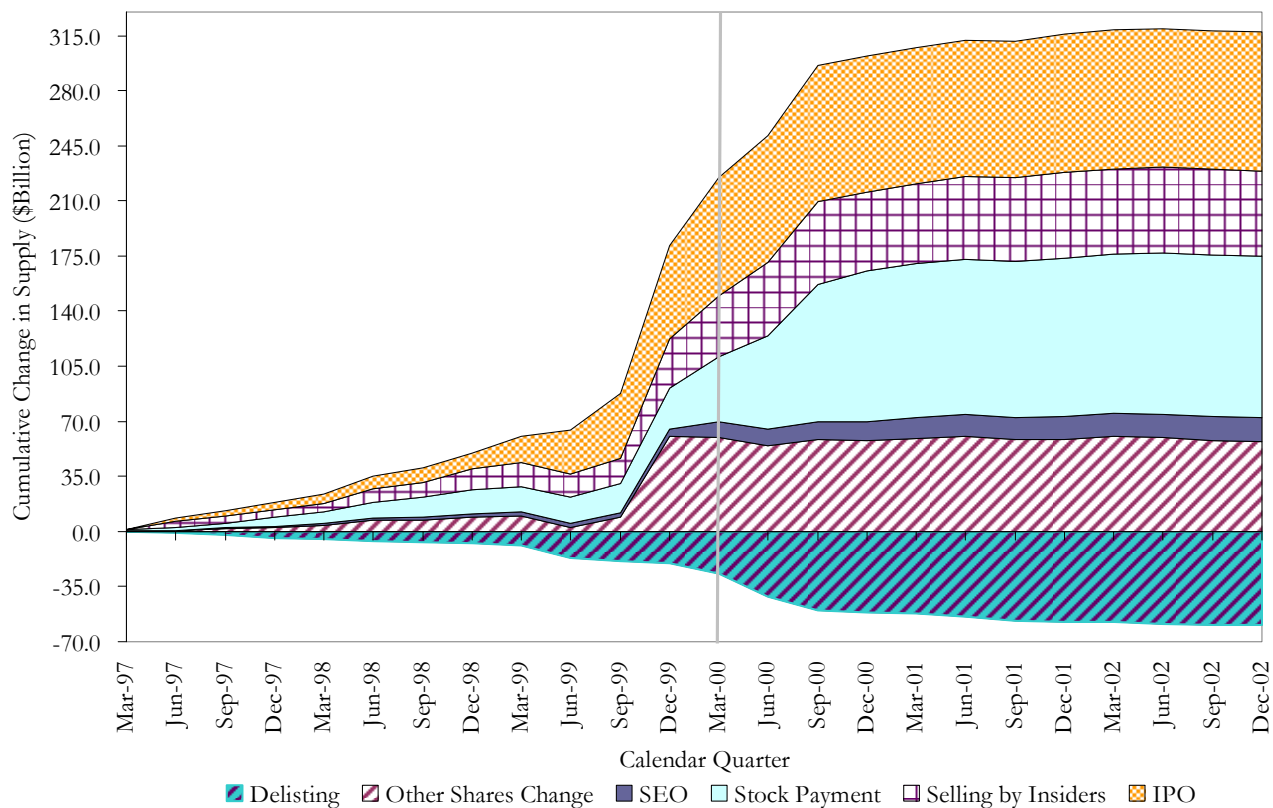
**Panel A. Cumulative change in demand for technology stocks: Institutions and individuals**



**Panel B. Cumulative change in demand for technology stocks: 13f institution types**



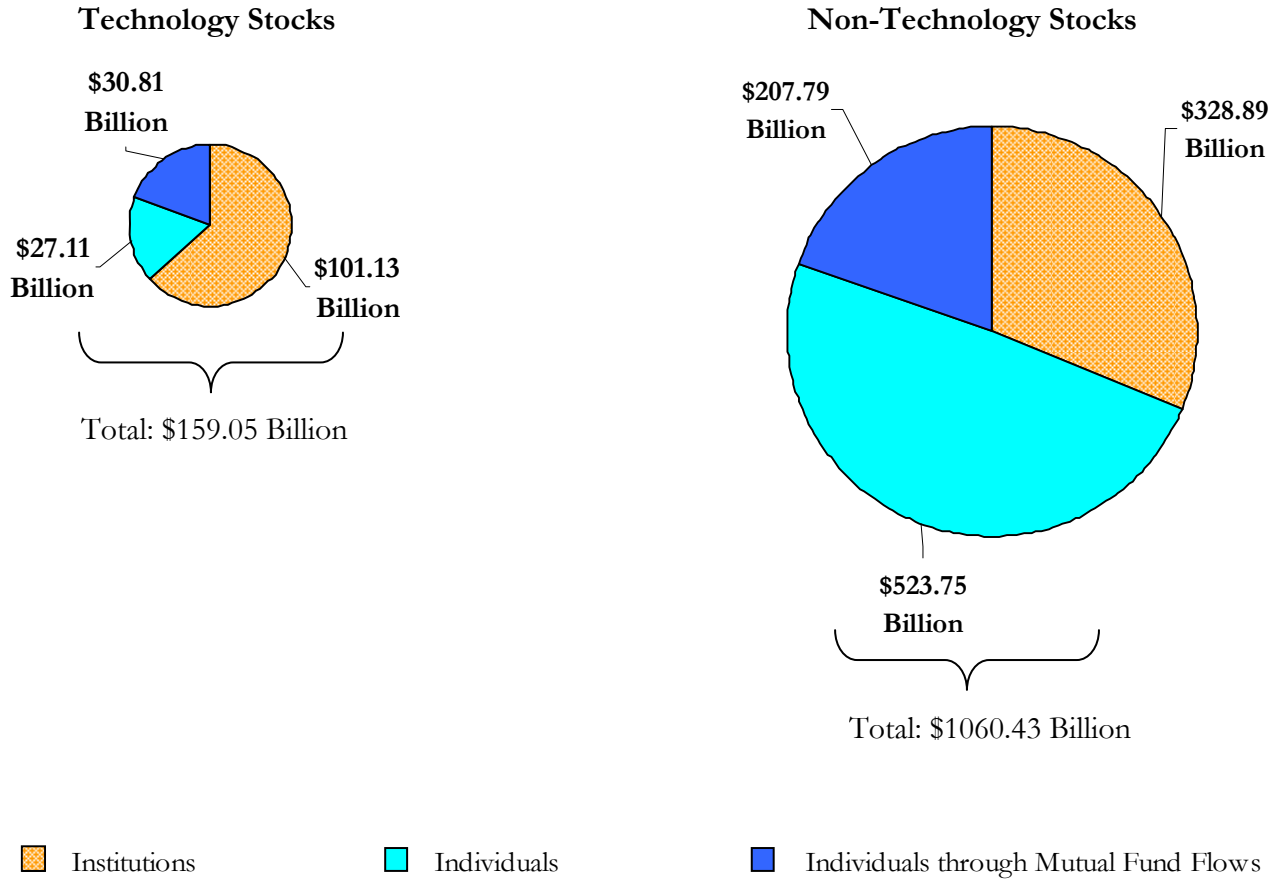
**Figure 2. Cumulative change in demand for technology stocks.** We calculate quarterly changes in demand for NASDAQ technology stocks (three-digit SIC code=737 with ordinary common shares, excluding Microsoft) during the 1997 to 2002 period. We require a firm to be in the technology sector at both the beginning and the end of the quarter to be included in the sample. Quarterly change in demand for an investor group is the difference between end-of-quarter technology holdings and the buy-and-hold value of beginning-of-quarter technology holdings. The individual group is net of insiders. We further isolate the change in demand induced by mutual fund flows from change in demand by institutions. Change in demand induced by mutual fund flows is calculated by applying mutual fund flows for the merged CRSP-Thomson Financial sample to 13f mutual fund families. We describe the details of our approach in Internet Appendix E. Panel A plots cumulative changes in demand for institutions and individuals, and demand induced by mutual fund flows. Panel B plots cumulative changes for the six 13f institution types, where the change by mutual funds is net of flows.



