THE ROLE OF THE MEDIA IN THE INTERNET IPO BUBBLE[1]

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Abstract

The first part of this paper explores whether media coverage was different for internet IPOs as opposed to a matching sample of non-internet IPOs in the late 1990s. So we read all news items that came out between 1996 through 2000 on 458 internet IPOs and a matching sample of 458 non-internet IPOs – a total of 171,488 news items -- and classify each news item as good news, neutral news or bad news. We find, not surprisingly, that the media coverage was more intense for internet IPOs. Further, we document that the media hyped the good news for internet IPOs in the bubble period and hyped the bad news for internet IPOs in the post-bubble period. The second part of the paper explores whether this differential media coverage affected risk-adjusted returns. We find, surprisingly, that the market somewhat discounted the media hype: though net news (number of good news minus number of bad news) Granger caused risk-adjusted returns for both types of IPOs, the effect was lower for internet IPOs, especially in the bubble period.

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The offer price of StarMedia Network's initial public offering (IPO) on May 26, 1999 was $15. It shot up to $26.0625 at the end of the first trading day. Financial writer Sandra Block reported about this IPO in USA Today the next day: "Discriminating investors embraced StarMedia Network's initial public offering Wednesday, while spurning two other internet stocks. America Online, Yahoo and Prodigy offer bilingual products, but StarMedia boasts strong brand identity in Latin America, says Tom Taulli, an internet consultant. 'Everyone talks about the internationalization of the World Wide Web, but no one ever does anything about it,' Taulli says. 'That's where StarMedia really shines.'" By the end of 2000, the firm traded at $1.89 per share, which was 7.26% of its first day closing price, and 12.6% of its offer price. Today, StarMedia Network does not trade. Its stock was de-listed from Nasdaq on February 1, 2002, because of its inability to file quarterly financial reports.

The purpose of our paper is to examine the role of the media in the internet IPO bubble. We ask and answer the following two questions: was the media coverage for internet IPOs in the years 1996 through 2000 different from a matching sample of non-internet IPOs and, if yes, did this differential media coverage affect risk-adjusted returns. [2]

The first question belongs to a growing literature on bias in the financial media. How do the financial media choose which stories to cover? Of the stories they choose to cover, what is the slant given? And why is there a slant? Shiller (2000) writes: "The role of the news media in the stock market is not, as commonly believed, simply as a convenient tool for investors who are reacting directly to the economically significant news itself. The media actively shape public

[2] In this paper we look at stock returns after the first day of trading. In a companion paper, we look at stock returns at the first day of trading. The reason we separated our analysis is because the information dissemination during the pre-IPO book-building stage is very different from the information dissemination during the post-IPO stage. In the pre-IPO stage, institutions disseminate information and, therefore, the natures of these institutions are the significant control variables. A rich literature exists on what matters for the first day's return. In the post-IPO stage, on the other hand, the main source of information is the traded price itself. This, therefore, becomes the paramount control variable in this paper.

attention and categories of thought, and they create the environment within which the stock market events we see are played out." He believes that the financial media strives to enhance interest by attaching news stories to stock price movements that the public has already observed, thereby creating a positive feedback effect. Dyck and Zingales (2003a) note that there is a pro-company bias in the financial media, which is stronger during a boom, and is weaker and is sometimes reversed during a bust. They argue that this is because of incentives. Reporting good news during booms allows media access to the company, but this access is not important during busts because the company does not want to share news. Dyck and Zingales (2003b) find empirical support in that media spin affects the stock market response to earnings announcements. Mullainathan and Shleifer (2003) demonstrate that the media can slant the presentation of the news to cater to the preferences of their audience. Baron (2004) explains why persistent media bias can exist in a competitive equilibrium; his is a supply-side theory in which bias originates with journalists who have a preference for influence and are willing to sacrifice wages to exercise it.

The second question belongs to a large literature on how media news affects returns. According to classical asset pricing models, news will affect returns if it affects expectations of future cash flows and/or expectations of the discount rate. By filtering, aggregating and repackaging information into news items, the media reduce the cost of collecting and certifying relevant information, and therefore can have significant impact on financial markets. In an early paper, Niederhoffer (1971) observes large price movements following world event headlines; the market appears to overreact to bad news. Mitchell and Mulherin (1994) document a weak relationship between the amount of publicly reported information, approximated by the number of daily Dow Jones news stories, and the aggregate trading activity and the price movements in securities markets. Chan (2003) shows stocks with large price movements, but no identifiable news, show reversal in the next month, and prices are slow to reflect bad public news.

Another reason why media news may affect returns was given by Merton (1987). He argued that investors will buy and hold only those securities which they are aware of. The most common way to facilitate investors' awareness is to promote the visibility of the firm through media. Falkenstein (1996) documents that mutual funds avoid stocks with low media exposure. Barber and Odean (2003) provide direct evidence that individual investors tend to buy stocks that are in the news. Antweiler and Frank (2004) and Wysocki (1999) find that the volume of stock messages posted on internet stock message boards predicts subsequent stock returns and market volatility. Tetlock (2003) provides evidence that media coverage affects market index returns and aggregate trading volume. Antunovich and Sarkar (2003) find that stocks with higher media exposure have bigger liquidity gains and lower excess returns on the pick day. Chen, Noronha, and Singal (2002) show that media exposure increases following additions to the S&P 500 index, and price changes around S&P 500 index additions are consistent with greater investor awareness of the added stocks.

It is likely that the media bias and/or its effect were more pronounced for internet IPOs in the late 1990s. There are many reasons for believing this.

First, the media was more likely to be interested in internet IPOs, because in this period there were so many of them, and many of them had dramatic first-day returns.[3]

Second, as the internet industry was new, there was no history of cash flows of comparable firms that had gone public. This made valuations difficult, and so expectations of future cash flows for internet IPOs were more likely to be sensitive to media news.[4]

[3] Ritter and Welch (2003) show that in the late 1990s, volume and initial return fluctuations were mostly driven by the large number of internet IPOs during 1999 and 2000, and their almost complete disappearance in 2001. On the other hand, the number of old-economy IPOs remained at about 100 firms per year, before, during, and after the bubble. At the peak of the internet IPO wave (the second half of 1999), 282 firms went public, compared to 46 IPOs offered during the first half of 2001 (Benveniste, Ljungqvist, Wilhelm and Yu 2003). The average initial returns for internet IPOs during 1999 and 2000 was 89%, comparing to 17% of all IPOs in 1996 (Ljungqvist and Wilhelm 2003).

Third, the limits to arbitrage were more binding for internet IPOs during the period of 1996-2000,[5] so the divergence of stock prices from their fundamental value was likely to be greater for internet IPOs. Further, institutional investors did not attempt to trade against market movements, but actively rode with both the run-up and run-down of the stock.[6] Rational traders were not able to dampen this effect of noise traders because the latter added systematic noise risk.[7]

Fourth, and finally, as there is now growing agreement that the spectacular rise and spectacular fall of internet IPOs in the late 1990s can not be explained by fundamentals, it is natural to seek other possible explanations.[8] A good place to begin looking for other explanations is to formally explore the role of the media in the internet IPO bubble.[9]

A literature focusing on the relation between media and IPO firms has already started to emerge. Examining the post-offer performance of a sample of IPOs, Loughran and Marietta-Westberg (2002) find that investors over-react to positive-return news events and under-react to negative news events. Johnson and Marietta-Westberg (2004) show that the increase in idiosyncratic volatility for IPO firms over time is Granger-caused by the increase in news in

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[4] Blanchard and Watson (1982) made the argument that bubbles are more likely to occur in markets where there is greater uncertainty about the fundamentals. Hirota and Sunder (2002) provide experimental evidence.

[5] Ofek and Richardson (2003) and Lamont and Thaler (2003) pointed out that arbitrage was restricted due to short sale constraints and lack of shares to short.

[6] See Brunnermeier and Nagel (2004) and Griffin, Harris and Topaloglu (2003).

[7] DeLong, Shleifer, Summers and Waldman (1990) is a useful place to start exploring this idea.

[8] Ofek and Richardson (2002) conclude that internet stock price levels were too high to be justified by even exceptional levels of expected earnings growth. Loughran and Ritter (2004) find evidence consistent with the argument that positive investor sentiment temporarily inflated the market prices on the internet IPOs during the bubble period. Cooper, Dimitrov and Rau (2001) document dramatic price increases following corporate name changes to internet-related dotcom names, regardless of the firm's level of involvement with the internet.

[9] Shiller (2000) believes that the stock price increases in the late 1990s was driven by irrational euphoria among individual investors, fed by an emphatic media, which maximized TV ratings and catered to investor demand for pseudo-news. Professional investors "are not immune from the effects of the popular investing culture that we observe in individual investors" (p.18).

recent decades. The extent of pre-IPO media exposure is found to be positively related to IPO underpricing both in US (Reese 1998 and Ducharme, Rajgopal and Sefcik 2001a) and in other countries (Ho, Taher, Lee and Fargher 2001). The pre-IPO media hype is related to the IPO's short-term and long-term volume (Reese 1998). It has also been shown that hot internet IPOs receiving more pre-issue media attention experience worse post-offer return performance (Ducharme, Rajgopal and Sefcik 2001b). On the other hand, an IPO's initial return has a positive influence on the number of subsequent newspaper citations. Demers and Lewellen (2003) show that media coverage increases with greater IPO underpricing, suggesting IPO underpricing publicize stocks to investors who buy the stock in the after-market. Our paper differs from this literature in that we do not focus on the pre-IPO stage or on the first day's return, but follow IPOs over their rise and fall in the period 1996 through 2000. Second, unlike most of the above papers, we not only look at numbers of news items, but also their type (good, bad or neutral).

Was the media coverage different for internet IPOs? We read all news items that came out between 1996 through 2000 on 458 internet IPOs and a matching sample of 458 non-internet IPOs – a total of 171,488 news items – and classify each news item as good news, neutral news or bad news. We find, not surprisingly, that the media coverage was more intense for internet IPOs. All types of news – good, bad, or neutral – were more for internet IPOs than for non-internet IPOs in both the bubble period and in the post-bubble period. Second, we document that the net news (good news minus bad news) was more positive for internet IPOs in the bubble period, and more negative for internet IPOs in the post-bubble period. Third, we document that net news increased after a positive stock return, and decreased after a negative stock return for internet firms. This provides some evidence in favor of Shiller's (2000) positive feedback hypothesis. Interestingly, the positive feedback was asymmetric. During the bubble period, net news *increases* regardless of whether the previous stock return is positive or negative. However, during this bubble period, the increase after a positive stock return was *larger* for internet IPOs than for non-internet IPOs. These findings reverse in the post-bubble period. In the post-bubble period, net news *decreases* regardless of whether the previous stock return is positive or negative. However, during this post-bubble period, the decrease in net news after a negative stock return was *larger* for internet IPOs than for non-internet IPOs. Our results are robust to whether we define the bubble in calendar time (the period that ended March 24, 2000) or define it in event time (the firm-specific period that ended on the day the firm's stock price peaked). We, therefore, make the following conclusion about media coverage of IPOs in the late 1990s: it seems that the media was hyping the good news about internet IPOs in the bubble period, and hyping the bad news about internet IPOs in the post-bubble period.

Did this differential coverage affect risk-adjusted stock returns? We check whether news in the media, measured by numbers and type, Granger caused abnormal returns, where abnormal returns is the error term of a Fama-French (1993) three factor model. We find, not surprisingly, that good news increases risk-adjusted returns the next period, and bad news decreases risk-adjusted returns the next period, and so net news (good news minus bad news) increases risk-adjusted returns the next period. We find, surprisingly, that the effect of net news on next period's risk-adjusted return was lower for internet IPOs, especially during the bubble period. In addition, during the post-bubble period, the effect of good news matters more on next period's risk-adjusted return for internet IPOs than for non-internet IPOs. Our results are robust to whether we risk-adjust individual stocks, or whether we risk-adjust a portfolio consisting of either internet or non-internet stocks. We, therefore, make the following conclusion: though the media hyped up the good news about internet IPOs in the bubble period and hyped up the bad news about internet IPOs in the post-bubble period, the market somewhat discounted the media hype, especially during the bubble period.

Our paper is organized as follows. Section II discusses how we obtained our data. Section III gives our results on differential media coverage of internet IPOs as opposed to a matching sample of non-internet IPOs. Section IV answers whether the differential media coverage affected risk-adjusted returns. Section V covers various tests for robustness that we conducted, including an experiment to check the validity of our technique of classifying news. We conclude in Section VI.

II. DATA

A. The IPO sample

We start with a large sample of firms that went public between January 1996 and December 2000. After excluding unit offers, rights offers, closed-end mutual funds, REITs, and ADRs, our search of the Thomson Financial's SDC database yielded 2,603 completed issues.

We identify and extract 461 internet companies from this sample using the reference list from Loughran and Ritter (2004). We cross-check our internet IPO issues with Loughran and Ritter (2002) and Ljungqvist and Wilhelm (2003) to correct errors in the SDC data. We remove one issue that went public twice and was, therefore, counted twice during our sample period. That leaves us with 459 internet IPOs.

For the remaining 2,142 issues in this SDC sample, we first manually check for misclassification, and exclude 9 issues which are in fact ADRs, 1 belonging to unit trusts, 2 misclassified as IPOs, 2 without filing, offer or trading price information in SEC, news sources and CRSP, and 1 foreign offer with a minor tranche in the US. Then, we extract a matching set of non-internet IPOs from the rest of 2,127 issues based on offer size and offer date as follows: for each of the internet IPO, we impose a 20% band on its offer size, and choose the matching firm with the closest offer date among candidates. Matches are formed without replacement. So we have a matching sample of 459 non-internet IPOs.

Since we study the effect of media on returns of IPO firms during the boom and bust of the internet bubble period, we expect each of our sample firms to have some degree of news coverage. There is one firm in our non-internet sample where we cannot identify any news report from Factiva using various combination of search. We therefore removed this firm from our analysis. Excluding or including this firm in our sample does not change our results. Our final sample contains 458 internet IPOs and a matching 458 non-internet IPOs.

Offer characteristics such as offer size, venture-capital backing, and the stock exchange in which the IPO first traded, are from SDC. Stock prices and daily returns are from CRSP. Fama-French factors are obtained from French's website.[10] We manually collect missing founding date for 193 issues within the non-internet sample and 222 issues within the internet sample from SEC filing prospectuses, subsequent 10-Ks, or news sources.

B. The news sample

We define the media to be the Dow Jones Interactive Publications Library (DJI) of past newspapers, periodicals, and newswires. After DJI's conversion to Factiva in June, 2003, we create a customized list that includes major news and business publication sources worldwide.[11] This list is consistent with the news sources in DJI prior to its conversion. We choose Dow Jones Interactive and Factiva because they provide by far the most complete sources of media coverage across time and stocks. As pointed out by Chan (2003), this source does not suffer from gaps in coverage, and is the best approximation of public news for general investors. We do not include magazines, since it is difficult for us to pin down precisely when the information is publicly available. We also exclude investment newsletters, analyst reports and other sources that are not available to the general audience.[12] There are more sources in Factiva towards the end of our

[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[11] The resulting list of data sources includes Dow Jones Asia, Europe, Africa, North America, South America, Australia and New Zealand and contains all the English language sources of daily news.

