Driving the Presence of Investor Sentiment: the Role of Media Tone in IPOs

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Abstract

This paper examines whether the media can drive the presence of investor sentiment around the IPO event through the tone channel. Using word frequency analysis to define whether one newspapers article is positive or negative and measuring media tone as the number of positive in excess of negative newspapers articles in the pre-IPO period, we find robust evidence that media tone is positively related to IPO first-day returns while negatively related to long-run abnormal returns for a sample of Chinese book-built IPOs over the 2005-2012 period. One positive newspapers article can predict not only an increase of up to 6.95 percentage points in first-day returns but also a decrease of 10.93 percentage points in three-year abnormal returns. Further analysis suggests that media tone tends to increase first-day retail trading and attracts more retail investors to subscribe new shares in the primary market. Taken together, these findings are consistent with our hypothesis that media tone drives retail demand for IPOs, leading to a temporary deviation from fundamentals in post-IPO prices.

JEL Classification: G32
Keywords: IPO, Media Tone, Investor Sentiment, China

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Abstract

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I. Introduction

The role of investor sentiment in post-IPO prices is well studied. Theoretically, Derrien (2005), Ljungqvist et al. (2006), and Cornelli et al. (2006) show that issuers/underwriters can take advantage of sentiment investors, retail investors or small investors, when pricing new issues, which generates high first-day returns and abnormally low returns in the long run. Empirically, using "grey" market prices available to a unique sample in European countries to measure the presence of investment sentiment in the pre-IPO market, Cornelli et al. (2005) find consistent evidence that high grey market prices indicating over-optimism are a good predictor of first-day aftermarket prices and price reversals in the long run, while low grey market prices indicating excessive pessimism are not. Using actual when-issued trades for German IPOs during 1999 and 2000, Dorn (2009) also find consistent evidence that the volume of grey market trading across customers of a German retail brokerage is positively related to first-day returns while negatively related to the long-run stock performance.

However, estimating the impact of investor sentiment on post-IPOs is empirically challenging. Part of the reason is that the relationship between first-day returns and measures for the presence of investor sentiment will be underestimated when information on investor sentiment revealed in the book-building process can be used to price IPOs. The theoretical literature has identified two distinct channels through which information, including the information on the presence of investor sentiment, can influence the offer price. To the extent that the presence of investor sentiment is private information, Benveniste and Spindt (1989) show that useful private information revealed in the book building process should be used partly to price IPOs thus new issues should be underpriced. To the extent that the presence of investor sentiment is public information, for example, information that can be inferred from trading in the grey market as documented by Aussenegg et al. (2006), Derrien (2005) show that a profit-maximizing underwriter who takes account of underwriting revenues and costly price support in the aftermarket should choose an optimal IPO price which only partially incorporates public information on the presence of investor sentiment. Either case, the offer price is affected by the presence of investor sentiment and the impact of investor sentiment will be cancelled out at first-day returns thus it is difficult to identify a positive (negative) relationship between first-day returns (long-term abnormal returns) and investor sentiment.

In this article, we use a sample of Chinese book-built IPOs issued over the 2005-2014 period to overcome this empirical difficulty. Note that the book-building practice in developed markets, such as the US, German and France, usually allows underwriters to allocated oversubscribed shares at their discretion so institutional investor are well motivated to reveal their useful information in exchange of more allocation for underpriced shares. However, underwriters are not allowed to do so in China. Instead, oversubscribed shares will be allocated pro rata among institutional investors. Since no compensation exists for revealing information, it is not surprising that little private information, including information on the presence of investor sentiment, can be gathered and incorporated into the offer price. The unique institutional arrangement enables us to quantify the impact of investor sentiment on post-IPO prices more accurately.