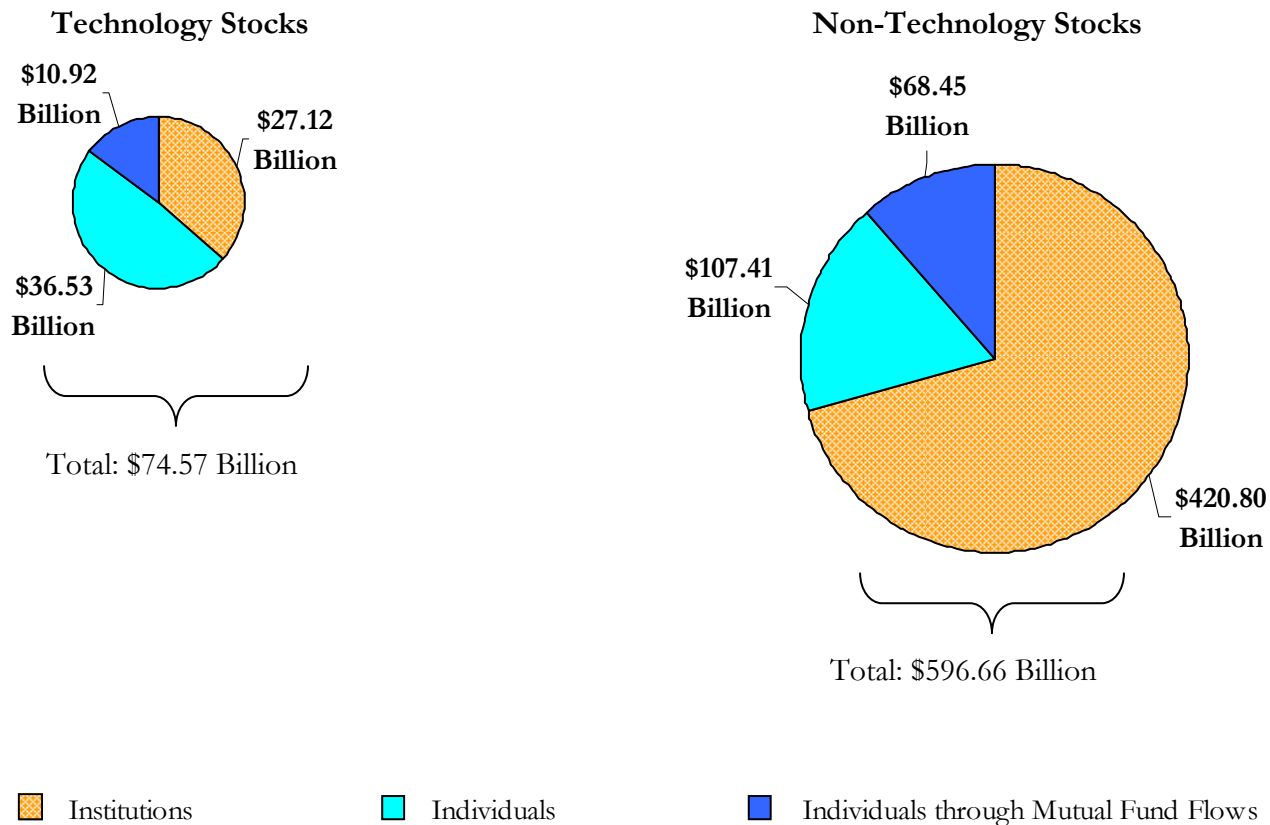
**Figure 3. Cumulative change in supply of technology stocks.** We calculate quarterly changes in supply of NASDAQ technology stocks (three-digit SIC code=737 with ordinary common shares, excluding Microsoft) during the 1997 to 2002 period. In each quarter, we calculate quarterly changes in the dollar supply of the technology sector due to: 1) delistings; 2) IPOs; 3) SEOs; 4) insider selling; 5) technology firms using stock payments to acquire interest in another firm; and 6) other share changes, which are changes in shares outstanding of technology firms due to reasons other than SEOs and stock payments. We include share repurchases in other share changes because the amount of repurchases is very small. We describe the calculation details in Internet Appendix I. We plot the cumulative changes in quarterly supply measured in billion dollars.