[12] So we also could not include the following: Factiva Aviation Insurance Digest, Factiva Marine Insurance Digest, Dow Jones Emerging Market Reports, Dow Jones Commodities Service, Dow Jones Money Management Alert, and Dow Jones Professional Investor Report.

sample period. However, the difference will not be crucial to our results, as our sample period is relatively short, and all the econometric analyses are benchmarked with the non-internet sample during the same period.

For each IPO in our sample, we "search by name" in Factiva for the period between 90 days prior to the public offer and the end of December, 2000. Since the book building period of most IPOs in our sample lasts 13 weeks, this includes the majority of media coverage during the pre-IPO stage for each firm. Occasionally, we collect news reports from Factiva using "search by keyword" instead of "search by name." [13] This occurs mainly for firms involved in mergers during or after our sample period (Factiva drops all indexing after a merger, even if it just happened this year).[14] We hand-collect all the news articles in which the IPO firm was mentioned. In particular, we do not limit our news articles only to those news items where the firm is only mentioned in the headline or in the lead paragraph, because this could potentially exclude a large volume of news reports that actually cover the firm.

There are a total of 171,488 news items. We classify each news item into one of three categories: "good", "bad" or "neutral". Good news items (bad news items) are defined as news items which carry positive (negative) statements or implications about the firm. Neutral news items are news items that cannot be classified as good or bad.[15] There are two ways of classifying news items: mechanically using a content analysis software or using human judgment. The advantage of the former method over the latter method is that it is less expensive, it is faster, and

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[13] There is a subtle distinction between "search by keyword" and "search by name" of an IPO firm in Factiva. When "search by keyword" is used, Factiva returns virtually all news articles that at least mentioned the name of the firm once, which could be noisy. On the other hand, news articles generated by "search by name" are more related to the firm, and therefore more focused.

[14] Prior to late March of 2004, Factiva re-indexed all the previous news reports about a target firm involved in a merger to the acquirer. A search by a firm's name in this case only returns news items where both the target and the acquirer are reported. After late March 2004, this particular situation was solved as Factiva introduced an updated version of its database.

[15] We do not classify news based on previous returns as in Chan (2003), because doing so automatically assumes the direction of causality.

it is consistent. The disadvantage of the former method over the latter method is that it is prone to making serious mistakes. If a software is programmed to classify a news item as good if it detects a number of positive words, it is bound to misclassify a news item as good if the news contains many good words about the competition, and few bad words about the firm. The software may also misclassify a news item as neutral if there are no obvious positive or negative words in the article, whereas a human will judge correctly from the context that the article is good news or bad news about a firm. So we chose human judgment for classification.

We read each of the 171,488 news items individually, and classify each news item as either "good", "bad" or "neutral" using our judgment. Our judgment is based on the content of each individual news item, without forming a new expectation after each piece of news. This method of human judgment has obvious drawbacks, the most important of which is lack of consistency. To reduce possible time-varying judgment errors, we randomize by having one author start from the last firm that went public in the internet IPO sample and read the news in reverse chronological order, while the second author starts from the first firm that went public in the non-internet IPO sample and read the news in chronological order. Later on, when we conduct the regression analysis, we difference news variables to remove the firm effect. This also removes the author bias effect, if we assume that the author's bias is constant within a firm.

However, even with the randomization approach and the fixed-effect estimation, we could still face possible judgment error as the same piece of news may be categorized differently by different human beings over time. So we conducted an experiment to verify the consistency of our judgments. Though we will delay the discussion of this experiment to the "robustness tests" section of this paper, it should be pointed out here that we did exhibit consistency in our judgment. Correlations between our classification of news items and the classification of the same news items made by other participants in the experiment were strongly positive.

We define the degree of media coverage as the number of news items about a sample IPO firm during a specific period. For the pre-IPO period (up to the offer day), news items are counted and classified for the whole period, as there is no price information during this period. For the post-IPO period, news items are classified and counted on a daily basis. For any given day, we aggregate news items about the same subject from multiple media sources and do not distinguish between "real news" and "spin-news". This research design is created with the intent to investigate the impact of the intensity of the media coverage, and is based on the fact that different type of media may reach different types of investors. In addition, the criterion for estimating the influence of individual media is ambiguous, and very often the same contents will be covered by various media sources. [16]

C. Summary IPO Statistics

Table 1 reports summary statistics of offer characteristics obtained from SDC and CRSP, broken down by internet and non-internet IPOs. The internet firms appear to be much younger. The average IPO is over 9 years old at the time of its offering for the non-internet sample, but is less than 5 years old for the internet sample. Although the difference in age between the two samples drops substantially when we examine the median instead of the mean firm age, it is still highly significant.

Nearly seventy percent of internet IPO firms are VC-backed, significantly different from the fifty-five percent of non-internet IPOs that are VC-backed. This is in line with Aggarwal,

[16] Surprisingly, when we disaggregated the media into the top ten by circulation (Associated Press News Wire, Chicago Tribune, Daily News, NY, Dow Jones News Service, Houston Chronical, LA Times, Reuters News, New York Times, Wall Street Journal, USA Today) and the wire services only (Associated Press News Wire, Dow Jones News Service, and Reuters News), we found that the former covered internet firms with more intensity (the top ten media sources account for 58.74% of the media coverage for internet firms and only 55.66% of the media coverage for non-internet firms), but the latter showed no differential preferences (53.28% for internet firms vs. 52.17% for non-internet firms).

Krigman and Womack (2002), who document 58.7% of internet IPOs and 43.8% of non-internet IPOs are VC-backed during the period of 1994-1999.

About sixty-seven percent of internet firms operate in what we refer to as “high-tech” industries (three-digit SIC codes 283, 357, 366, 367, 381, 382, 383, 384, 737, 873, and 874).[17] Interestingly, sixty-three percent of non-internet firms belong to the “high-tech” category as well, and the difference between the two samples is not significant either economically or statistically. This reflects the “high-tech” industry clustering in the sample period of 1996-2000. Correlated with this feature, most of the firms in the two samples trade on Nasdaq.

We also report the main offering characteristics that occur during the book-building period (from the registration date to the offer date) between the internet and non-internet IPOs. Because of our method of constructing the matching non-internet sample, the average gross proceeds are around $88 million for both samples. The width of the filing price range, defined as the difference between the high and low prices suggested in the preliminary prospectus and often viewed in the IPO literature as a proxy for *ex ante* uncertainty about a firm’s value, is virtually the same between the two samples. However, the average expected offer price, reflected in the mean of the indicative price range included in the issuer’s S-1 filing, is significantly higher for the non-internet sample ($13.24 compared to $12.14 for the internet sample). This is in sharp contrast with the final offer price, where the internet issues on average are set a higher price ($14.76 versus $13.67 of the non-internet sample). Accordingly, in terms of price revisions, measured as the percentage change between the final offer price and the expected offer price, the average internet firm revises its price much more than the average non-internet firms, 23% versus 4.15%, and this difference is highly significant.

[17] This definition follows Benveniste, Ljungqvist, Wilhelm and Yu (2003) and “Hi Tech Industry Group” defined by SDC, and covers industries such as pharmaceuticals, computing, computer equipment, electronics, medical and measurement equipment, software and biotech industries.

The most distinguishing feature of the sample is the first-day returns, calculated as the percentage change between the final offer price and the first-day closing price, which we take from CRSP tapes if available with seven days of the offer date (as in Lowry and Schwert (2002).) The internet firms averaged a stunning 83.72% first-day return during our sample period, which is similar to the 89% first-day return documented by Ljungqvist and Wilhelm (2003) for internet IPOs during 1999 and 2000. This first-day return is more than twice in size compared to the non-internet sample (41%), even though the majority of our non-internet sample IPO firms are also high-tech oriented.

III. MEDIA COVERAGE

In this section we investigate whether the media treated internet IPOs and non-internet IPOs differently. We explore this question for the entire sample period of 1996-2000, as well as for sub-periods.

We select two measures of peaks, and then break down our sample into two sub-periods: before and after the peak. Throughout this paper, we use *before the peak* and *bubble period* interchangeably, and *after the peak* and *post-bubble period* interchangeably. The first peak definition is a market-wide definition. On March 24th, 2000, the Nasdaq 100 index reached its highest point in our 1996 to 2000 sample period. We take this date to be the market peak. The second peak definition is intended to capture shifts in individual stocks, and is calculated as the date at which the firm's market capitalization reaches the highest point in the sample period. The sub-periods defined using the first definition of a peak (March 24, 2000) are, therefore, in *calendar time*, whereas the sub-periods defined using the second definition of a peak (firm peak) are in *event time*.

A. Unconditional Media Coverage

First, we examine the unconditional media coverage of the internet IPO sample and the non-internet sample, without taking into account the impact of previous price movements on this coverage. Figures 1-a through 1-e and Figures 2-a through 2-e provide a visual presentation of these patterns over various periods of time. In Figures 1-a through 1-e, news items for the two samples are aggregated over time and firms, while in Figures 2-a through 2-e, the news items are per day per firm. Figures 1-a and 2-a cover the entire sample period. Figures 1-b (1-c) and figures 2-b (2-c) report the degree of media coverage before (after) the peak, where the peak is the day in which the firm's stock price peaked. Figures 1-d (1-e) and figures 2-d (2-e) report the degree of media coverage before (after) the peak, where the peak is March 24, 2000.

Compared to the non-internet sample, the internet sample had significantly higher media coverage in all the three measures (total number of news, good news, and bad news), during all the three time periods (entire sample period, before and after the peak, however you define the peak). This was true in the aggregate, as well as per firm per day basis.

Interestingly, as shown in Figures 1-b, 1-d, 2-b and 2-d, during the bubble period, internet IPO firms have more net news, defined as the difference between the number of good news and bad news, than their matching sample. This indicates that media reported relatively more good news than bad news for the internet firms than they did for the non-internet firms in the bubble period, suggesting media generally not only provided more coverage but also had a more optimistic view, whether rational or not, about internet firms in the bubble period.

However, Figures 1-c, 1-e, 2-c and 2-e reveal that post peak, there was a dramatic shift in media sentiment. Internet IPO firms have more negative net news than their matching sample post-bubble. This indicates that media reported relatively more bad news than good news for the internet firms than they did for the control firms in the post-bubble period, suggesting media had a more pessimistic view, whether rational or not, about internet firms in the post-bubble period.

Finally, note the following asymmetry: the relative pessimism on internet firms over non-internet firms in the post-bubble period was *higher* than the relative optimism on internet firms over non-internet firms in the bubble period. This asymmetry appears to be in line with the casual observation that the media builds up heroes, only to tear them down when the opportunity presents itself.

Table 2 documents results from formal statistical tests that corroborate the conclusions that we obtained from the above informal ocular tests. Panel A of Table 2 shows the pattern of media coverage before and after a peak, where the peak is defined as March 24, 2000. There is a significant difference in media coverage between internet firms and non-internet firms during the bubble period. Prior to market peak, an internet firm receives on average 1.04 pieces of news reports per day and 21.04 per month. Among these news items, 0.39 per day and 7.98 per month are good news, which are more than twice the amount of good news a non-internet firm receives. The difference is statistically significant. The net news in the bubble period, measured by the difference between number of good news and bad news, averages 0.10 per day and 2.17 per month for an internet firm, significantly higher than the 0.07 per day and 1.42 per month coverage for a non-internet firm.

After the market peak, with an average of 0.65 news items per day and 14.01 news items per month, an internet firm still receives over twice the media attention than a non-internet firm. However, the media seems to be more pessimistic about internet firms during this sub-period. The net news is -2.28 per month and -0.12 per day for an internet firm, compared to -0.19 per month and -0.01 per day for a non-internet firm.

Panel B of Table 2 shows the same pattern of media coverage under a different measure of peak, where the peak is defined as the day a firm's price peaked in the period 1996 to 2000. Both these panels in Table 2 lead us to conclude that during the bubble period the market was more optimistic about internet IPOs than it was about non-internet IPOs, but during the post-bubble period, the market was more pessimistic about internet IPOs than it was about non-internet IPOs.

Since large offers tend to attract more public attention, we further break down our sample into two sub-samples, large and small IPOs, based on the median gross proceeds of the combined two samples. In two alternative and separate classifications, we break down our sample into tech and non-tech IPOs, as well as VC-backed and non VC-backed IPOs. Our previous conclusions of media bias hold, regardless of the size of the offer, the technological nature of the firm, and whether or not the issue is backed by venture capitalists.

Finally, we confirm the asymmetry we had noticed before: the relative pessimism on internet firms over non-internet firms in the post-bubble period (net news was -0.12 per day for internet firms and -0.01 per day for non-internet firms) was *higher* than the relative optimism on internet firms over non-internet firms in the bubble period (net news was 0.10 per day for internet firms and 0.07 per day for non-internet firms.)

B. Conditional Media Coverage

Next, we explore conditional news coverage between the two groups of firms during our sample period. Specifically, do the media report more good news than bad news when the previous period experiences a price increase, and do the media report more bad news than good news when the previous period was a price decrease? If yes, this would be consistent with the positive feedback hypothesis discussed in Shiller (2000).

Graphic illustrations of this test are given in Figures 3-a to 3-h in both calendar time and event time, and in aggregate and per-firm basis. We notice that the optimism of the media, captured by the net news items per month (the difference between the number of good news and the number of bad news per month), moves along with market capitalization for both internet and non-internet firms in calendar time (Figure 3-b) and in event time (Figure 3-f). This effect is about the same for internet firms and non-internet firms in the pre-peak period, but it is much stronger for internet firms in the post-peak period. The significant difference between the two samples post-peak suggests the media are more pessimistic about falling prices for internet firms than they are about falling prices for non-internet firms in this period.

Not only is media sentiment positively linked with price levels, but also is its interest. Notice that media coverage, as captured by the total news per month, moves along with market capitalization for both internet and non-internet firms in calendar time (Figure 3-a) and in event time (Figure 3-e). The effect is stronger for internet firms both in the pre-peak period as well as in the post-peak period.

Finally, note that the net news per firm spiked before March 24, 2000 (Figure 3-d), or before the firm reached its maximum value (Figure 3-h), suggesting media sentiment turns before market peaks. We explore this tantalizing result formally in the next section, where we ask whether media sentiment Granger-causes returns.

The findings from Figures 3-a to 3-h are corroborated formally in Table 3. We report the results based on two arbitrarily selected cutoff points about the degree of price movement: price increases or decreases more than 0% and 1% from previous day for daily study, and 0% and 10% from previous month for monthly analysis. Alternative cutoff points do not change our results qualitatively. Using abnormal returns instead of raw returns yields virtually identical results and hence these results are not reported.

Panel A of Table 3 reveals that if prices increased in the previous period, net news was positive this period for both internet stocks (0.07 per day) and for non-internet stocks (0.05 per day). If prices decreased in the previous period, net news was negative this period for internet stocks (-0.06 per day), but still positive this period for non-internet stocks (0.01 per day). Examining alternative cutoff points for previous price movements yields the same pattern. This means that Shiller's (2000) positive feedback hypothesis works especially for internet shares.