The other reason that we use Chinese IPO sample is because we can explore a new channel through which media influence the presence of investor sentiment. We argue that the media can influence the presence of investor sentiment through both the attention channel and the tone channel. The former has been well studied in the US and elsewhere, including Cook et al. (2006), Liu et al. (2009), Huang and Chen (2013), and Liu et al. (2014), while the latter has not since US media are prohibited from containing any hard information which is previously unknown in the IPO prospectus due to the IPO quiet-period restriction. Indeed, according to Cook et al. (2006), over 99% of news articles under their study are non-negative and primarily descriptive stories. Fortunately, this barrier does not exist in China thus Chinese media can report relevant information and express their optimism and pessimism in their newspapers articles. Our preliminary analysis reveals that there are significant variations in media slant - less than 5% of pre-IPO media coverage is neutral, which is rather different from the case in the US, and the remaining newspapers articles are positive and optimistic most of time, though they can go negative and pessimistic in some occasions. This test setting in China thus provides a unique chance for us to examine whether media can influence the presence of investor sentiment, even after controlling for the attention channel that we have already known.

We hypothesize that there is a positive relationship between pre-IPO media tone and first-day returns, while there is a negative relationship between pre-IPO media tone and long-term stock performance. Previous studies report evidence that there is an established link between post-IPO prices and the presence of investor sentiment, including Miller (1977), Derrien (2005), Ljungqvist et al. (2006), Cornelli et al. (2006). Miller (1977) theoretically demonstrates that short-term equilibrium prices following IPOs can be upward biased, due to uncertainty in investor expectation about the firm and short sale constraints. Using a model where the post-IPO price depends on its intrinsic value and investor sentiment, Derrien (2005) shows that IPOs can be overvalued while still exhibit positive initial returns. Ljungqvist et al. (2006) theoretically analyze the optimal choice of an IPO firm in response to the presence of investor sentiment. Their central prediction is that while IPO stocks can be overvalued by taking advantage of sentiment investors, they must be underpriced on average in order to compensate regular investors for taking on the risk that they might not be able to sell their allocated shares to sentiment investors before sentiment demands disappear. Using prices from grey markets to proxy for small investors' overvaluation, Cornelli et al. (2006) find consistent evidence that high grey market prices which indicates their overoptimism is a good predictor of first-day aftermarket prices and subsequent reversals. To the extent that media tone can drive the presence of investor sentiment leading to abnormally high first-day closing prices, we expect a positive relationship between first-day returns and media tone in the pre-IPO period. We also expect a negative relationship between long-term abnormal returns media tone in the pre-IPO period, since initial overvaluation due to the media tends to reverse in a longer period of time.

We manually collect all newspapers articles three months before the offer date of an IPO and between the offering and listing dates. We count the number of newspapers articles over these two periods where the name or the stock ID of a particular IPO firm is mentioned. We use word frequency which is widely used in the contextual analysis to identify the tone of relevant newspapers articles for our baseline analysis. Specifically, we define a newspapers article to be positive (negative) if there are a larger number of positive (negative) than negative (positive) words. Newspapers articles that do not include any positive or negative words or have the same amount of positive and negative words are defined as neutral ones. We define media tone as the number of positive in excess of negative newspapers articles.

Using 1,126 Chinese book-built IPOs issued over the 2005-2012 period, we find evidence consistent with our media tone hypothesis. There is indeed a positive relationship between first-day returns and media tone, even after controlling for the number of newspapers articles. One positive newspapers article can lead to an increase of up to 6.95 percentage points in first-day returns, which is economically significant given the average first-day return is 60.2%. We also find that there is a negative relationship between long-term performance, measured as buy-and-hold abnormal returns (BHARs) over 36 event months using IPO firms and their otherwise comparable non-IPO firms, and media tone, even after controlling for the number of newspapers article over the same period. One positive newspapers article can predict a decrease of 8.87%-10.93% in BHARs, which is economically significant given the average BHAR is -14.50%. We obtain qualitatively similar results when we use Jensen's alpha estimated from the Fama-French three-factor regression over the 36 post-IPO calendar months as alternative measure for long-run abnormal returns. Taken together, these findings suggest that media-expressed tone can drive the presence of retail investors around the IPO event, leading to high first-day returns and low post-IPO abnormal returns in the long run.