**Panel A. Cumulative change in demand from January 1, 1997 to March 31, 2000**

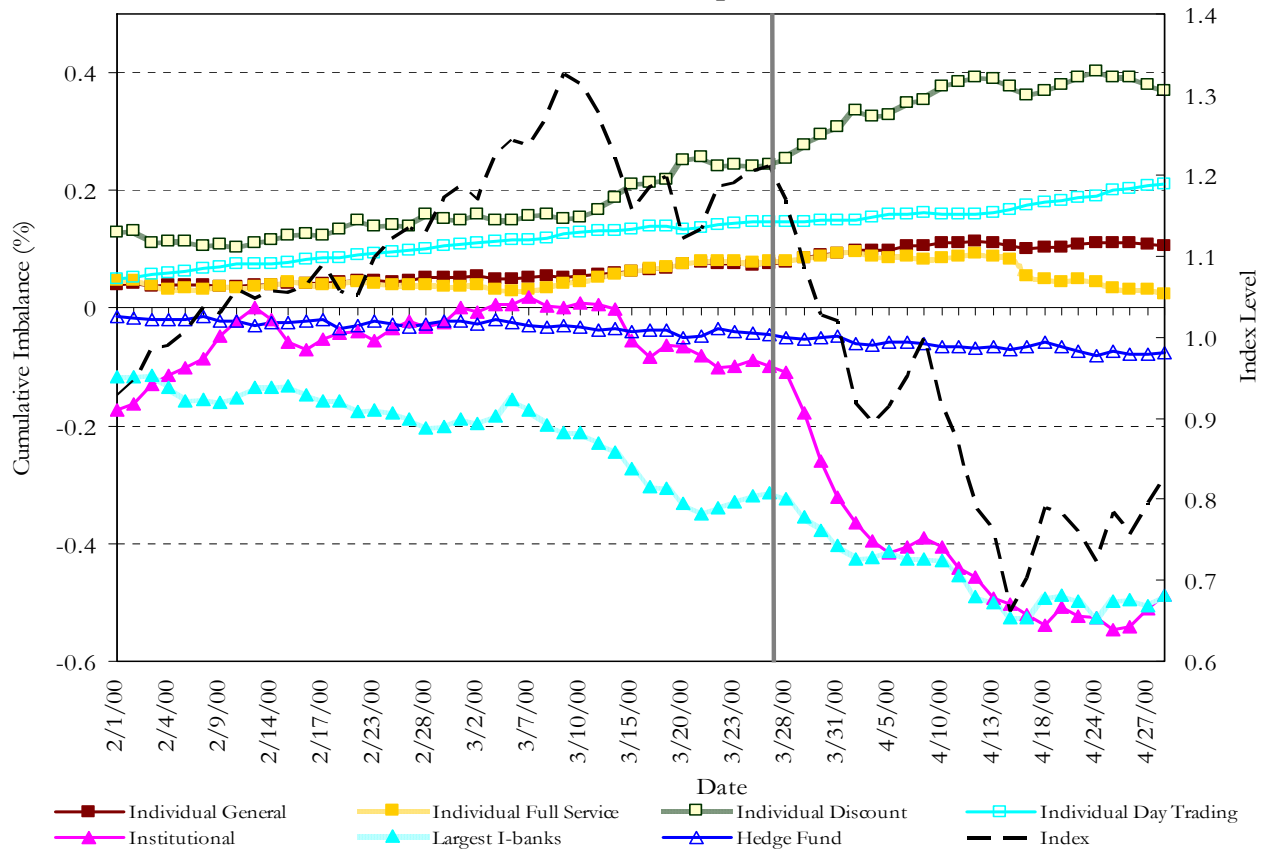


**Panel B. Cumulative change in demand from April 1, 2000 to March 31, 2001**

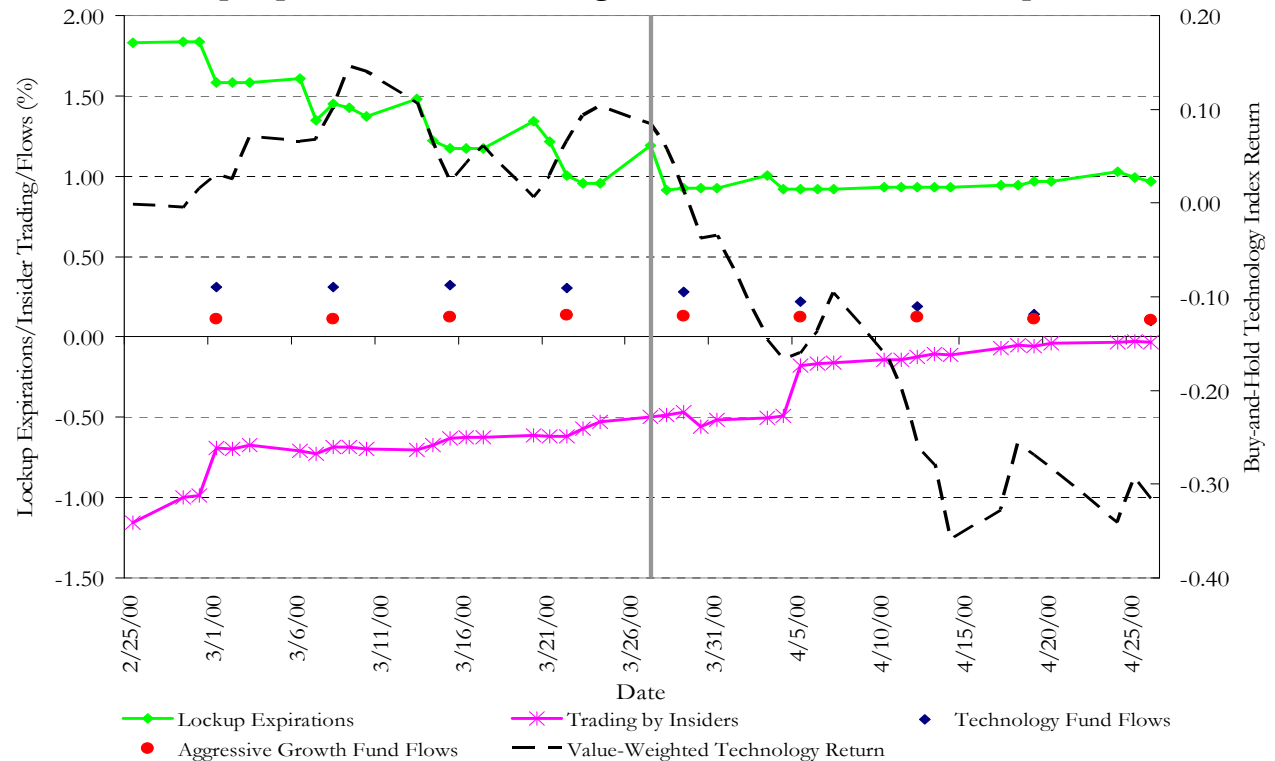


**Figure 4. Cumulative change in demand for technology and non-technology stocks.** In Panel A, we first calculate quarterly changes in demand from January 1997 to March 2000 for technology stocks (three-digit SIC code=737 and exchange code=3, excluding Microsoft) and non-technology stocks (three-digit SIC code≠737 or exchange code≠3) with ordinary common shares. We require a firm to be in the technology (non-technology) sector at both the beginning and the end of the quarter to be included in the technology (non-technology) sample. Quarterly change in demand for technology (non-technology) stocks by an investor group is the difference between end-of-quarter technology (non-technology) holdings and the buy-and-hold value of beginning-of-quarter technology (non-technology) holdings. The individual group is net of insiders. We further isolate the change in demand induced by mutual fund flows from the change in demand by institutions. Change in demand induced by mutual fund flows is calculated by applying mutual fund flows for the merged CRSP-Thomson Financial sample to 13f mutual fund families. We describe the details of our approach in Internet Appendix E. We then sum the quarterly changes in demand from January 1997 to March 2000. Panel B plots the corresponding changes in demand from April 2000 to March 2001.

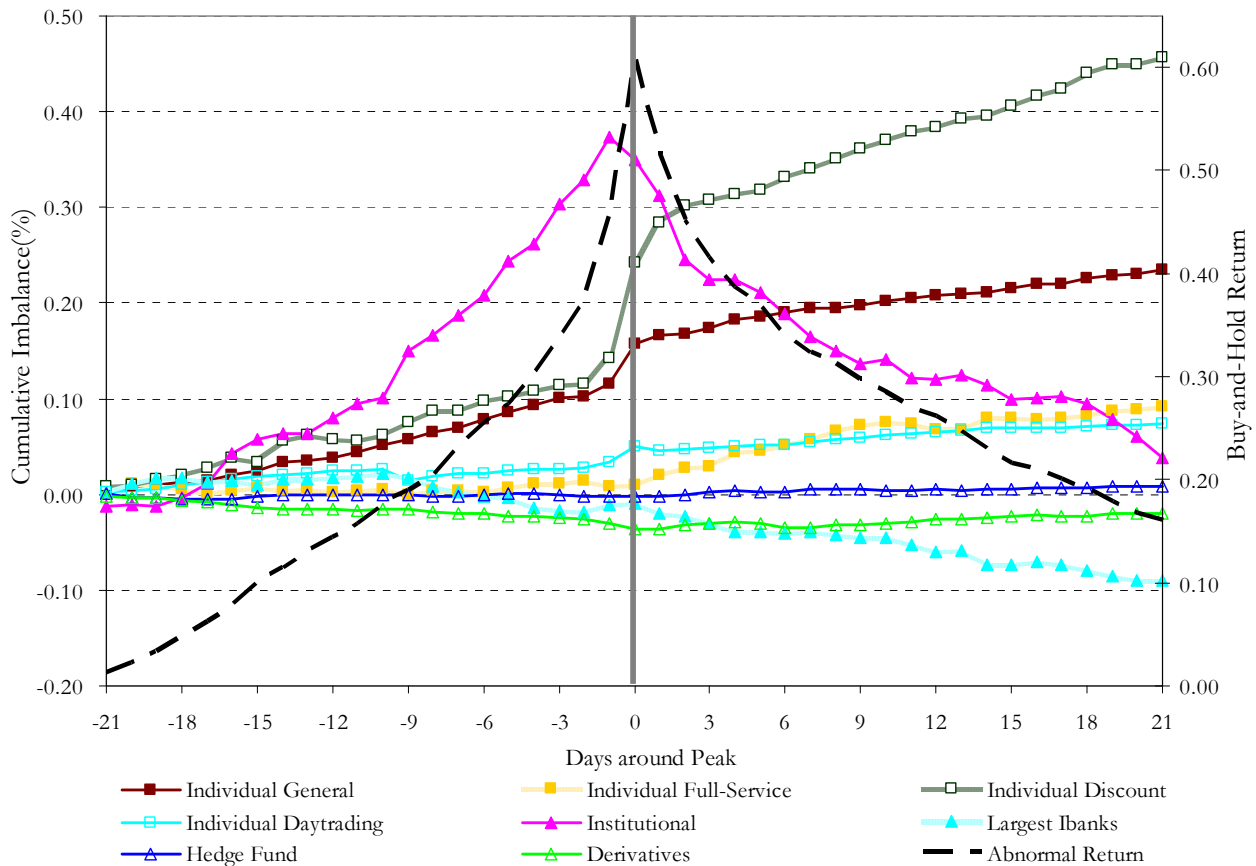
**Panel A. Cumulative imbalances around the market peak**