The analysis of the bubble and the post-bubble stages in Panels B and C of Table 3 leads to more interesting results. It seems that only one leg of the positive feedback hypothesis worked in the bubble stage, and another leg of the positive feedback hypothesis worked in the post-bubble stage. In the bubble stage, if prices increased in the previous period, net news was positive this period, but if prices decreased in the previous period, net news was not negative this period. In the post-bubble stage, if prices decreased in the previous period, net news was negative this period, but if prices increased in the previous period, net news was not positive this period.

Interestingly, during the bubble period, this asymmetry was both economically and statistically stronger for internet stocks when we examine net news per month. In the post-bubble period, this asymmetry is stronger for internet stocks whether we use net news per day or net news per month. This suggests that in the bubble stage, the media tended to ignore bad news in price falls, especially for internet stocks; and in the post-bubble stage, the media tended to ignore the good news in price rises, especially for internet stocks. These results remain whether the peak is defined in calendar time or in event time.

IV. EFFECT OF MEDIA COVERAGE ON STOCK RETURNS

In the previous section we document the differences in media coverage between internet firms and non-internet firms. In this section, we examine the influence of this differential media coverage on stock returns. We first conduct the analysis at the firm level, and then conduct the analysis at the portfolio level.

A. Firm-Level Analysis

We first estimate the abnormal return of a firm's stock by fitting a Fama-French (1993) 3-factor model for each firm. We use contemporaneous Fama-French factors to control for the most recent market-wide information to ensure the conservativeness of our news analysis. Our results are almost identical with respect to both economic and statistical significance if lagged factors are selected.

We then examine the impact of different types of news on daily and monthly abnormal returns, respectively, by including number of good news (*GN*), bad news (*BN*), and net news (*NN*) *per firm* from the previous period (either day or month) in the regression model. Net news is simply number of good news minus number of bad news *per firm* from the previous period (either day or month). In addition, all these news variables are differenced, which removes firm effects.

We isolate the bubble period by interacting the news variables with *PostPeak*, a dummy which equals 1 if it is after the market peak of March 24, 2000, and zero otherwise. We include lagged abnormal return from the previous period to be consistent with the Granger causality test. Lagged abnormal return also serves as a control variable for liquidity (Pastor and Stambaugh 2003). To account for the vast differences in the amount of news for internet and non-internet firms, we include $log(1 + TN_{t-1})$ as a control variable, where TN_{t-1} is the total news *per firm* from the previous period (either day or month). The regression analysis is conducted for the internet IPO sample and the non-internet IPO sample separately.

Table 4 reports the daily returns results from the least-square estimation of the regression models. *p*-values are based on Newey-West standard errors (one lag). Although not reported, our results remain unchanged when we re-estimate Table 4 for various lagged Newey-West standard errors (up to five lags). Winsorizing at the 1^{st} and 99^{th} percentile also gives similar results.

From the first two columns, note that the number of good news from previous period is positively related to the current abnormal returns, and bad news from the previous period is negatively related to the current abnormal returns. This indicates that conditional on previous abnormal returns, good news leads to higher abnormal returns while bad news leads to lower abnormal returns for both internet and non-internet IPO firms. This result also suggests that the human judgment we used when classifying news as good, bad or neutral was prudent *ex post*.

Interestingly, during the bubble period, one additional previous good news item generates on average 7.0 and 19.1 basis points in returns for an internet firm and a non-internet firm respectively. This is confirmed in Table 4, where the difference in coefficients associated with the number of good news between internet IPO sample and non-internet IPO sample is negative (-0.121) and significant (p = 0.04) during the bubble period. This suggests that even though good news leads to higher abnormal returns, this effect is lower for internet firms during the bubble period. Given there are 0.389 good news items per internet firm per day, and only 0.148 good news items per non-internet per day during the bubble period (Table 2), the *total* effect of good news next day during the bubble period was an additional 2.72 basis point return for internet firms and a very similar 2.83 for non-internet firms.

Notice also that the coefficient associated with the interaction term between good news and post-bubble dummy (*PostPeak*) is positive (0.156) and significant (p = 0.00) *only for* internet firms. Given the overwhelming volume of negative news about internet firms post-peak, this suggests that compared to the bubble period, good news about internet firms appear to be more credible during the post-bubble period.

Similarly, although Table 4 shows that bad news leads to lower abnormal returns, the difference in coefficients associated with bad news (*BN*) between internet IPO sample and non-internet IPO sample is positive and highly significant for both the bubble and the post-bubble periods, suggesting that even though bad news leads to lower abnormal returns, this effect is lower for internet IPOs in both the periods.

The above results of Table 4 – the market relatively downplays the good news of internet firms in the bubble period, and relatively downplays the bad news of internet firms in all periods – are further confirmed when we look at Columns (3) and (4) in Table 4. Net news positively Granger-causes returns for internet IPOs, but the effect is lower in all periods compared to non-internet IPOs. Further, net news about internet firms are significantly more credible during the post-bubble period, as the coefficient associated with the interaction term between net news and post-bubble dummy (*PostPeak*) is highly significant for internet IPO firms.

Although the results are not reported in Table 4, we also analyze the impact of media coverage on monthly returns. Unlike the results on daily returns, we find no impact of monthly news on monthly abnormal returns. Including or excluding a fourth factor, the momentum factor, changes neither the statistical significances nor our conclusions. We interpret these non-results simply as evidence in favor of market efficiency. If markets are efficient, the impact of news on returns should be immediate; it should not take a month for prices to incorporate information.

B. Portfolio Analysis

Table 4 examines the impact of media on individual firm returns. In order to capture the effect of media on the entire internet group, we now extend our analysis from firm level to portfolio level. We form the following four portfolios: equally-weighted and value-weighted internet portfolios and equally-weighted and value-weighted non-internet portfolios. We then replicate our analysis in Table 4 for internet portfolios and non-internet portfolios. We do this for both daily and monthly returns.

Table 5 reports the results from estimating the portfolio returns using a regression model similar to the one presented in Table 4. Again, both alternative specification of Newey-West standard errors (up to five lags) and winsorizing at the 1^{st} and 99^{th} percentile yield virtually the same results and these results are therefore omitted from the table.

For the internet portfolio, previous average good news per firm in the portfolio has no impact on risk-adjusted portfolio returns during the bubble period, but leads to positive abnormal portfolio returns during the post-bubble period. Net news analysis confirms this result: previous average net news per firm in the internet portfolio has no impact on risk-adjusted portfolio returns during the bubble period, but leads to positive abnormal portfolio returns during the post-bubble period. This is not seen in the non-internet portfolio. As a matter of fact, the difference in coefficients associated with average net news per firm between internet IPO portfolio and non-internet IPO portfolio is only significant for the post-bubble period.

We make the following conclusion from the portfolio analysis: when examined at the portfolio level, net news about internet firms was less credible in the bubble period than net news about non-internet firms (economically, but not statistically different), and net news about internet firms was more credible in the post-bubble period than net news about non-internet firms (economically and statistically different). This conclusion is weaker than our conclusion from the individual firm analysis in Table 4, where we had an economically and statistically significant difference in both the bubble and the post-bubble periods.

Although results are omitted from Table 5, we again find monthly news per firm in the portfolio does not impact monthly returns, which is another evidence of market efficiency.

V. ROBUSTNESS OF OUR RESULTS

A. Change of information environment within the sample period

On October 23, 2000, the SEC implemented the Regulation Fair Disclosure Law requiring that materials disclosures by publicly traded companies be disseminated so that the disclosures are simultaneously accessible to all concerned. Prior to the adoption of this law, selective disclosure such as disclosing important nonpublic information to securities analysts or selected institutional investors or both was permissible. By enforcing this law, the SEC intended to eliminate informational advantages that can result in possible wealth transfer from the general investing public to a select few. So the information content in news was expected to improve as hitherto private information now became publicly available through news. We take into account this possible regime change in our data set by including a dummy variable in our regression analysis which is 1 before October 23, 2000, and zero otherwise. The coefficient associated with the post-regulation dummy is negative and significant, suggesting the abnormal returns are lower after the implementation of the law. However, our qualitative results in Table 4 do not change.

B. Alternative variable specifications

We further check the robustness of our results by replacing the number of good news with the sum of good news and neutral news. In another check, we replace the number of bad news with the sum of bad news and neutral news. We obtain similar results from the first alternate measure of good news, and even stronger results from the second alternative measure. To take into account the process of information dissemination, we re-define GN_{t-1} as the average of GN_{t-1} and GN_{t-2} (BN_{t-1}, NN_{t-1} and TN_{t-1} are redefined analogously), and re-estimate our model in Table 4 and Table 5. Our results are robust to these alternative definitions.

For Table 3, we substitute the raw returns with abnormal returns to capture the effect of risk-adjusted returns on media reporting. For Table 4, we replace the abnormal return at t-1 by the sum of two-day abnormal returns at t-1 and t-2. Again, our results remain virtually unchanged.

C. Alternative sample specification

C.1. Exclusion of price-driven news items

Most of our news is about economic fundamentals, but a few of our news is about the previous period's price movement. Through the process of news collection and classification, we had observed that the second type of news occurs most frequently during the first month after a firm goes public. So we re-estimate Tables 4 and 5 by excluding the first-month data of each firm. The analyses are conducted for both daily and monthly returns. Again, our results remain qualitatively unchanged.

C.2. Paired matching: Early termination due to mergers, liquidations, bankruptcy and delisting

In this paper, we investigate the impact of the media on IPO firms' returns during the bubble and post-bubble periods by comparing the media coverage between internet IPO firms and a matching sample of non-internet IPO firms. There are 31 internet issues acquired later during the sample period, 19 of which are acquired by firms outside the internet sample. In addition, there are 2 internet firms liquidated, 1 bankrupted, and 2 de-listed. It is possible that an internet IPO firm is terminated earlier from our internet sample while the returns of its matched non-internet firm are still included in the non-internet sample.

To check the robustness of our results, we first re-estimate Table 4 using sub-samples in which all the firms terminated prior to the end of the sample period are dropped. Neither the signs of the key coefficients nor the statistical significance levels change, except for the coefficient associated with number of bad news for internet firms, which remains negative but becomes marginally significant. Second, to ensure a perfect paired-matching in our analysis, we construct another two sub-samples which require both the individual internet IPO firm and its matching firm have non-missing values in returns on any given day within the same period. Again, our results do not change. The exceptions, however, are the changes of statistical powers for the difference in coefficients associated with good news between internet IPO sample and non-internet IPO sample, and for the coefficient associated with bad news for internet firms. Both become insignificant although the signs remain negative.

D. Boredom: Are investors over-exposed to the news?

The key result in this paper, that the market discounts the media coverage for internet IPO firms, especially during the bubble period, may also be explained by investors' limited attention (Daniel, Hirshleifer and Teoh, 2002, and Hirshleifer and Teoh, 2003) and over-exposure to the news reports at that time. Given the substantially high volume of media coverage on internet firms during the bubble period, investors who have been surrounded by the news about the same type of firms in the past may eventually "grow tired" of any reports about internet stocks, and hence may discount the impact of the news.

D.1. The cumulative effect

To check this claim, we first examine the cumulative news exposure by re-estimating our regression model in Table 4 with additional four control variables. For each firm in our sample, we multiply cumulative total number of news of the firm up to date to each of the following independent variables of interest in Table 4: good news, the interaction term between good news and the post-bubble dummy, bad news, and the interaction term between bad news and the post-bubble dummy. These new control variables take into account the impacts of news in the past as a measure of cumulative degree of media exposure since the firm's public offering, and should offset the marginal impacts of the original variables if there is any boredom of media coverage from investors.

Surprisingly, we do not find evidence of boredom. The coefficients of our original variables of interests remain unchanged and significant, with a slight increase in the magnitude, but the coefficients associated with the four new control variables are not significant at all.

D.2. The non-linear effect

Instead of number of good news, bad news, net news and total news, we take a log transformation of these key variables and re-estimate Table 4. The idea behind this is an appreciation of the fact that the effect of news decreases as the number of news items increase. There are some improvements in statistical significance, as the coefficients associated with number of bad news and the interaction term between bad news and post-bubble dummy become highly significant for internet IPO firms. However, the difference in coefficients associated with bad news between internet IPO sample and non-internet IPO sample becomes insignificant.

E. Lockup expiration

Most IPOs feature lockup agreements, which prevent insiders from selling their shares to the market over a specified period. The typical lockup lasts 180 days and covers most the shares that are not sold in the IPO. Field and Hanka (2001) show that the popular press has interest in lockup expiration and find negative but prominent abnormal return around the scheduled unlock day.

To correct for the possible unusual impact of news coverage around lockup expiration, we re-estimate the regression model in Table 4 by removing the returns and news data of each firm in our sample in its sixth month after the offer date. We find no evidence that the event of lockup expiration affects our results during this sample period. The economical interpretation and statistical significance associated with the key coefficients remain qualitatively unchanged.

F. Learning

It can be argued that our main result – the market "discounts" news coverage for internet firms – is driven entirely by the learning process of investors about internet firms. Learning curves flatten out over time, and as many internet firms went public later in the sample period than earlier, their average slope for internet firms may have been lower than the average slope for non-internet firms.

We re-estimate our regressions using only the data between 1996 and 1998. Surprisingly, we find the market discounts the net news about internet firms more during this sub-sample period.

G. Experiment with news classification

To ensure that our categorization is consistent, we conducted a small experiment (Human Subject Study # 04-9087, approved on April 22, 2004). We selected one firm from each of the two samples: Yahoo! from internet stocks, and Sapient Inc. from non-internet stocks. These two firms are among the earliest IPOs in the combined sample, and this ensures that we can utilize news from all stages of the internet boom and the subsequent bust. We then recruited seven undergraduate students to participate in the experiment and divided them into two groups of three and four each.[18] The three students in the first group were each given 100 random news items about Yahoo! and the four students in the second group were each given 100 random news items about Sapient Inc. The undergraduates were instructed to use their own judgment to categorize each news article into good, bad, or neutral, except in cases of news about insider trading (sells are automatically bad, buys are automatically good) or news about analyst recommendations.

The experiment occurred on April 23, 2004, and lasted about two hours. Each student received a payment of $50 for his participation in this experiment. The resulting number of instances of agreement between the authors and each undergraduate is presented in Table 6.

From Panel A, the control firm news results in relatively few disagreements. The authors agree in 71% of cases. Though unreported, that number jumps to over 97% if neutral classifications are ignored. Undergraduates 1, 2, and 4, agree to a similar degree, suggesting that anyone reading news for non-internet firms comes to roughly the same conclusion. Only undergraduate number 3 appears to classify news differently. While individuals may disagree, these disagreements appear to be random and cancel out on average.

Panel B demonstrates that news on internet firms is harder to interpret. The authors agree in 65% of cases, though that number jumps to 90% when neither chooses a neutral classification. This differential arises mainly from the fact that Author 1 is less conservative in assigning classifications. Interestingly, since Author 2 was responsible for much of the internet data collection, this fact suggests that the effect of news on internet returns is actually slightly upward biased. Even with this potential bias, we are able to determine that internet firms have a significantly lower marginal response to news items than do control firms. The undergraduates

[18] We actually recruited eight undergraduate students, but one did not show up at the time of the experiment.

appear to have considerably different opinions about the impact of news. Again, though the individuals differ in their opinions, an average constructed from individual classifications shows disagreements canceling out in the aggregate.