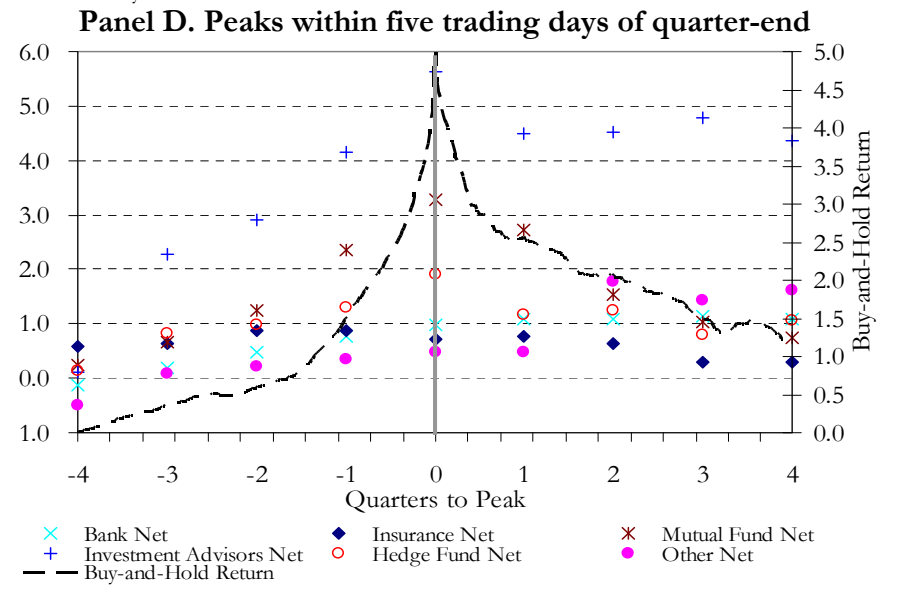
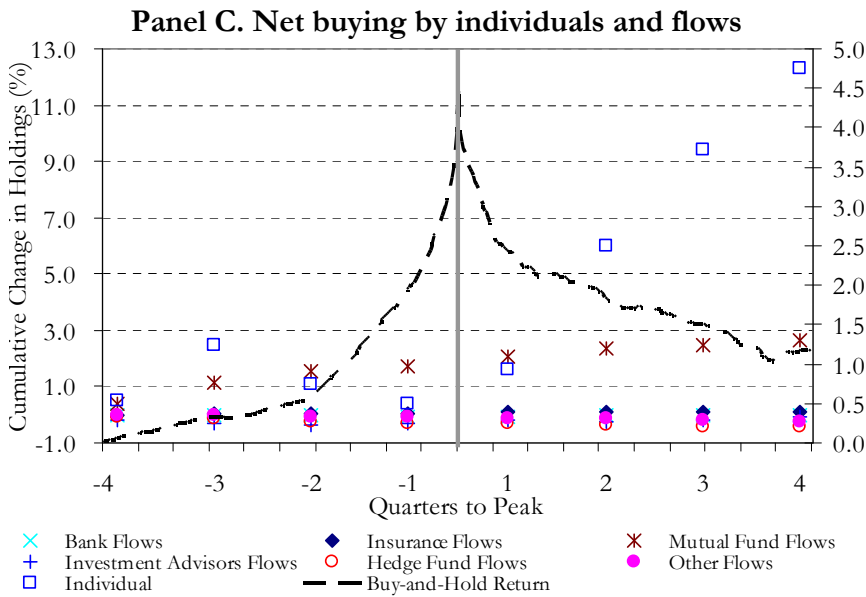
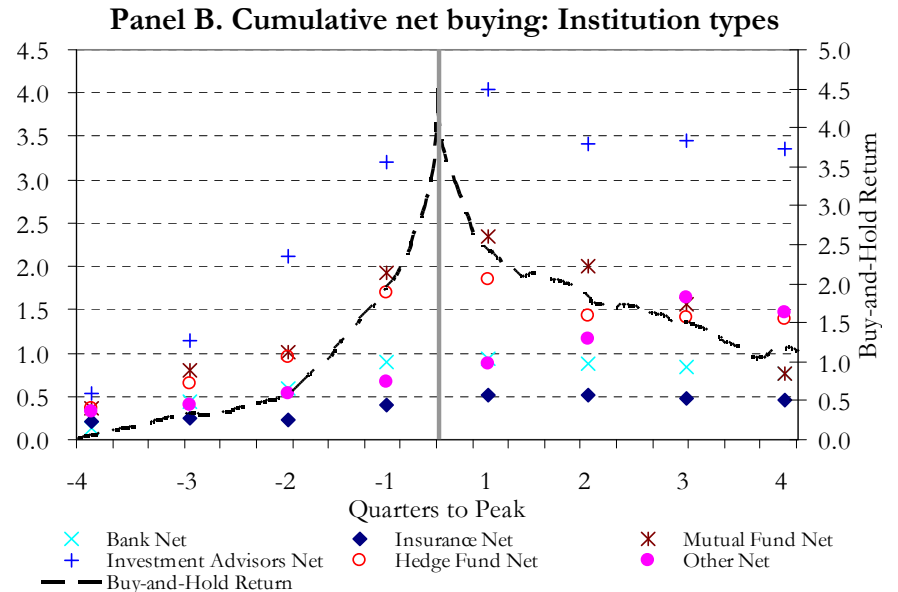
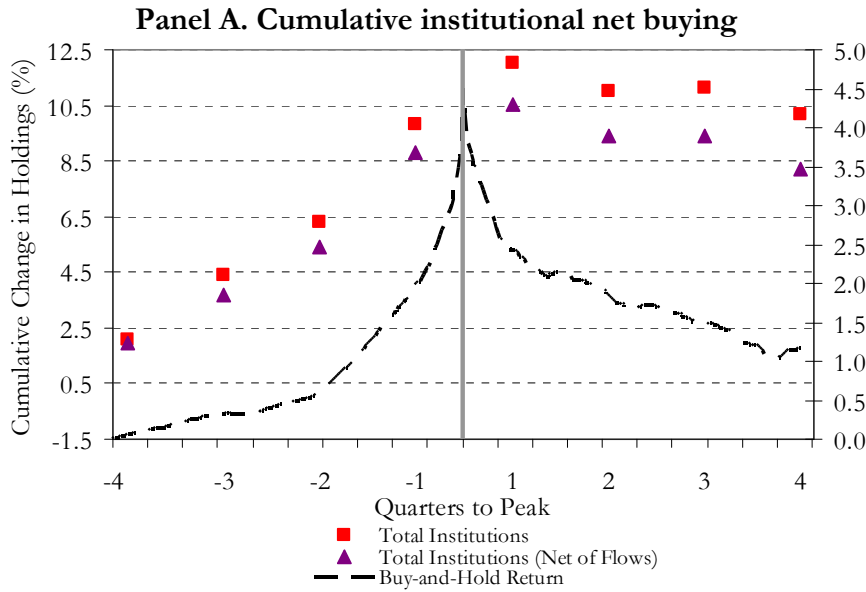
**Panel B. Lockup expirations, insider trading, and flows around the market peak**