CONCLUSION

ISDEX, an authoritative and widely cited internet stock index, rose from 100 in January 1996 to 1100 in February 2000 – an incredible increase of about 1000% in four years – only to fall down to 600 in May 2000 – an incredible decrease of about 45% in four months. Amongst bubbles in history, this internet bubble ranks amongst the most spectacular.

Though there is much agreement that such a spectacular rise and fall of internet stock prices cannot be explained by fundamentals, there is less agreement of what can explain it. In this paper, we explore the role of the media in this internet bubble. We ask and answer the following two questions: was the media coverage for internet IPOs in the years 1996 through 2000 different from a matching sample of non-internet IPOs and, if yes, did this differential media coverage affect risk-adjusted returns.

Our answer to the first question is the following. The media coverage was more intense for internet IPOs: there were more total news, more good news and more bad news for internet IPOs than for a matching sample of non-internet IPOs. Further, we document that the media hyped the good news for internet IPOs in the bubble period and hyped the bad news for internet IPOs in the post-bubble period: net news (good news minus bad news) was more positive for internet IPOs in the bubble period, and more negative for internet IPOs in the post bubble period. Finally, we note that though positive feedback – positive (negative) price changes leads to increase (decrease) in net news – was particularly pronounced for internet stocks.

Our answer to the second question is the following. We find that the market somewhat discounted the media hype: though net news Granger caused risk-adjusted returns for both types of IPOs, the effect was lower for internet IPOs, especially in the bubble period.

REFERENCE

Aggarwal, Rajesh, Laurie Krigman, and Kent L. Womack, 2002, Strategic IPO underpricing, information momentum, and lockup expiration selling, *Journal of Finance* 66, 105-137.

Antunovich, Peter, and Asani Sarkar, 2003, Fifteen minutes of fame? The market impact of internet stock picks, Working Paper, The Federal Reserve Bank of New York.

Antweiler, Werner, and Murray Z. Frank, 2004, Is all that talk just noise? The information content of internet stock message boards, *Journal of Finance*, forthcoming.

Barber, Brad, M., and Terrance Odean, 2003, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, Working Paper, University of California, Davis and University of California, Berkeley.

Baron, David, P., 2004, Persistent media bias, Working Paper, Stanford University.

Benveniste, Lawrence, Alexander P. Ljungqvist, William J. Wilhelm Jr., and Xiaoyun Yu, 2003, Evidence of information spillovers in the production of investment banking services, *Journal of Finance* 58, 577-608.

Blanchard, Olivier, J., and Mark W. Watson, 1982, Bubbles, rational expectations and financial markets, in *Crises in the Economic and Financial System*, ed. by P. Wechtel. Lexington, Lexington Books.

Brunnermeier, Markus, and Stefan Nagel, 2004, Hedge funds and the technology bubble, *Journal of Finance* 59, 2013-2040.

Chan, Wesley, 2003, Stock price reaction to news and no-news: drift and reversal after headlines, *Journal of Financial Economics* 70, 223-260.

Chen, Honghui, Gregory Noronha, and Vijay Singal, 2002, Investor awareness and market segmentation: Evidence from S&P 500 Index changes, Working Paper, University of Baltimore.

Cooper, Michael J., Orlin Dimitrov, and P. Raghavendra Rau, 2001, A Rose.com by any other name, *Journal of Finance* 56, 2371-2388.

Daniel, Kent, David Hirshleifer, and Siew Hong Teoh, 2002, Investor psychology in capital markets: evidence and policy implications, *Journal of Monetary Economics* 49, 139-209.

DeLong, J., Andrei Shleifer, Lawrence Summers, and Robert Waldman, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.

Demers, Elizabeth, and Katharina Lewellen, 2003, The marketing role of IPOs: evidence from internet stocks, *Journal of Financial Economics* 68, 413-437.

Ducharme, Larry, Shivaram Rajgopal, and Stephan Sefcik, 2001a, Lowballing for 'Pop': The case of internet IPO underpricing, Working Paper, University of Washington.

Ducharme, Larry, Shivaram Rajgopal, and Stephan Sefcik, 2001b, Why was internet IPO underpricing so severe? Working Paper, University of Washington.

Dyck, Alexander, I. J., and Luigi Zingales, 2003a, The bubble and the media, in Peter Cornelius, and Bruce Kogut, eds.: *Corporate Governance and Capital Flows in a Global Economy*, Chapter 7 (Oxford University Press, New York).

Dyck, Alexander, I. J., and Luigi Zingales, 2003b, The media and asset prices, Working Paper, Harvard University and University of Chicago.

Falkenstein, Eric, G., 1996, Preferences for stock characteristics as revealed by mutual fund portfolio holdings, *Journal of Finance* 51, 111-135.

Fama G, and Kenneth French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Field, Laura, and Gordon Hanka, 2001, The expiration of IPO shares lockups, *Journal of Finance* 56, 471-500.

Griffin, John, Jeffrey H. Harris and Selim Topaloglu, 2003, Investor behavior over the rise and fall of Nasdaq. Working Paper, University of Texas.

Hirota, Shinichi, and Shyam Sunder, 2002, Stock market as a "beauty contest": Investor beliefs and price bubbles sans dividend anchors. Working Paper, Waseda University and Yale University.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337-386.

Ho, Beauty, Maya Taher, Robert Lee, and Neil L. Fargher, 2001, Market sentiment, media hype and the underpricing of initial public offerings: The case of Australian technology IPOs, Working Paper, University of New South Wales.

Johnson, William, C., and Jennifer Marietta-Westberg, 2004, The effect of news on volatility: A study of IPOs, Working Paper, Michigan State University.

Lamont, Owen and Richard Thaler, 2003, Can the market add and subtract? Mispricing in tech stock carve-outs, *Journal of Political Economy* 111, 227-268.

Loughran, Tim, and Jennifer Marietta-Westberg, 2002, When any news is bad news: extreme events following an initial public offering. Working Paper, Notre Dame University.

Loughran, Tim, and Jay Ritter, 2002, Why don't issuers get upset about leaving money on the table in IPOs? *Review of Financial Studies* 15, 413-443.

Loughran, Tim, and Jay Ritter, 2004, Why has IPO underpricing changed over time? *Financial Management* 33, 5-37.

Lowry, Michelle, and G. William Schwert, 2002, IPO market cycles: Bubbles or sequential learning? *Journal of Finance* 57, 1171-1200.

Ljungqvist, Alexander, and William J. Wilhelm, Jr., 2003, IPO pricing in the dot-com bubble, *Journal of Finance* 58, 723-752.

Merton, Robert, 1987, Presidential address: A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483-510.

Mitchell, Mark, L., and J. Harold Mulherin, 1994, The impact of public information on the stock market, *Journal of Finance* 49, 923-950.

Mullainathan, Sendhil, and Andrei Shleifer, 2003, The market for news, Working Paper, MIT and Harvard University.

Niederhoffer, Victor, 1971, The analysis of world events and stock prices, *Journal of Business* 44, 193-219.

Ofek, Eli, and Matthew Richardson, 2002, The valuation and market rationality of internet stock prices, *Oxford Review of Economic Policy* 18, 265-287.

Ofek, Eli, and Matthew Richardson, 2003, DotCom mania: The rise and fall of internet stock prices, *Journal of Finance* 58, 1113-1137.

Pastor, Lubos, and Robert Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.

Reese, William, Jr., 1998, IPO underpricing, trading volume, and investor interest, Working Paper, Tulane University.

Ritter, Jay, and Ivo Welch, 2003, A review of IPO activity, pricing, and allocations, *Journal of Finance* 57, 1795-1830.

Shiller, Robert, 2000, *Irrational Exuberance*. Princeton University Press, Princeton, NJ.

Tetlock, Paul, 2003, Giving content to investor sentiment: The role of media in the stock market, Working Paper, University of Texas.

USA Today, May 27, 1999, A star shines among IPOs Net services firm StarMedia's stock soars 74%.

Wysocki, Peter, D., 1999, Cheap talk on the web: The determinants of postings on stock message boards, Working Paper, University of Michigan.

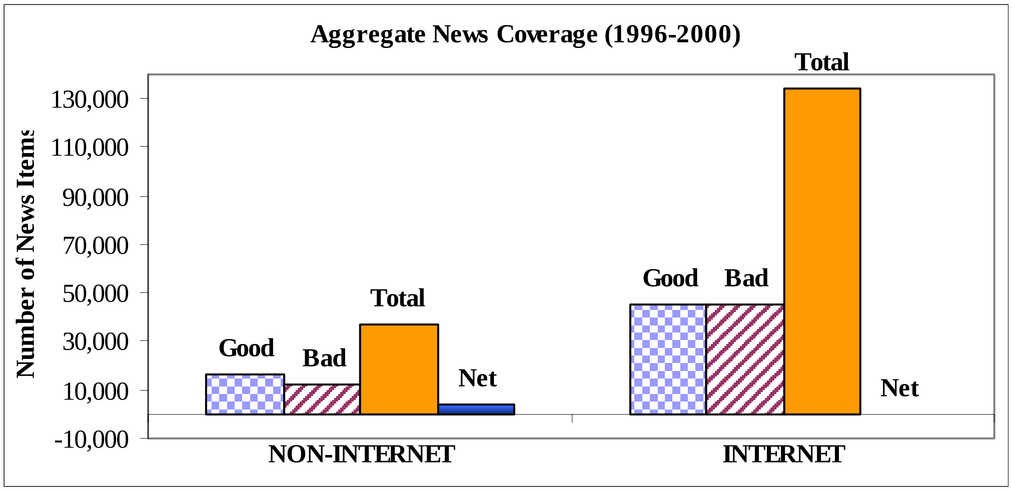

Figure 1-a. Aggregate news coverage for the entire sample period (1996-2000)

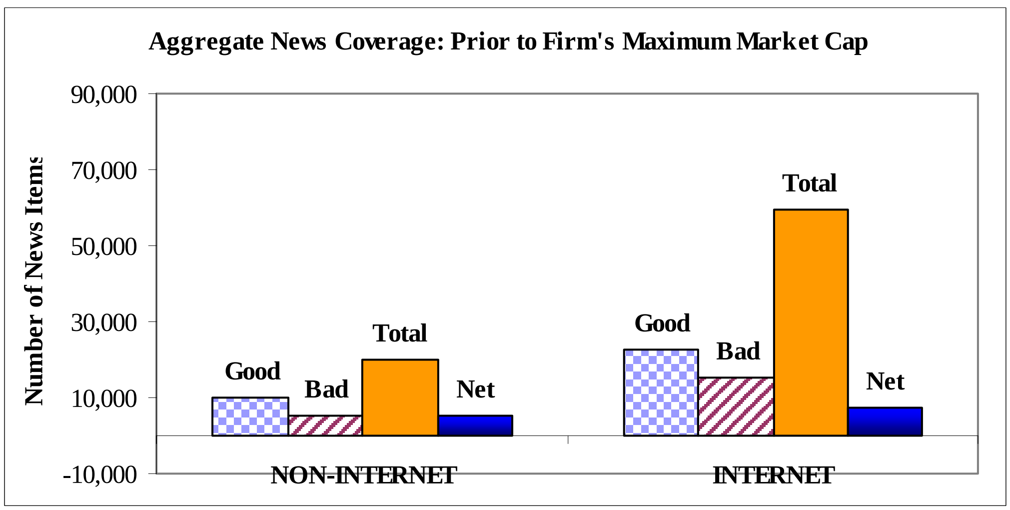

Figure 1-b. Aggregate news coverage prior to firm's maximum market cap

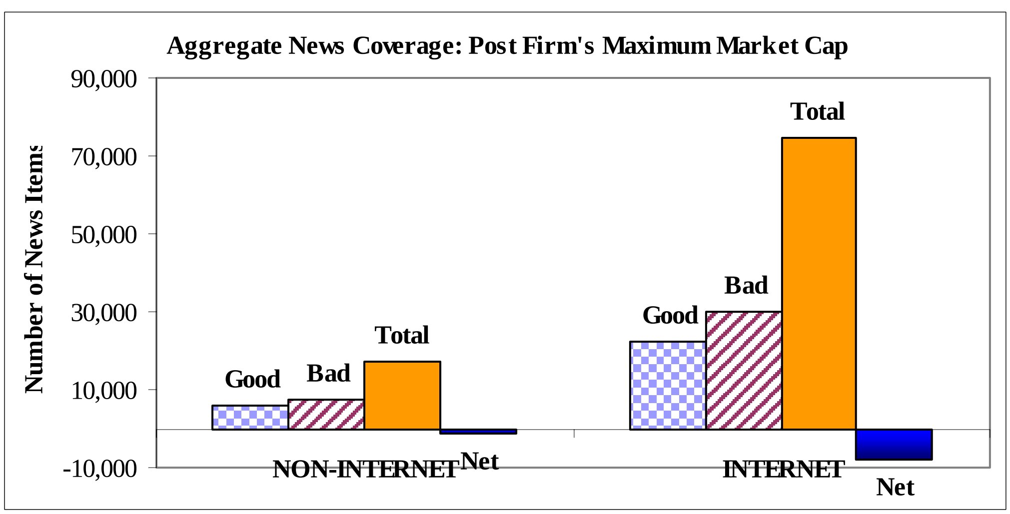

Figure 1-c. Aggregate news coverage post firm's maximum market cap

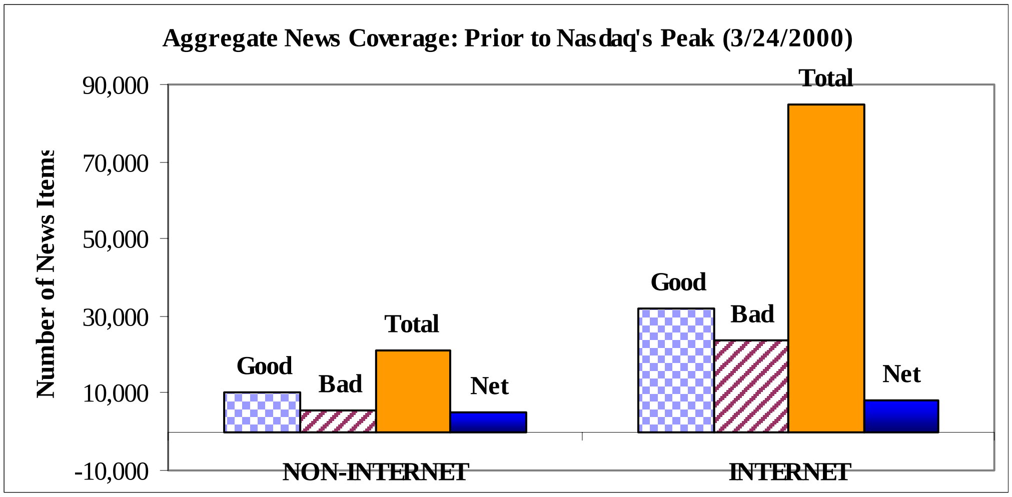

Figure 1-d. Aggregate news coverage prior to Nasdaq's Peak (March 24, 2000)

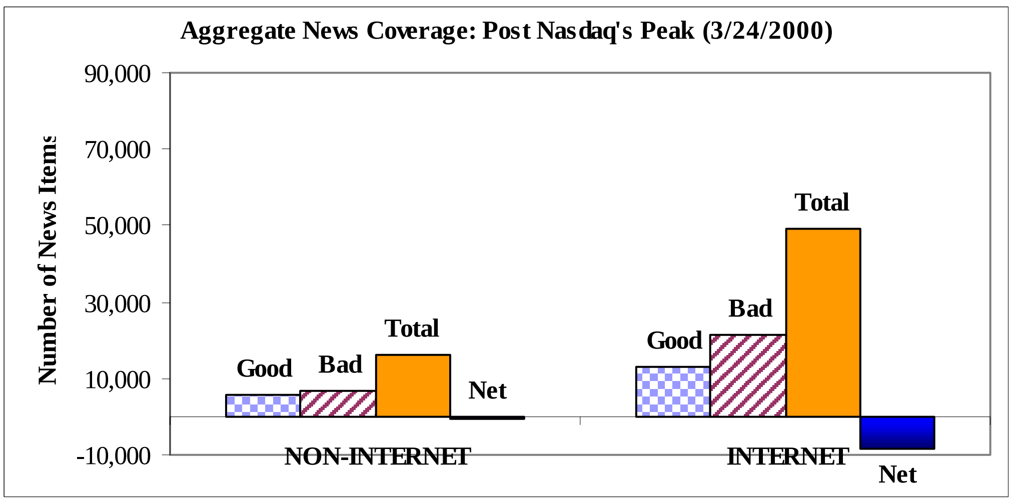

Figure 1-e. Aggregate news coverage post Nasdaq's Peak (March 24, 2000)

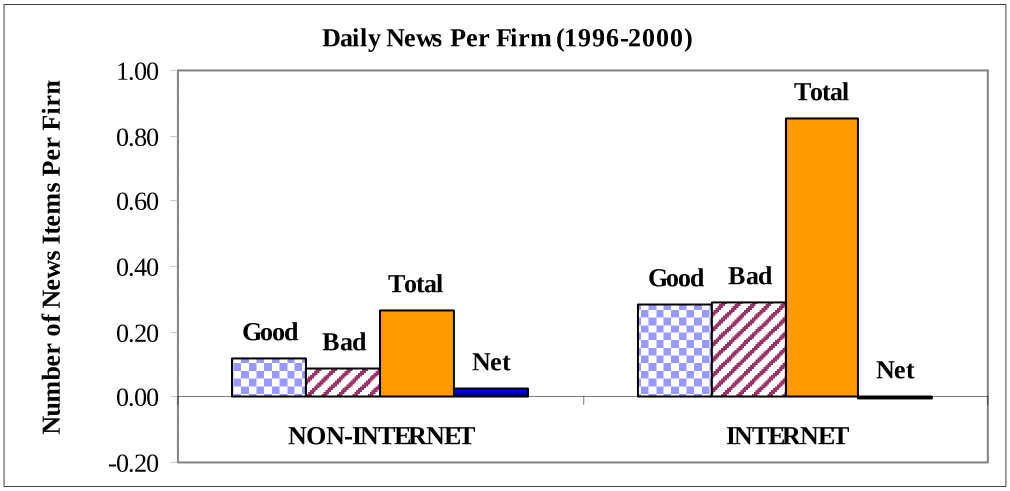

Figure 2-a. Daily average news coverage per firm for the entire sample period (1996-2000)

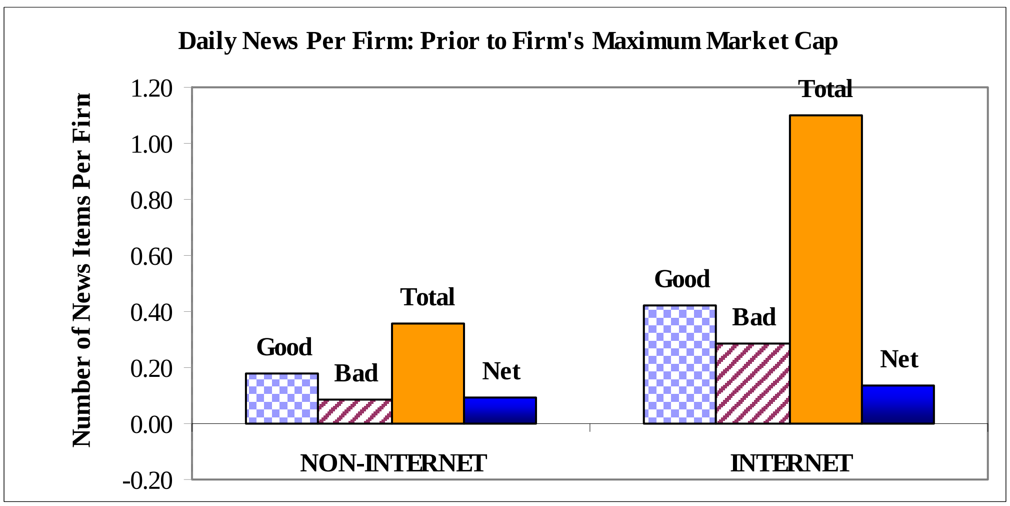

Figure 2-b. Daily average news coverage per firm prior to firm's maximum market cap

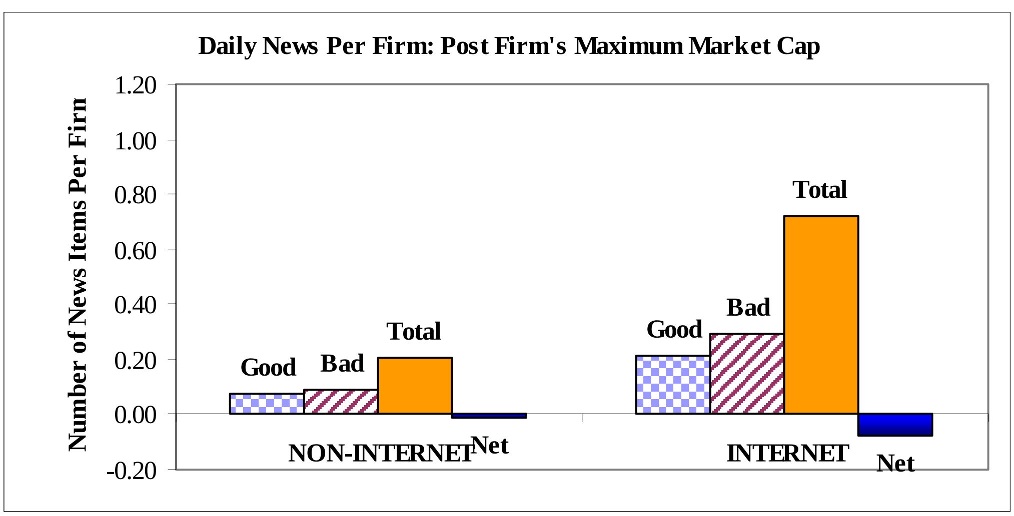

Figure 2-c. Daily average news coverage per firm post firm's maximum market cap

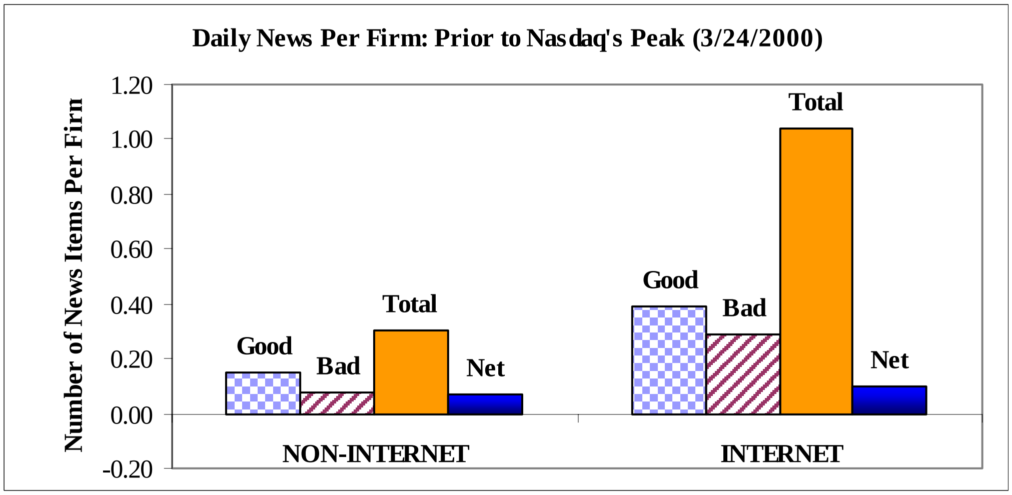

Figure 2-d. Daily average news coverage per firm prior to Nasdaq’s Peak (March 24, 2000)

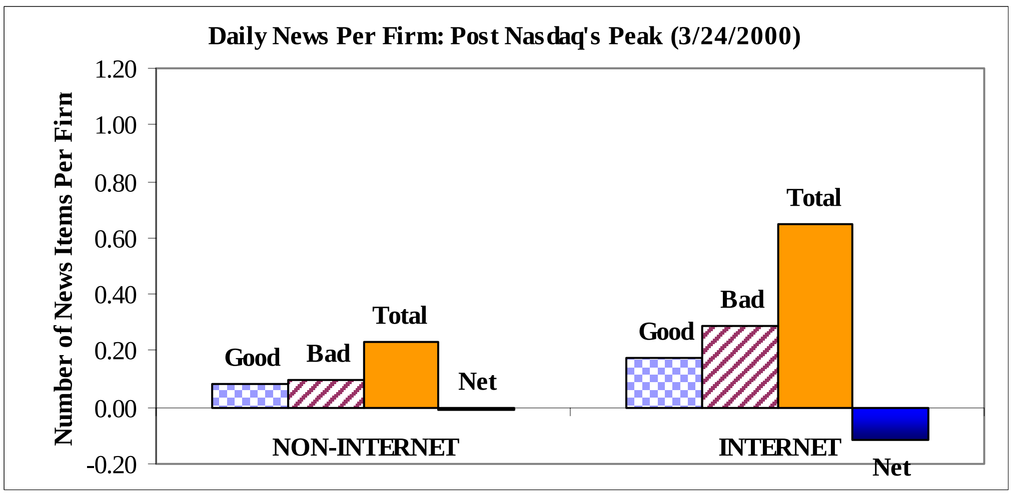

Figure 2-e. Daily average news coverage per firm post Nasdaq’s Peak (March 24, 2000)

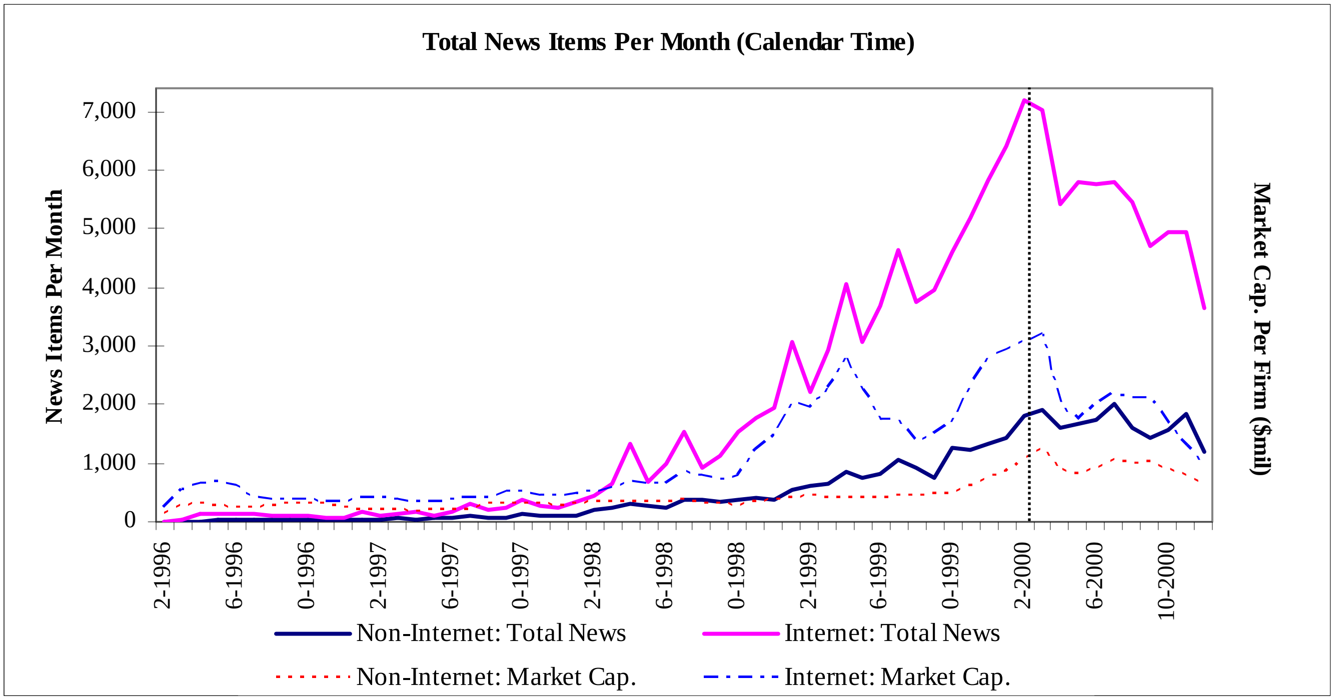

Figure 3-a. Total number of news articles per month for the entire sample period (1996-2000)

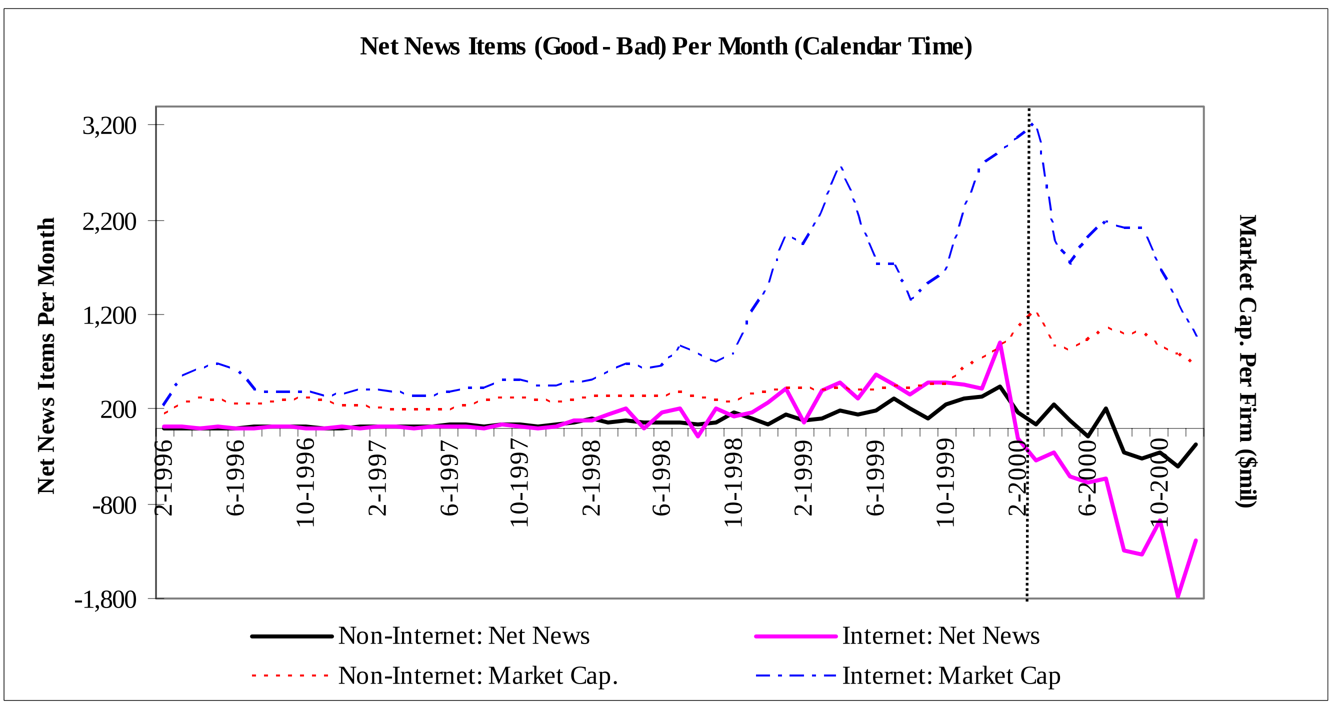

Figure 3-b. Net number of news articles (good – bad) per month for the entire sample period (1996-2000)