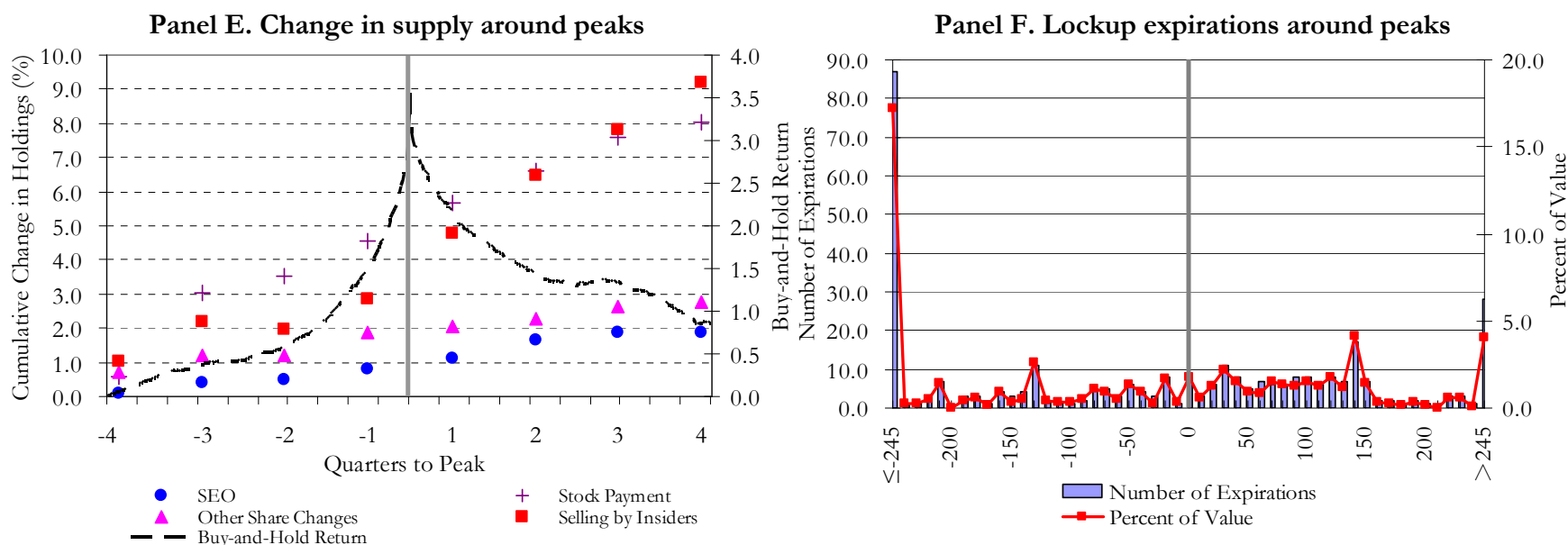


**Figure 5. Cumulative imbalances, lockup expirations, insider trading, and mutual fund flows around the market peak.** Panel A plots the index level and cumulative imbalances for various investor groups for the value-weighted technology sector from February 1, 2000 to April 28, 2000. The daily imbalance is the difference between buy and sell volumes expressed as a percentage of shares outstanding. The technology sector comprises all NASDAQ stocks with ordinary common shares and three-digit SIC code 737, excluding Microsoft. We start cumulating imbalances and index levels on January 3, 2000. Panel B plots lockup expirations, insider trading, technology mutual fund flows, and aggressive growth fund flows around March 27, 2000. Daily lockup expirations are total dollar value of expiring lockup shares on that day divided by total market value of the technology sector. Daily insider trading is total dollar value of insider net buying (buys minus sells) on that day divided by total market value of technology stocks. We convert weekly AMG flows of technology funds and aggressive growth funds into flow-induced buying of technology stocks as percentages of total market value of the technology sector. We describe the details in Internet Appendix G. Lockup expirations, insider trading, and flows are presented as the sum for the past 30-day window.