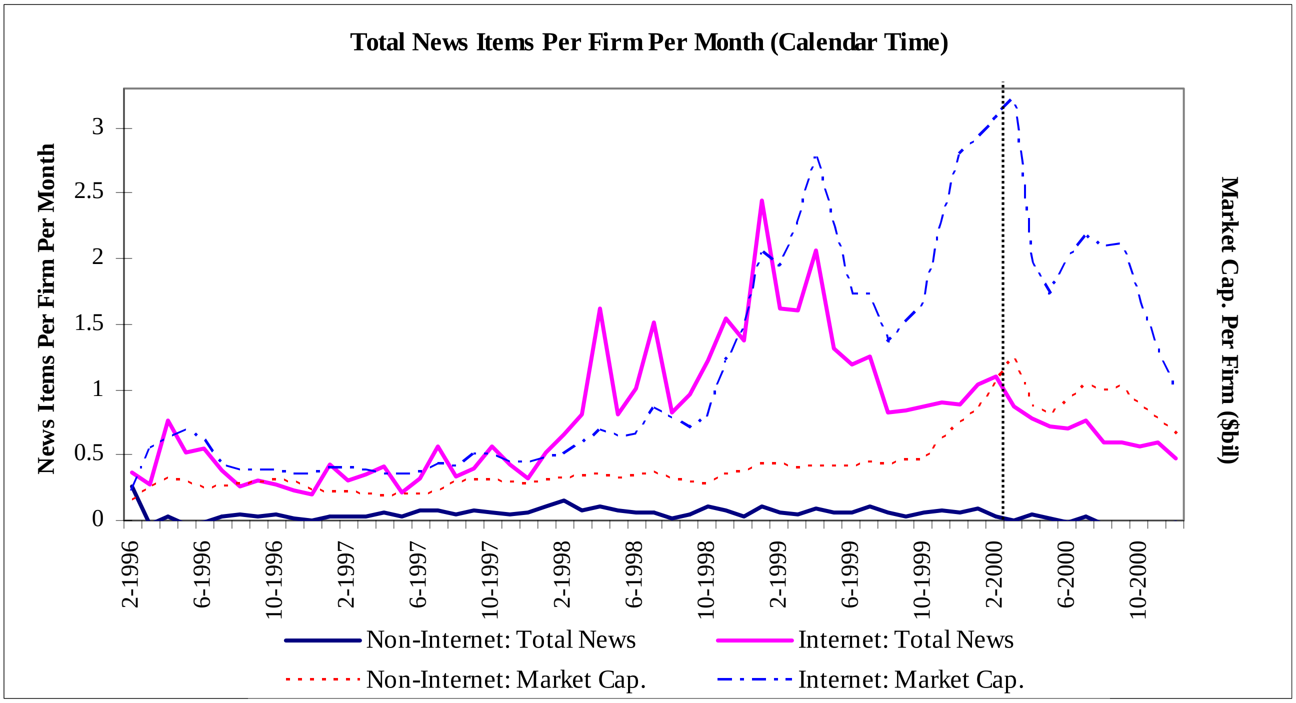

Figure 3-c. Total news articles per firm per month for the entire sample period (1996-2000)

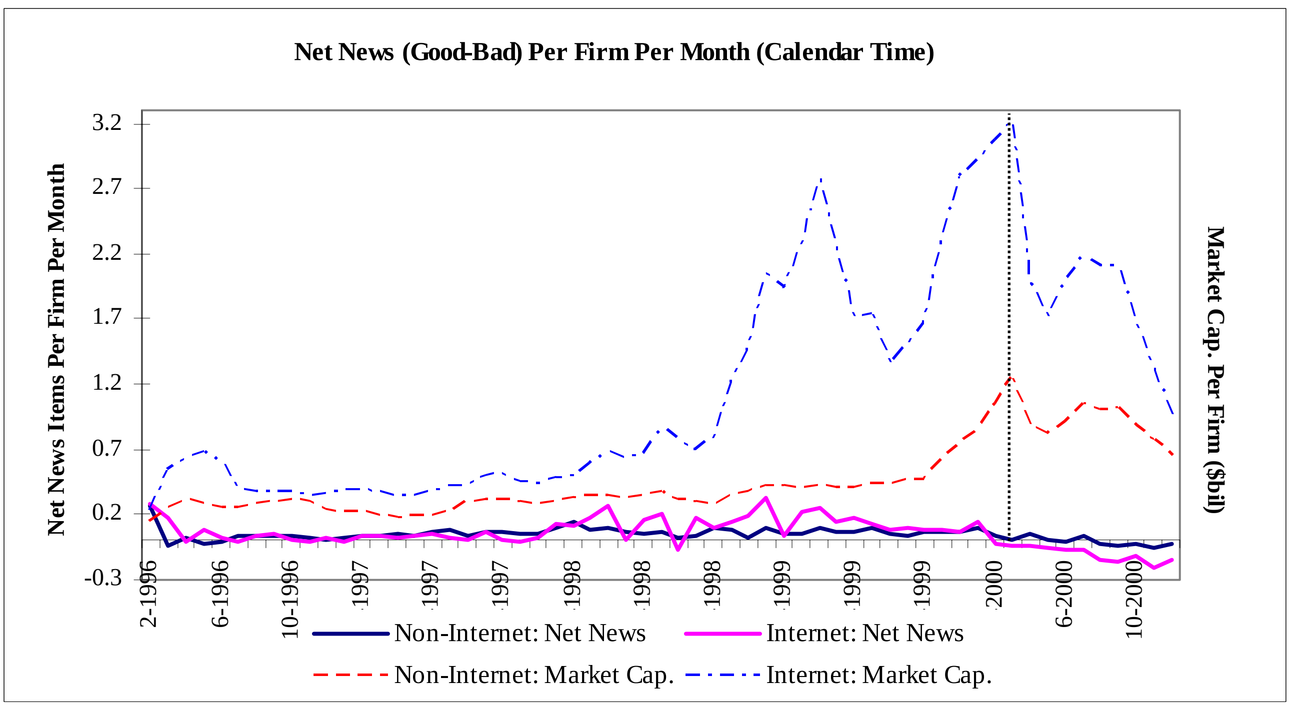

Figure 3-d. Net number of news articles (good – bad) per firm per month for the entire sample period (1996-2000)

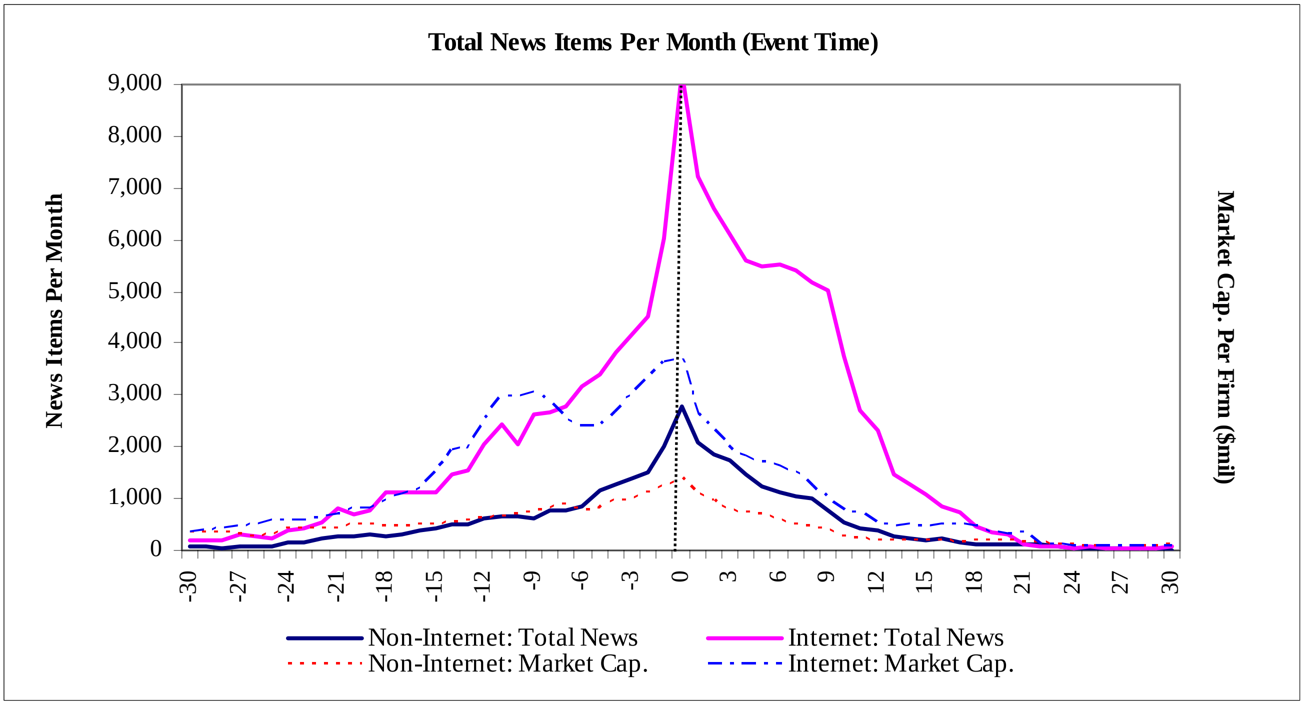

Figure 3-e. Total number of news articles per month based on firm's maximum market cap

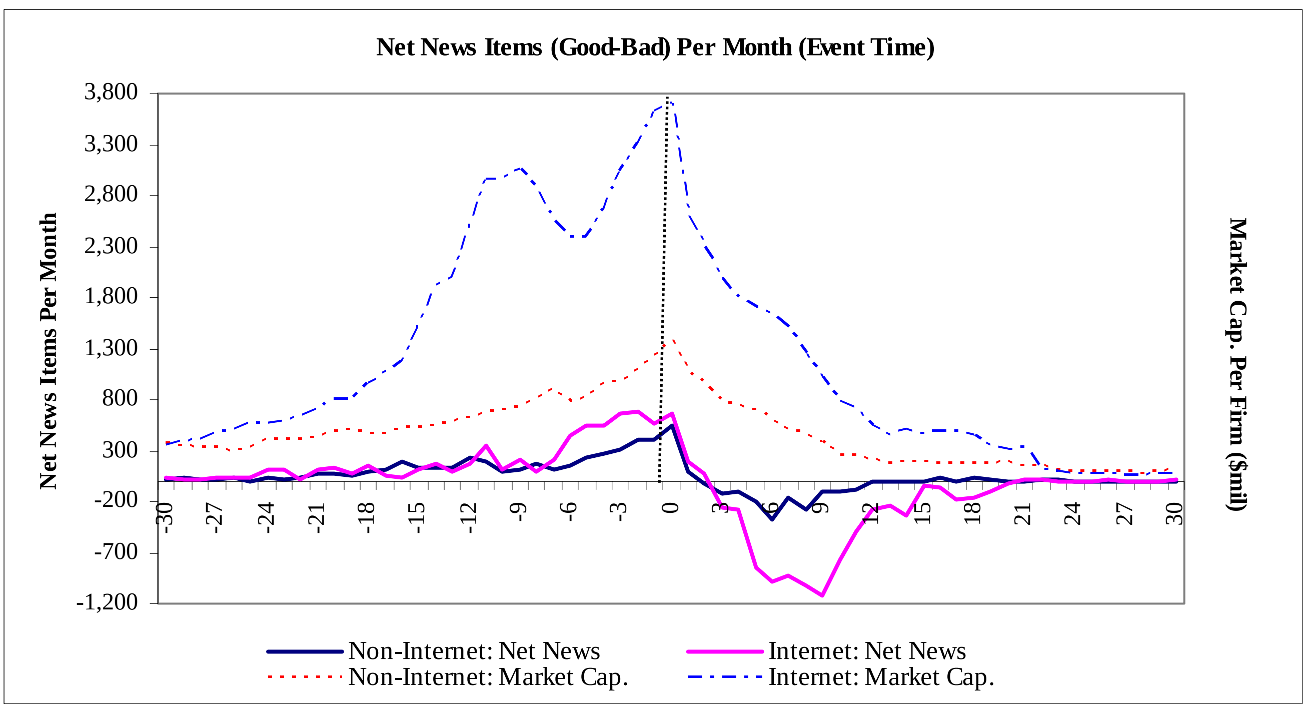

Figure 3-f. Net number of news articles (good – bad) per month based on firm's maximum market cap

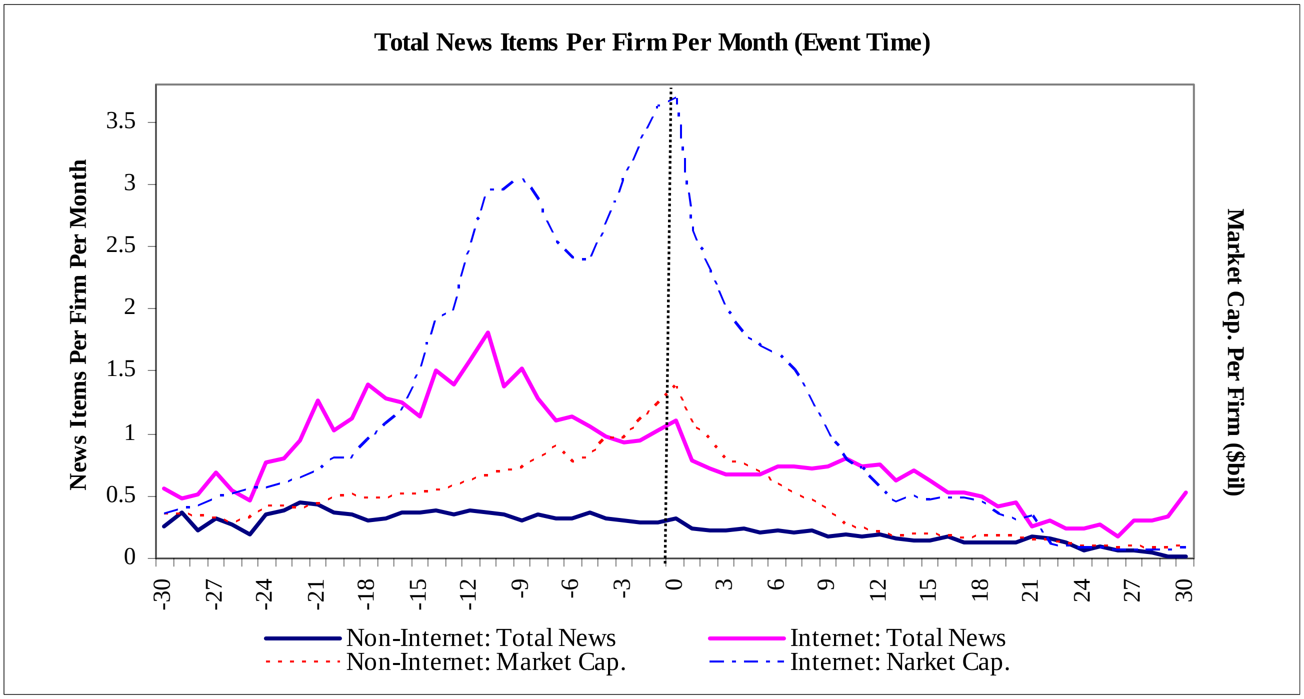

Figure 3-g. Total number of news articles per firm per month based on firm's maximum market cap

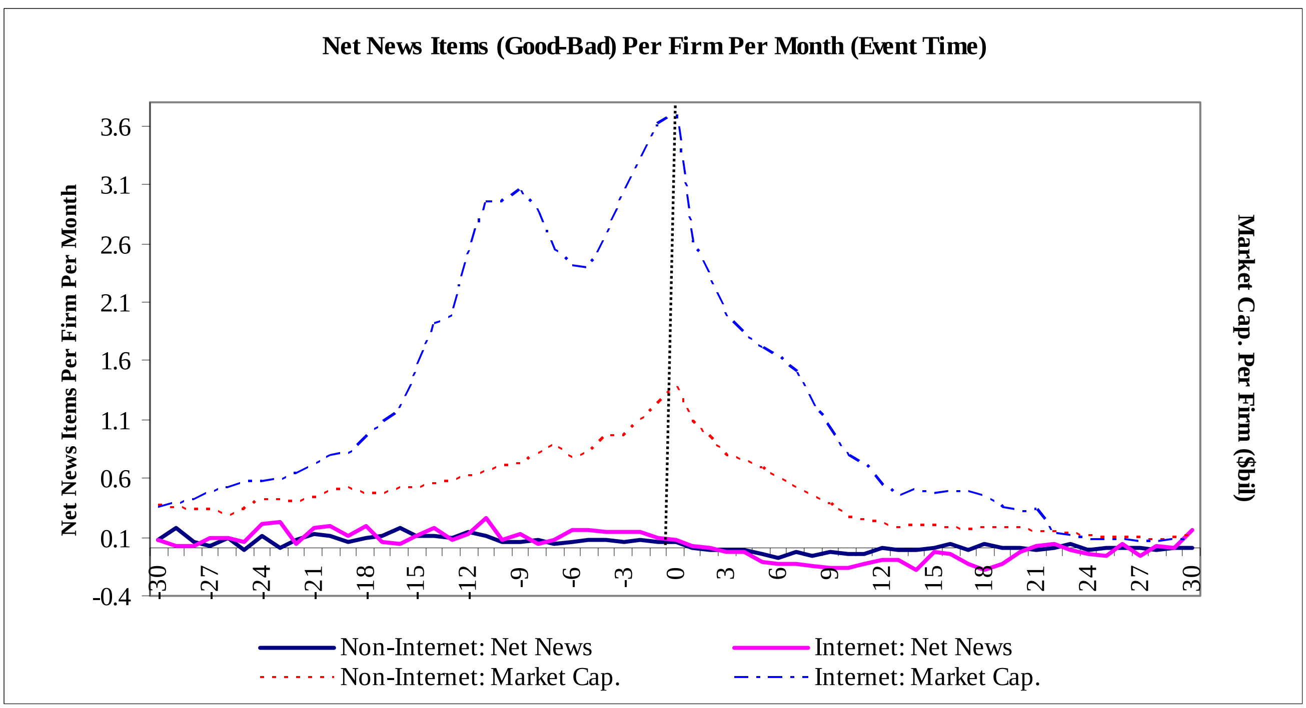

Figure 3-h. Net number of news articles (good – bad) per firm per month based on firm's maximum market cap

Table 1. Descriptive statistics of sample firms

The sample period is 1996-2000. Internet IPOs are identified as in Loughran and Ritter (2003). Gross proceeds do not include the over-allotment option. The expected offer price is calculated as the midpoint of the indicative filing range. Price revisions are the percentage change between the expected and final offer prices. Initial return is the first-day close price over the offer price, minus one. Gross spread is the total manager's fee expressed as the percentage of offer price. Information regarding venture capital backing is from Securities Data Corporation (SDC). Length of the book building period is the pre-IPO stage between the filing day (when a company files a preliminary prospectus with the SEC) and the pricing day (when the final offer price is set). Age is IPO year minus founding year. We manually collect missing founding date for 193 issues within the non-internet sample and 222 issues within the internet sample from SEC prospectuses, subsequent 10-Ks, or news sources. "High-tech" industries are classified by the first three-digit SIC codes 283, 357, 366, 367, 381, 382, 383, 384, 737, 873, and 874 covering industries such as pharmaceuticals, computing, computer equipment, electronics, medical and measurement equipment, biotech, and software industries. This definition follows Benveniste, Ljungqvist, Wilhelm and Yu (2003) and "Hi Tech Industry Group" defined by SDC. ***, **, * represents difference from non-internet sample at 1%, 5% and 10% level (two-sided, Satterthwaite test for means and Wilcoxon signed rank test for medians), respectively.

		Non-Internet Sample	Internet Sample	Statistical Significance
Gross proceeds (in $MM)				
	Mean	87.96	88.22	
	Std. Dev.	122.72	124.54	
	Median	60.50	61.05	
	No. of obs.	458	458	
Filing price range				
	Mean	1.98	1.96	
	Std. Dev.	0.46	0.57	
	Median	2	2.00	
	No. of obs.	458	456	
Expected offer price				
	Mean	13.24	12.14	***
	Std. Dev.	3.45	4.34	
	Median	13	11.5	***
	No. of obs.	458	456	
Final offer price				
	Mean	13.67	14.76	***
	Std. Dev.	4.67	5.62	
	Median	13	14	**
	No. of obs.	458	458	
Price revisions				
	Mean	4.15%	23.00%	***
	Std. Dev.	27.66%	37.29%	
	Median	0.00%	18.18%	***
	No. of obs.	458	456	
Initial returns				
	Mean	41.09%	83.72%	***
	Std. Dev.	68.07%	100.57%	
	Median	17.68%	49.17%	***
	No. of obs.	458	458	
Gross Spread				
	Mean	6.97%	7.09%	**
	Std. Dev.	0.58%	0.99%	
	Median	7.00%	7.00	
	No. of obs.	458	458	

Fraction Venture Capital Backed	Mean	54.59%	69.65%	***
Length of book-building period (in days)				
	Mean	104.57	91.46	**
	Std. Dev.	94.93	47.65	
	Median	77	77	
	No. of obs.	457	455	
Firm age (in Years)				
	Mean	9.56	4.84	***
	Std. Dev.	12.49	4.64	
	Median	5	3	***
	No. of obs.	434	444	
Fraction of high tech issues	Mean	62.45%	67.47%	
Fraction of issues traded at				
NYSE		8.95%	1.09%	
Nasdaq		87.12%	95.63%	
American		1.31%	0.87%	
OTC or Small Cap Market		2.63%	2.41%	

Table 2. Difference in media coverage

The news item data is hand-collected from Dow Jones Interactive and Factiva for both internet and non-internet sample IPOs. We read and classify them as good, bad or neutral news. Net news is the difference between the number of good news and the number of bad news. For each sample, we report the average daily and average monthly news item per firm before and after the peak, where the peak is measured in both *calendar time*, centered on March 24th, 2000 when Nasdaq's composite index QQQ reached its highest value, and *event time*, when a firm reaches its own maximum market cap during the sample period. Large IPOs are issues with offer sizes greater than the combined sample median. The remaining issues are classified as small IPOs. *p*-values testing the difference in the degree of media coverage between the pre-peak period and post-peak period are based on Satterthwaite standard errors and are reported in column (3) and (6) respectively. *p*-values testing the difference in the degree of media coverage between internet sample and non-internet sample are based on Satterthwaite standard errors and reported in column (7) and (8) respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Internet IPOs			**Non-Internet IPOs**			***p*-value for difference between**	
	Before	After	*p*-value	Before	After	*p*-value	(1) and (4)	(2) and (5)
Panel A: Calendar Time								
Daily News Items								
Total News	1.035	0.649	*0.000*	0.303	0.231	*0.000*	*0.000*	*0.000*
Good News	0.389	0.171	*0.000*	0.148	0.085	*0.000*	*0.000*	*0.000*
Bad News	0.292	0.286	*0.258*	0.080	0.096	*0.000*	*0.000*	*0.000*
Net News	0.098	-0.115	*0.000*	0.068	-0.011	*0.000*	*0.000*	*0.000*
Large IPOs								
Total News	1.154	0.731	*0.000*	0.365	0.261	*0.000*	*0.000*	*0.000*
Net News	0.131	-0.132	*0.000*	0.099	-0.004	*0.000*	*0.001*	*0.000*
Small IPOs								
Total News	0.941	0.528	*0.000*	0.263	0.191	*0.000*	*0.000*	*0.000*
Net News	0.072	-0.089	*0.000*	0.047	-0.020	*0.000*	*0.001*	*0.000*
Tech IPOs								
Total News	1.055	0.683	*0.000*	0.331	0.253	*0.000*	*0.000*	*0.000*
Net News	0.100	-0.114	*0.000*	0.058	-0.025	*0.000*	*0.000*	*0.026*
Non-Tech IPOs								
Total News	1.038	0.593	*0.000*	0.278	0.202	*0.000*	*0.000*	*0.000*
Net News	0.097	-0.118	*0.000*	0.075	0.007	*0.000*	*0.044*	*0.000*
VC Backed IPOs								
Total News	1.282	0.746	*0.000*	0.352	0.263	*0.000*	*0.000*	*0.000*
Net News	0.086	-0.151	*0.000*	0.071	-0.026	*0.000*	*0.092*	*0.000*
Non-VC Backed IPOs								
Total News	0.675	0.427	*0.000*	0.270	0.193	*0.000*	*0.000*	*0.000*
Net News	0.120	-0.030	*0.000*	0.065	0.007	*0.000*	*0.000*	*0.000*
Monthly News Items								
Total News	21.039	14.008	*0.300*	6.002	4.928	*0.000*	*0.000*	*0.000*
Good News	7.980	3.792	*0.000*	2.966	1.830	*0.000*	*0.000*	*0.000*
Bad News	5.808	6.068	*0.000*	1.546	2.021	*0.000*	*0.000*	*0.000*
Net News	2.173	-2.276	*0.000*	1.420	-0.192	*0.000*	*0.000*	*0.000*
Large IPOs								
Total News	23.531	16.357	*0.000*	7.470	5.592	*0.000*	*0.000*	*0.000*
Net News	3.015	-2.618	*0.000*	2.206	0.103	*0.000*	*0.022*	*0.000*
Small IPOs								
Total News	20.079	11.658	*0.000*	5.308	4.254	*0.000*	*0.000*	*0.000*
Net News	1.742	-1.929	*0.000*	1.048	-0.492	*0.000*	*0.002*	*0.000*
Tech IPOs								
Total News	21.446	14.653	*0.000*	6.578	5.426	*0.000*	*0.000*	*0.000*
Net News	2.174	-2.221	*0.000*	1.258	-0.484	*0.000*	*0.000*	*0.000*

Non-Tech IPOs								
Total News	21.178	13.004	*0.000*	5.560	4.351	*0.000*	*0.000*	*0.000*
Net News	2.263	-2.394	*0.000*	1.556	0.187	*0.000*	*0.000*	*0.000*
VC Backed IPOs								
Total News	26.037	16.062	*0.000*	6.952	5.651	*0.000*	*0.000*	*0.000*
Net News	1.949	-3.007	*0.000*	1.532	-0.497	*0.000*	*0.000*	*0.000*
Non-VC Backed IPOs								
Total News	13.911	9.302	*0.000*	5.429	4.139	*0.000*	*0.000*	*0.000*
Net News	2.611	-0.550	*0.000*	1.348	0.171	*0.000*	*0.000*	*0.000*
Panel B: Event Time								
Daily News Items								
Total News	1.102	0.720	*0.000*	0.354	0.208	*0.000*	*0.000*	*0.000*
Good News	0.418	0.216	*0.000*	0.178	0.075	*0.000*	*0.000*	*0.000*
Bad News	0.283	0.292	*0.100*	0.088	0.088	*0.007*	*0.000*	*0.000*
Net News	0.135	-0.076	*0.000*	0.090	-0.014	*0.000*	*0.000*	*0.000*
Large IPOs								
Total News	1.206	0.808	*0.000*	0.406	0.242	*0.000*	*0.000*	*0.000*
Net News	0.180	-0.091	*0.000*	0.121	-0.011	*0.000*	*0.000*	*0.000*
Small IPOs								
Total News	1.024	0.608	*0.000*	0.312	0.173	*0.000*	*0.000*	*0.000*
Net News	0.101	-0.056	*0.000*	0.066	-0.016	*0.000*	*0.000*	*0.000*
Tech IPOs								
Total News	1.168	0.731	*0.000*	0.387	0.227	*0.000*	*0.000*	*0.000*
Net News	0.130	-0.072	*0.000*	0.086	-0.035	*0.000*	*0.000*	*0.000*
Non-Tech IPOs								
Total News	1.045	0.705	*0.000*	0.323	0.187	*0.000*	*0.000*	*0.000*
Net News	0.156	-0.081	*0.000*	0.096	0.009	*0.000*	*0.000*	*0.000*
VC Backed IPOs								
Total News	1.348	0.829	*0.000*	0.393	0.243	*0.000*	*0.000*	*0.000*
Net News	0.125	-0.120	*0.000*	0.098	-0.037	*0.000*	*0.000*	*0.001*
Non-VC Backed IPOs								
Total News	0.681	0.520	*0.000*	0.323	0.176	*0.000*	*0.000*	*0.000*
Net News	0.164	0.007	*0.000*	0.085	0.008	*0.000*	*0.916*	*0.000*
Monthly News Items								
Total News	21.857	15.346	*0.000*	6.922	4.494	*0.000*	*0.000*	*0.000*
Good News	8.251	4.697	*0.000*	3.446	1.690	*0.000*	*0.000*	*0.000*
Bad News	5.655	6.079	*0.114*	1.733	1.829	*0.224*	*0.000*	*0.000*
Net News	2.596	*-1.382*	0.000	1.713	*-0.139*	0.000	*0.000*	*0.000*
Large IPOs								
Total News	23.009	17.974	*0.000*	5.380	7.839	*0.000*	*0.000*	*0.000*
Net News	3.640	-1.715	*0.000*	0.143	2.152	*0.000*	*0.000*	*0.000*
Small IPOs								
Total News	22.007	12.976	*0.000*	6.328	3.827	*0.004*	*0.000*	*0.000*
Net News	2.128	-1.075	*0.000*	1.428	-0.351	*0.000*	*0.000*	*0.018*
Tech IPOs								
Total News	22.915	15.509	*0.000*	7.392	4.984	*0.000*	*0.000*	*0.000*
Net News	2.381	-1.274	*0.000*	1.588	-0.571	*0.000*	*0.160*	*0.000*
Non-Tech IPOs								
Total News	21.200	15.181	*0.000*	6.488	4.029	*0.000*	*0.000*	*0.000*
Net News	3.267	-1.568	*0.000*	1.865	0.302	*0.000*	*0.000*	*0.000*
VC Backed IPOs								
Total News	26.931	17.561	*0.000*	7.557	5.337	*0.000*	*0.000*	*0.000*