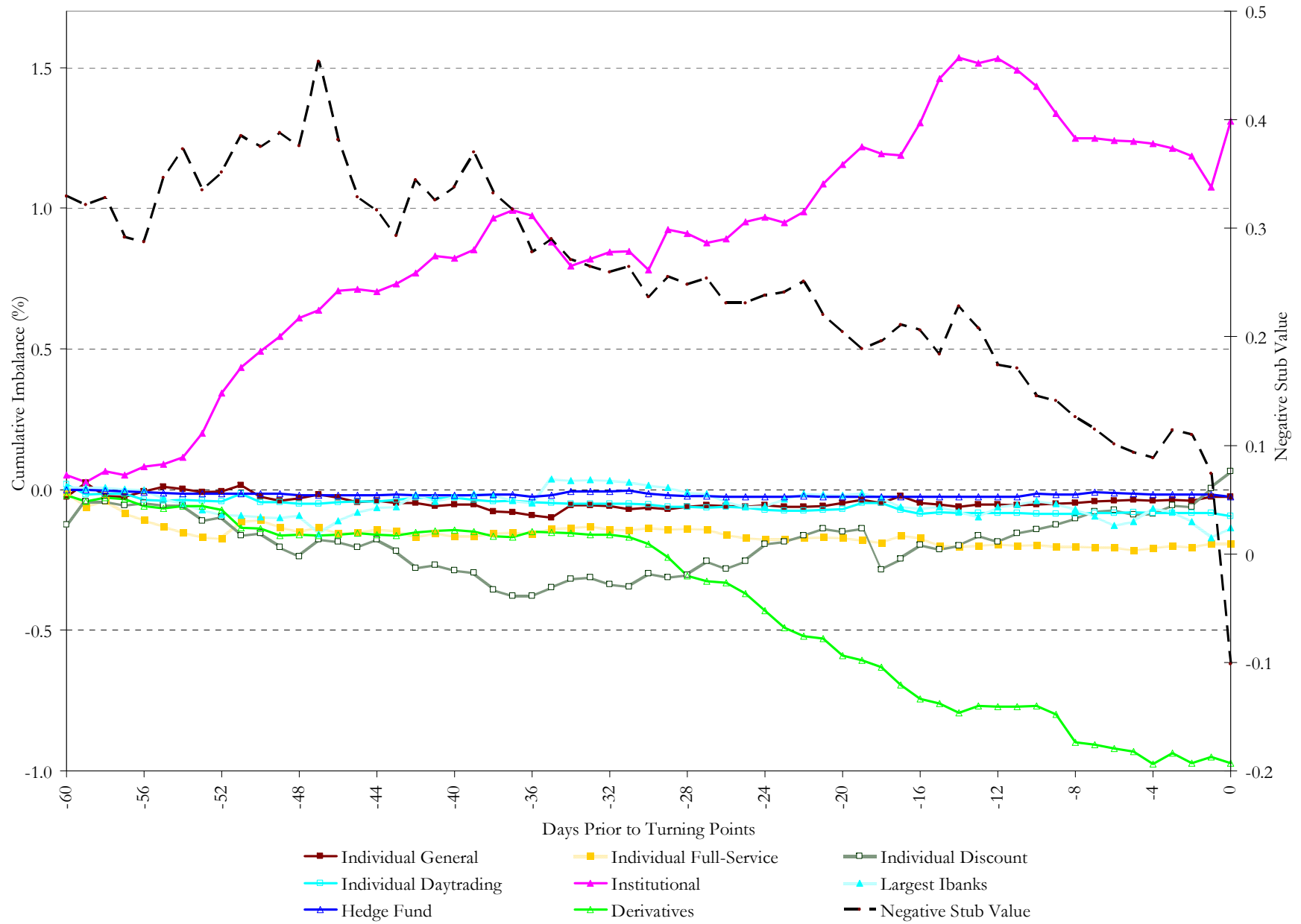


**Figure 6. Cumulative imbalances around individual stock peaks: [-21, 21] window.** For all NASDAQ stocks with ordinary common shares and three-digit SIC code 737 at some point from January 1997 to December 2000, we identify the individual peaks during the same period. In the event of a tie, we choose the first peak. Next, we eliminate stocks for which the peak is within the first or last 21 days of trading or the three-digit SIC code is different from 737 at the time of the peak. This gives us 580 technology stock peaks. When two stocks peak on the same day, we take the equal-weighted average of the two observations to avoid clustering. This gives us 279 different peak days. This figure plots the cross-sectional averages of the buy-and-hold return and cumulative imbalances for various investor groups for 43 trading days surrounding individual peaks. Daily imbalance is the difference between buy and sell volumes expressed as a percentage of shares outstanding.





**Figure 7. Demand and supply around individual stock peaks.** We analyze demand and supply around individual peaks for NASDAQ technology stocks (three-digit SIC code=737 with ordinary common shares, excluding Microsoft) during the period from January 1997 to December 2000. There are 580 technology stock peaks (279 event days) during this period. When stocks peak in the same quarter, we take the equal-weighted average of the observations. Panel A plots cross-sectional averages of the buy-and-hold return and cumulative net buying for aggregate 13f institutions during the eight quarters surrounding individual peaks. Quarterly institutional net buying for a stock is calculated as the difference between end-of-quarter institutional holdings and the buy-and-hold value of beginning-of-quarter holdings, expressed as a percentage of the stock’s market capitalization at the end of the quarter. “Total Institutions” is cumulative net buying and “Total Institutions (Net of Flows)” is cumulative net buying minus net buying induced by flows (net active buying). Calculations of flow-induced net buying for mutual funds and other 13f institution types are described in Internet Appendices B and F. Quarter 1 marks the end of the quarter containing the peak, which is on average 33 trading days after the peak for our sample. Quarter -1 marks the end of the quarter prior to the peak. Panel B plots the cumulative net active buying excluding flows for the six 13f institution types. Panel C plots the cumulative net buying induced by flows and by individuals directly. Individual net buying is calculated similar to institutional net buying by using individual ownership (net of insiders). Panel D plots cumulative institutional net active buying around 95 price peaks that occur within five trading days ( $[-5, 5]$  window) of the end of a quarter, where quarter 0 refers to the end of the quarter that coincides with the individual price peak. Panel E plots the cumulative change in the supply of shares around individual price peaks due to SEOs, insider selling, stock payments for mergers and acquisitions, and other changes in shares outstanding. Panel F plots the lockup expirations relative to price peaks for the 333 technology firms that have both individual peaks and lockup expirations during the 1997 to 2002 period. Number of lockup expirations at  $t$  refers to the total number of IPO and SEO lockup expirations during the 10-day window of  $(t-5, t+5]$ . Day 0 refers to the day of the peak. For the amount of lockup expirations at  $t$ , we first sum for each firm the value of expiring shares during the window  $(t-5, t+5]$  as a percentage of the firm’s market capitalization. We then average the amount across event firms.





**Figure 8. Cumulative imbalances in overpriced carve-outs.** This figure plots simple averages of cumulative imbalances for various investor groups for the six overpriced carve-outs (UBID, Retek, PFSWeb, Xpedior, Palm, and Stratos Lightwave) studied in Lamont and Thaler (2003) during the 60-day window prior to the date on which overpricing is corrected. Negative stub value for a carve-out is calculated as follows:

$$NStub_{it} = \frac{Own_{it} - ME_{it}}{ME_{it}},$$

where  $NStub_{it}$  is negative stub value for carve-out  $i$  on day  $t$ .  $Own_{it}$  is the dollar value of the parent firm's ownership of carve-out  $i$  on day  $t$ , and  $ME_{it}$  is the parent firm's market capitalization on day  $t$ . Our negative stub value is Lamont and Thaler's stub times minus one – we flip the sign of their stub value so that a positive stub value indicates an overpriced carve-out. Day 0 is the date on which stub value becomes negative (when clear overpricing is corrected). Daily imbalance is the difference between buy and sell volumes expressed as a percentage of shares outstanding.

**Table I**  
**Distribution of Trades by Investor Group and Correlations between NASDAQ and 13f Imbalances**

Panel A reports the percentages of share volume, dollar value of trading (\$ volume), and number of trades that can be attributed to each of the nine investor groups, and the average trade size for each group for the technology sector from January 2, 1997 to March 27, 2000. The technology sector comprises all NASDAQ stocks with ordinary common shares (CRSP share codes 10 or 11) and three-digit SIC code 737, which stands for computer programming, data processing, and other computer-related services. Microsoft is excluded. A detailed description of the method used for classifying the investor groups is in Appendix B. All figures are based on client trading only. Panel B reports the correlations among quarterly imbalances for aggregate institutional (sum of institutional, largest investment banks, hedge fund, and derivatives) and mixed investor groups calculated from NASDAQ data and quarterly changes in institutional ownership computed using Thomson Financial 13f data for the technology sample during the 1997 to 2002 period. Quarterly imbalance for the institutional (mixed) investor group is the difference between institutional (mixed) buy and sell volumes for that quarter scaled by total number of shares outstanding at the beginning of the quarter. Quarterly change in institutional ownership from Thomson Financial 13f data is the quarterly change in holdings as a fraction of the total number of shares outstanding at the beginning of the quarter. Any firm-quarter for which there was a stock split in the previous, current, or next quarter is dropped from the sample. Results are provided for the full sample and 13f institutional ownership quartiles. We first compute cross-sectional correlations for each quarter and then average over time. *t*-statistics are reported in parentheses.