Net News	2.406	-2.269	*0.000*	1.821	-0.585	*0.000*	*0.000*	*0.080*
Non-VC Backed IPOs								
Total News	13.282	11.241	*0.000*	6.445	3.770	*0.000*	*0.000*	*0.000*
Net News	3.159	0.316	*0.000*	1.647	0.259	*0.000*	*0.000*	*0.767*

Table 3. The double standard of media coverage

This table reports the difference in media coverage between internet and non-internet sample firms, following a price increase or decrease from previous date. The news item data is hand-collected from Dow Jones Interactive and Factiva for both internet and non-internet sample IPOs. We read and classify them as good, bad or neutral news. Net news is the difference between the number of good news and the number of bad news. RET_{t-1} is the stock return on day t-1 for daily analysis, and month t-1 for monthly analysis. k% = 1% for daily news analysis, and 10% for monthly news analysis. Using abnormal returns instead of raw returns yields virtually identical results and is hence omitted. TN_t and NN_t are the average number of total news and net news (good news – bad news) collected on period t (day or month) per firm conditional on the previous period (t-1) price movement. Nasdaq Market Peak is March 24, 2000, the day when Nasdaq 100 index reaches its highest level during the sample period. Firm Market Cap. Peak is the firm-specific day when a firm achieves the highest market capitalization during the sample period. The last two columns present the p-values based on Satterthwaite standard errors testing the difference in conditional mean number of news between the two samples.

	(1)	(2)	(3)	(4)	(5)	(6)
	Internet IPOs		**Non-Internet IPOs**		***p* value of test for**	
	TN_t	NN_t	TN_t	NN_t	(1)=(3)	(2)=(4)
Panel A: Entire Period (1996-2000)						
Daily News						
$RET_{t-1}>0$	0.928	0.072	0.284	0.045	*0.000*	*0.000*
$RET_{t-1}<0$	0.836	-0.058	0.272	0.013	*0.000*	*0.000*
$RET_{t-1}> k\%$	0.934	0.078	0.288	0.049	*0.000*	*0.000*
$RET_{t-1}< -k\%$	0.838	-0.063	0.273	0.010	*0.000*	*0.000*
Monthly News						
$RET_{t-1}>0$	20.237	0.627	5.618	0.569	*0.000*	*0.783*
$RET_{t-1}<0$	15.904	-0.464	5.334	0.601	*0.000*	*0.000*
$RET_{t-1}> k\%$	21.345	0.714	6.171	0.587	*0.000*	*0.636*
$RET_{t-1}< -k\%$	16.045	-0.665	5.592	0.643	*0.000*	*0.000*
Panel B: Sub-Periods						
Prior to Nasdaq Market Peak (January, 1st, 1996 to March 24, 2000)						
Daily News						
$RET_{t-1}>0$	1.126	0.186	0.325	0.089	*0.000*	*0.000*
$RET_{t-1}<0$	1.006	0.026	0.310	0.050	*0.000*	*0.002*
$RET_{t-1}> k\%$	1.141	0.200	0.334	0.094	*0.000*	*0.000*
$RET_{t-1}< -k\%$	1.015	0.026	0.310	0.047	*0.000*	*0.014*
Monthly News						
$RET_{t-1}>0$	23.364	2.028	6.030	1.307	*0.000*	*0.014*
$RET_{t-1}<0$	19.017	2.298	5.978	1.513	*0.000*	*0.002*
$RET_{t-1}> k\%$	24.364	2.049	6.740	1.365	*0.000*	*0.047*
$RET_{t-1}< -k\%$	20.029	2.424	6.563	1.676	*0.000*	*0.019*
Post Nasdaq Market Peak (March 24, 2000 to December 31st, 2000)						
Daily News						
$RET_{t-1}>0$	0.681	-0.071	0.240	-0.001	*0.000*	*0.000*
$RET_{t-1}<0$	0.659	-0.146	0.237	-0.022	*0.000*	*0.000*
$RET_{t-1}> k\%$	0.683	-0.072	0.240	0.003	*0.000*	*0.000*
$RET_{t-1}< -k\%$	0.663	-0.151	0.240	-0.022	*0.000*	*0.000*
Monthly News						
$RET_{t-1}>0$	15.034	-1.703	5.130	-0.304	*0.000*	*0.000*
$RET_{t-1}<0$	13.614	-2.496	4.818	-0.130	*0.000*	*0.000*
$RET_{t-1}> k\%$	16.107	-1.602	5.550	-0.262	*0.000*	*0.000*
$RET_{t-1}< -k\%$	13.470	-2.662	4.929	-0.063	*0.000*	*0.000*

Panel C: Sub-Periods

Prior to Firm Market Cap. Peak						
Daily News						
RET_{t-1}>0	1.183	0.217	0.364	0.108	*0.000*	*0.000*
RET_{t-1}<0	1.077	0.057	0.364	0.074	*0.000*	*0.093*
RET_{t-1}> k%	1.201	0.234	0.378	0.116	*0.000*	*0.000*
RET_{t-1}< -k%	1.093	0.061	0.375	0.075	*0.000*	*0.198*
Monthly News						
RET_{t-1}>0	25.159	2.229	6.640	1.342	*0.000*	*0.014*
RET_{t-1}<0	18.668	2.949	7.191	2.066	*0.000*	*0.003*
RET_{t-1}> k%	26.162	2.322	7.230	1.223	*0.000*	*0.008*
RET_{t-1}< -k%	19.437	3.073	7.781	2.298	*0.000*	*0.035*
Post Firm Market Cap. Peak						
Daily News						
RET_{t-1}>0	0.765	-0.021	0.219	-0.006	*0.000*	*0.029*
RET_{t-1}<0	0.725	-0.111	0.216	-0.024	*0.000*	*0.000*
RET_{t-1}> k%	0.766	-0.021	0.218	-0.004	*0.000*	*0.019*
RET_{t-1}< -k%	0.726	-0.117	0.215	-0.026	*0.000*	*0.000*
Monthly News						
RET_{t-1}>0	16.364	-0.633	4.692	-0.132	*0.000*	*0.040*
RET_{t-1}<0	14.886	-1.721	4.390	-0.143	*0.000*	*0.000*
RET_{t-1}> k%	17.138	-0.690	5.156	-0.023	*0.000*	*0.029*
RET_{t-1}< -k%	14.915	-1.910	4.561	-0.138	*0.000*	*0.000*

Table 4. The effects of media coverage on returns

The news item data is hand-collected from Dow Jones Interactive and Factiva for both internet and non-internet IPO samples. We read and classify them as good, bad or neutral news. Net news is the difference between the number of good news and the number of bad news. The dependent variable in this regression is the daily abnormal return from fitting a Fama-French 3-factor model for each firm for the combined sample firms. GN_{t-1}, BN_{t-1}, NN_{t-1} and TN_{t-1} are the number of good news, bad news, net news, and total news *per firm* at day *t*-1. We then difference news variables GN_{t-1}, BN_{t-1} and NN_{t-1} to remove firm fixed effect. *PostPeak* is a dummy variable equal to 1 if it is after March 24, 2000, and 0 otherwise. $ABRET_{t-1}$ is the abnormal return at day *t*-1. *p*-values based on Newey-West standard errors are reported in parentheses. ***, **, * = significant at 1%, 5% and 10% (two-sided), respectively.

Daily Abnormal Returns	**Internet IPOs**	**Non-Internet IPOs**	**Internet IPOs**	**Non-Internet IPOs**	**Difference in coefficients between Internet and Non-Internet IPOs**	
	(1)	(2)	(3)	(4)	*pre-peak*	*post-peak*
Intercept	-0.234***	-0.074***	-0.227***	-0.066***		
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*		
Variables of Interests						
GN_{t-1}	0.070***	0.191***			-0.121**	0.060
	(0.00)	*(0.00)*			*(0.04)*	*(0.40)*
$GN_{t-1}\times PostPeak$	0.156***	-0.024				
	(0.00)	*(0.75)*				
BN_{t-1}	-0.106***	-0.288***			0.181***	0.250***
	(0.00)	*(0.00)*			*(0.00)*	*(0.00)*
$BN_{t-1}\times PostPeak$	-0.110*	-0.179**				
	(0.06)	*(0.04)*				
NN_{t-1}			0.073***	0.204***	-0.131***	-0.093*
			(0.00)	*(0.00)*	*(0.01)*	*(0.10)*
$NN_{t-1}\times PostPeak$			0.147***	0.110*		
			(0.00)	*(0.10)*		
Control Variables						
$log(1+TN_{t-1})$	0.899***	0.897***	0.811***	0.843***		
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*		
$log(1+ TN_{t-1})\times PostPeak$	-0.759***	-0.872***	-0.700***	-0.839***		
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*		
PostPeak	0.042	-0.004	-0.034	-0.009		
	(0.36)	*(0.92)*	*(0.49)*	*(0.83)*		
$ABRET_{t-1}$	0.037***	-0.022***	0.029***	-0.009		
	(0.00)	*(0.01)*	*(0.00)*	*(0.38)*		
$ABRET_{t-1}\times PostPeak$	-0.106***	-0.023**	-0.099***	-0.036***		
	(0.00)	*(0.03)*	*(0.00)*	*(0.00)*		
R-squared	0.007	0.004	0.006	0.003		
Number of observations	157,000	139,000	157,000	139,000		

Table 5. Portfolio analysis

This table reports portfolio analyses based on the internet sample and the non-internet sample. The dependent variable is the daily internet (non-internet) portfolio return constructed both equally-weighted (EW) and value-weighted (VW). GN_{t-1}, BN_{t-1}, NN_{t-1} and TN_{t-1} are the average number of good news, bad news, net news, and total news per firm in the portfolio at day t-1. *PostPeak* is a dummy variable equal to 1 if it is after March 24, 2000, and 0 otherwise. $ABRET_{t-1}$ is the abnormal portfolio return at day t-1. p-values based on Newey-West standard errors are reported in parentheses. ***, **, * = significant at 1%, 5% and 10% (two-sided), respectively.

	Internet IPOs				**Non-Internet IPOs**				**Difference in coefficients between Internet and Non-Internet IPOs**			
									Pre-Peak		*Post-Peak*	
Daily Abnormal Portfolio Returns	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Intercept	-0.109	-0.262	-0.107	-0.258	-0.089	-0.202***	-0.060	-0.222***				
	(0.44)	*(0.11)*	*(0.45)*	*(0.11)*	*(0.24)*	*(0.01)*	*(0.45)*	*(0.01)*				
Variables of Interests												
GN_{t-1}	-0.023	-0.502			0.813*	0.005			-0.836	-0.506	9.546***	8.140***
	(0.95)	*(0.30)*			*(0.06)*	*(0.99)*			*(0.14)*	*(0.46)*	*(0.00)*	*(0.01)*
$GN_{t-1}\times PostPeak$	6.617***	6.697***			-3.765*	-1.949						
	(0.00)	*(0.00)*			*(0.08)*	*(0.44)*						
BN_{t-1}	-0.626	-0.560			-0.246	-0.384			-0.379	-0.176	3.876	3.202
	(0.22)	*(0.42)*			*(0.46)*	*(0.17)*			*(0.53)*	*(0.81)*	*(0.20)*	*(0.36)*
$BN_{t-1}\times PostPeak$	-1.927	-2.319			-6.182**	-5.698**						
	(0.24)	*(0.28)*			*(0.02)*	*(0.05)*						
NN_{t-1}			0.141	-0.230			0.513*	0.206	-0.371	-0.436	3.601*	3.173
			(0.68)	*(0.61)*			*(0.09)*	*(0.50)*	*(0.42)*	*(0.43)*	*(0.07)*	*(0.22)*
$NN_{t-1}\times PostPeak$			4.310***	4.688***			0.338	1.080				
			(0.00)	*(0.01)*			*(0.82)*	*(0.60)*				
Control Variables												
$log(1+TN_{t-1})$	0.578	1.006**	0.285	0.527*	0.113	0.936**	0.237	0.853**				
	(0.11)	*(0.02)*	*(0.24)*	*(0.07)*	*(0.79)*	*(0.02)*	*(0.53)*	*(0.02)*				

log(1+ TN_{t-1})×PostPeak	-3.491**	-3.829**	-1.875	-2.272	1.601	0.077	-1.225	-2.146
	(0.03)	*(0.03)*	*(0.16)*	*(0.14)*	*(0.37)*	*(0.97)*	*(0.39)*	*(0.16)*
PostPeak	0.729	1.393	0.984	1.606*	0.567*	0.929***	0.222	0.676**
	(0.29)	*(0.11)*	*(0.17)*	*(0.06)*	*(0.08)*	*(0.01)*	*(0.50)*	*(0.05)*
$ABRET_{t-1}$	0.209***	0.161***	0.210***	0.162***	-0.059	0.025	-0.057	0.024
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.15)*	*(0.46)*	*(0.16)*	*(0.5)*
$ABRET_{t-1}$×PostPeak	-0.212**	-0.260***	-0.209**	-0.265***	0.362***	0.051	0.364***	0.059
	(0.03)	*(0.01)*	*(0.03)*	*(0.01)*	*(0.00)*	*(0.55)*	*(0.00)*	*(0.51)*
R-squared	0.063	0.036	0.060	0.033	0.033	0.021	0.023	0.016
Number of observations	1,254	1,255	1,256	1,257	1,226	1,226	1,227	1,228

Table 6. Agreement in news classification
Seven undergraduates read and classified one hundred news items into good, bad, or neutral news. Four undergraduates (U1-U4) read one hundred pieces of news from Sapient, Inc., a control firm; three undergraduates (U5-U7) read one hundred pieces of news from Yahoo!, an internet firm. This table shows the pairwise incidence of agreement between individuals; that is, the percent of one hundred news items to which two individuals both assign a value of good, bad, or neutral.

	Panel A: Sapient					Panel B: Yahoo!			
	Author 2	U1	U2	U3	U4	Author 2	U5	U6	U7
Author 1	71.00%	84.00%	71.00%	53.00%	70.00%	65.00%	44.00%	56.00%	71.00%
Author 2		71.00%	60.00%	48.00%	77.00%		36.00%	38.00%	52.00%
U1			67.00%	55.00%	72.00%				
U2				48.00%	70.00%				
U3					52.00%				
U4									
U5								55.00%	50.00%
U6									55.00%