Panel A: Volume, Number of Trades, and Trade Size for Investor Groups				
	% Share Volume	% \$ Volume	% # of Trades	Avg. Trade Size
Individual General	3.92	3.66	7.00	479
Individual Full Service	3.45	2.86	4.80	615
Individual Discount	10.52	10.22	19.14	471
Individual Day Trading	5.04	8.03	10.46	413
Institutional	27.16	25.08	14.46	1,610
Largest I-banks	9.62	10.63	3.06	2,692
Hedge Fund	0.64	0.78	0.79	695
Derivatives	1.86	2.50	2.29	693
Mixed	37.80	36.24	37.98	853

Panel B: Correlations between Quarterly Institutional and Mixed Imbalances from NASDAQ and Quarterly Changes in 13f Institutional Holdings						
	Full Sample		13f Institutional Ownership			
	Nasd Inst.	Mixed	Low Nasd Inst.	2 Nasd Inst.	3 Nasd Inst.	High Nasd Inst.
13f Inst.	0.27 (14.92)	-0.02 (-1.03)	0.03 (1.43)	0.21 (6.75)	0.29 (8.46)	0.38 (13.28)
Mixed	-0.45 (-15.49)		-0.40 (-8.87)	-0.49 (-13.93)	-0.45 (-13.05)	-0.47 (-15.52)

**Table II**  
**Firm Characteristics and Investor Trading for Technology and Non-technology Stocks,**  
**March 2000**

We first assign all CRSP stocks with ordinary common shares (CRSP share codes 10 or 11) into technology sector (three-digit SIC code=737, exchange code=3, excluding Microsoft) or non-technology sector (three-digit SIC code $\neq$ 737 or exchange code $\neq$ 3) stocks. We further assign stocks within the technology and non-technology sectors into two portfolios according to market capitalization as of March 31, 2000. Panel A reports value-weighted averages of firm characteristics and institutional and individual (net of insiders) trading for each portfolio. Returns are value-weighted buy-and-hold returns, where weights are given by market capitalization at the beginning of the return measurement period. For net active buying, we first take the difference between end-of-quarter holdings and the buy-and-hold value of beginning-of-quarter holdings. We further subtract net buying induced by mutual fund flows (calculation described in Internet Appendix E) to obtain net active buying. For individuals, we set flow-induced net buying to zero. We sum quarterly net active buying for the four quarters from April 1, 1999 to March 31, 2000 for each firm, and divide by the firm's market capitalization as of March 31, 2000. We then calculate value-weighted net active buying, where the weights are the market capitalization of March 31, 2000. Change in ownership is the difference between ownership at the end of March 2000 and March 1999. Ownership for an investor group is defined as shareholdings divided by total shares outstanding. Individual ownership is net of insiders. Ownership and change in ownership are weighted by market capitalization of March 31, 2000. We also report the percentage of total market capitalization of our sample accounted for by each portfolio. Panel B further reports value-weighted net active buying by different institution types.

Panel A: Value-weighted Returns and Trading								
	Tech		Non-tech		Tech – Non-tech			
	Small	Large	Small	Large	Small	<i>t</i> -stat	Large	<i>t</i> -stat
<i>Market Cap.</i>								
Fraction of CRSP ME Mar.00	0.001	0.067	0.008	0.924				
<i>Net Active Buying</i>								
Institutional Apr.99-Mar.00	0.020	0.067	-0.015	0.015	0.035	(2.16)	0.052	(2.17)
Individual Apr.99-Mar.00	0.097	0.037	0.026	0.025	0.071	(3.19)	0.012	(0.43)
<i>Change in Ownership</i>								
Institutional Apr.99-Mar.00	0.002	0.054	-0.013	0.002	0.016	(1.58)	0.052	(2.92)
Individual Apr.99-Mar.00	0.035	0.008	0.014	0.013	0.020	(1.44)	-0.005	(-0.20)
<i>Ownership</i>								
Institutional Mar.00	0.182	0.488	0.199	0.543	-0.017	(-0.74)	-0.055	(-0.29)
Individual Mar.00	0.456	0.231	0.463	0.374	-0.007	(-0.20)	-0.143	(-0.88)
Panel B: Value-weighted Buying by Institution Type: April 1, 1999 to March 31, 2000								
<i>Net Active Buying</i>								
Banks	0.006	0.009	-0.004	0.001	0.011	(2.20)	0.008	(2.96)
Insurance. Companies	-0.002	0.006	-0.005	0.001	0.003	(0.95)	0.005	(1.44)
Mutual Funds	-0.003	0.013	-0.002	0.005	-0.001	(-0.17)	0.008	(1.72)
Indep. Investment Advisors	0.008	0.019	-0.004	0.001	0.012	(1.66)	0.019	(2.55)
Hedge Funds	0.005	0.013	-0.002	0.005	0.006	(0.92)	0.008	(2.17)

**Table III****Firm Characteristics Sorted on the Difference between Institutional and Individual Trading up to March 2000: Top 25% CRSP Firms according to Market Capitalization**

The sample contains CRSP stocks with ordinary common shares (CRSP share codes 10 or 11) that are in the top quartile of CRSP according to market capitalization on March 31, 2000. We first assign sample firms into terciles according to the difference between institutional net active buying and individual net active buying. For net active buying, we first take the difference between end-of-quarter holdings and the buy-and-hold value of beginning-of-quarter holdings, divided by end-of-quarter market capitalization. We further subtract net buying induced by mutual fund flows (calculation described in Internet Appendix E) to obtain net active buying. We set flow-induced net buying to zero for individual investors. We then sum quarterly net active buying for the four quarters from April 1, 1999 to March 31, 2000. We report simple averages of price-to-sales ratios as of March 31, 2000, buy-and-hold returns, and P/S-adjusted returns for each portfolio. Price-to-sales ratio as of March 31, 2000 is price per share for March 31, 2000 divided by sales per share for most current fiscal year-end that is at least six months before March 31, 2000. P/S-adjusted return is the individual firm return minus the average return for the firm's P/S quartile on March 31, 2000. We also report the percentage of total market capitalization of the CRSP sample accounted for by each portfolio.

	Characteristics Mar.00		Buy-and-hold Returns			P/S-adj. Returns	
	Fraction CRSP ME	P/S Ratios	Apr.99-Mar.00	Apr.00-Mar.01	Apr.00-Dec.02	Apr.00-Mar.01	Apr.00-Dec.02
Institutional Buying	0.126	2.064	2.359	-0.171	-0.254	0.048	-0.055
Medium	0.381	1.353	0.540	0.043	0.019	0.149	0.041
Individual Buying	0.451	1.517	0.675	-0.017	-0.026	0.119	0.036
Inst. Buying – Indiv. Buying		0.548	1.685	-0.154	-0.228	-0.072	-0.091
<i>t</i> -statistics		(5.21)	(7.46)	(-4.00)	(-4.54)	(-2.14)	(-2.12)

**Table IV****Cross-sectional Regressions of Post-peak Returns on Pre-peak Investor Trading**

This table presents cross-sectional univariate regressions of post-peak returns on pre-peak investor trading for CRSP stocks with ordinary common shares (CRSP share codes 10 or 11). The samples include firms in the top 50% and 25% of the CRSP sample according to market capitalization on March 31, 2000. The dependent variables are buy-and-hold returns from April 1, 2000 to March 31, 2001, March 31, 2002, and December 31, 2002. In Panel A, the independent variables are institutional trading or individual trading from April 1, 1999 to March 31, 2000. We first calculate net buying for institutions and individuals by taking the difference between end-of-quarter holdings and the buy-and-hold value of beginning-of-quarter holdings, divided by end-of-quarter market capitalization. We then subtract (add) net buying induced by mutual fund flows (calculation described in Internet Appendix E) to construct quarterly institutional (individual) trading and sum over the four quarters from April 1, 1999 to March 31, 2000. In Panel B, the independent variables are institutional trading (excluding flows) in excess of individual trading (including flows) from April 1, 1999 to March 31, 2000. We standardize all variables in the cross-section and estimate with intercepts that are not displayed for brevity. *t*-statistics computed with White robust errors are in parentheses.

Panel A: Regressions of Post-peak Returns on One-year Pre-peak Trading by Institutions or Individuals						
	Top 50% Market Cap.			Top 25% Market Cap.		
	Return (Apr.00-Mar.01)	Return (Apr.00-Mar.02)	Return (Apr.00-Dec.02)	Return (Apr.00-Mar.01)	Return (Apr.00-Mar.02)	Return (Apr.00-Dec.02)
Institutional (Excl. Flows)	-0.13 (-3.47)	-0.12 (-3.55)	-0.12 (-3.65)	-0.20 (-8.16)	-0.16 (-8.23)	-0.15 (-7.65)
Adj.-R <sup>2</sup>	0.026	0.030	0.031	0.074	0.073	0.068
Individual (Incl. Flows)	-0.13 (-2.32)	-0.11 (-2.40)	-0.10 (-2.49)	-0.18 (-4.53)	-0.16 (-5.19)	-0.15 (-5.03)
Adj.-R <sup>2</sup>	0.015	0.014	0.013	0.021	0.025	0.022
Panel B: Regressions of Post-peak Returns on One-year Pre-peak “Institutional Trading – Individual Trading”						
Institutional - Individual	-0.02 (-0.88)	-0.03 (-1.59)	-0.03 (-1.89)	-0.10 (-3.23)	-0.07 (-3.06)	-0.08 (-3.27)
Adj.-R <sup>2</sup>	0.000	0.001	0.001	0.010	0.009	0.010

**Table V****News Articles and Investor Imbalances: Large Technology Firms**

The sample contains firms in the top 50% of the NASDAQ technology sector (three-digit SIC code=737 with ordinary common shares) according to market capitalization from January 2, 1997 to March 27, 2000. In Panel A, on each day  $t$  we assign stocks to portfolios according to whether their contemporaneous returns in excess of the technology index return are negative or positive and whether there are any news articles about the firm during the  $[t-3, t]$  window. We use news articles from the top 10 newswires. We calculate the equal-weighted average daily imbalance for each portfolio and investor group and then report the time-series means. Daily imbalance is the difference between buy and sell volumes expressed as 1/100 of a percentage of shares outstanding. We adjust daily imbalances for firm size by subtracting the average imbalance for the firm's size quartile in the technology sector. "Total Individual" is the sum of individual general, individual full-service, individual discount, and individual day trading groups. "Total Institution" is the sum of institutional, largest investment banks, hedge fund, and derivatives groups. Panel B is similar to Panel A, but assigns stocks to portfolios according to excess returns for the previous day.  $t$ -statistics are calculated for the differences between positive-return and negative-return portfolios. Significance at the 1% and 5% levels is denoted by \*\* and \*, respectively. Panel C presents time-series averages of coefficients, number of observations, and adjusted-R<sup>2</sup>s for cross-sectional regressions estimated each day (week, month) from January 2, 1997 to March 27, 2000. The dependent variables are daily (weekly, monthly) returns and the independent variables are contemporaneous daily (weekly, monthly) imbalances and their interactions with news dummies. Weekly or monthly imbalance is the sum of daily imbalances over the week (Thursday open to Wednesday close) or month. Weekly (monthly) returns are buy-and-hold returns over the week (month). For the daily cross-sectional regression on day  $t$ , news dummy equals one for a firm if there are any news articles about the firm in the top 10 newswires during the  $[t-3, t]$  window. For the weekly (monthly) cross-sectional regressions, news dummy equals one for a firm if there are any news articles about the firm in the top 10 newswires during the week (month). We standardize dependent and independent variables in each cross-section except for news dummies and estimate with intercepts that are not displayed for brevity.  $t$ -statistics computed using Newey-West standard errors with five lags are reported in parentheses.

Panel A: Imbalances Sorted on Contemporaneous Firm Returns							
	No News			News			News – No News
	Neg. Ret.	Pos. Ret.	Diff.	Neg. Ret.	Pos. Ret.	Diff.	Diff.
Indiv. General	-0.21	0.21	0.42**	-0.11	0.39	0.50**	0.08*
Indiv. Full Service	0.06	-0.13	-0.19**	0.19	-0.13	-0.33**	-0.14*
Indiv. Discount	0.55	-0.95	-1.50**	0.99	-0.62	-1.62**	-0.12
Indiv. Day Trading	-0.23	0.29	0.52**	-0.25	0.42	0.67**	0.15**
Institutional	-1.66	2.13	3.79**	-2.15	2.24	4.39**	0.60*
Largest I-banks	-0.49	0.48	0.97**	-0.76	0.88	1.63**	0.67**
Hedge Fund	0.06	-0.10	-0.16**	0.11	-0.04	-0.15**	0.01
Derivatives	0.17	-0.16	-0.32**	0.14	-0.30	-0.45**	-0.12**
Total Individual	0.17	-0.58	-0.75**	0.83	0.05	-0.78**	-0.03
Total Institution	-1.92	2.36	4.27**	-2.66	2.77	5.43**	1.15**

Panel B: Imbalances Sorted on Lagged Firm Returns							
Total Individual	0.11	-0.52	-0.63**	0.73	0.13	-0.61**	-0.02
Total Institution	-0.61	0.95	1.56**	-0.75	0.51	1.26**	0.30

Panel C: Fama-MacBeth Regressions of Returns on Contemporaneous Imbalances					
	Daily	Weekly	Monthly	Daily	Weekly
Indiv. General	0.15 (12.24)	0.09 (3.23)	0.01 (0.37)	0.14 (11.30)	0.08 (2.44)
Indiv. Full Service	0.01 (2.00)	0.01 (1.31)	0.01 (1.03)	0.02 (3.83)	0.02 (1.58)
Indiv. Discount	-0.13 (-15.65)	-0.12 (-5.66)	-0.18 (-6.18)	-0.14 (-16.04)	-0.14 (-6.54)
Indiv. Day Trading		0.18 (6.92)	0.12 (3.94)		0.19 (6.79)
Institutional	0.18 (29.10)	0.19 (11.80)	0.18 (7.38)	0.18 (28.94)	0.20 (11.48)
Largest I-banks	0.08 (21.81)	0.08 (8.31)	0.07 (5.19)	0.07 (20.64)	0.09 (8.49)
Hedge Fund		-0.07 (-7.66)	-0.01 (-0.64)		-0.09 (-6.87)
Mixed	0.13 (25.50)	0.11 (10.21)	0.11 (4.77)	0.14 (29.23)	0.13 (10.39)
$D_{News}$ x Indiv. General				0.12 (3.57)	0.01 (0.45)
$D_{News}$ x Indiv. Full Service				0.39 (0.83)	-0.03 (-1.25)
$D_{News}$ x Indiv. Discount				-0.11 (-1.11)	0.02 (0.80)
$D_{News}$ x Day Trading					0.00 (0.22)
$D_{News}$ x Institutional				0.01 (0.17)	0.01 (0.57)
$D_{News}$ x Largest I-banks				-0.07 (-0.91)	-0.01 (-0.57)
$D_{News}$ x Hedge Fund					0.00 (0.16)
$D_{News}$ x Mixed				0.05 (3.24)	-0.01 (-0.78)
Avg. N	244.8	244.4	257.7	244.8	244.4
Adj.-R <sup>2</sup>	0.185	0.231	0.194	0.233	0.265