To strengthen our claim that pre-IPO media tone can attract retail demands around the IPO event, we perform a number of additional tests. First, we examine whether media tone can affect retail trading on the first day of trading. Previous studies suggest that retail demands drive post-IPO prices, including Ofek and Richardson (2003), Cornelli et al., (2006), and Dorn (2009), and that investors tend to buy attention-grabbing stocks including stocks in the news, including Barber and Odean (2008) and Tetlock (2007). Consistent with our claim, we find robust evidence that there is a positive relationship between retail trading and media tone. One more positive newspapers articles can lead to an increase of 8.5%-10.1% in the proportion of retail trading on the first day of public trading, which is economically meaningful. This finding indicates that retail investors tend to overpay by a greater extent for IPO stocks that are more positively covered by the news media. Second, we examine whether media tone can affect investor participation in the IPO market. If the media can influence the buying decision of retail investors, we should observe a greater number of retail investors not only in the secondary market but also in the primary market. We use the rate of allocation in oversubscribed new issues among retail investors to measure the participation from retail investors. A low value of allocation rate indicates a strong demand from retail investors. We find that there is a negative relationship between the rate of allocation and media tone, indicating that media tone does indeed attract more retail investors to subscribe to new issues in the IPO market. Third, we examine whether the endogeneity problem associated with media tone can drive our results. This concern is possible since IPO firms can pay the media for positive newspapers articles to induce the presence of retail investors. A positive mean value of media tone on average also suggests that media tone is not a random variable. To alleviate the potential endogeneity concern associated with media tone, we use the number of negative newspapers articles instead to repeat our regression analysis because IPO firms are unlikely to pay the media for providing negative newspapers articles. We find that our regression results are robust to this alternative variable specification.

Our study contributes to the literature which focuses on the role of investor sentiment in the pricing of new issues, including Miller (1977), Derrien (2005), Ljungqvist et al. (2006), Cornelli et al. (2006) and Dorn (2009), in two important ways. First, most studies make one important assumption that the presence of investor sentiment is random thus unpredictable. For example, Derrien (2005) explicitly assumes that the intensity of noise traders' bullishness at the first-day of trading is a random variable uniformly distributed on a given range. Ljungqvist et al. (2006) make an explicit assumption that the probability of the hot market characterized by the presence of optimistic investors ending in the subsequent period is exogenously determined. In sharp contrast to theoretical analysis, evidence reported in several contemporaneous studies do not lend support to this assumption. For example, using the number of news headlines to proxy for marketing efforts by underwriters, Cook et al. (2006) find a positive link between the offer price revision and the presence of firms in the news media, and a positive link between underwriter compensation and underwriter's ability to market an IPO to sentiment investors. Using abnormal Google Search Volume Index to proxy for investor attention to the new issues, Da et al. (2011) report evidence that first-day returns tend to increase with investor attention. These empirical findings suggest that at least to some extent underwriters can influence the presence of investor sentiment.

We complement this literature by documenting a significant power of media in driving the presence of investor sentiment. Contrary to the exogenous nature of investor sentiment as assumed in prior studies, we identify a new channel through which the media can influence the presence of investor sentiment and post-IPO prices.

Second, we document an important role of the media in driving retail demands for IPOs through not only the number of newspapers articles but also the tone of these newspapers articles. Liu et al. (2009) report a positive relationship between the number of news items and IPO underpricing for a sample of 3,637 US IPOs between the 1980-2004 period. They also find evidence that price revisions tend to increase with the number of news items. Following Liu et al. (2009), Huang and Chen (2013) find a positive relationship between the number of newspapers articles and IPO underpricing for a sample of 86 Chinese IPOs. More recently, Bajo and Raimondo (2014) examine the relationship between media sentiment and the pricing of IPOs. Their results, based on 3,061 US IPOs issued over the 1995-2013 period, show that New York Times coverage positively influences both IPO underpricing and price revisions. Our study not only confirms that there is a positive relationship between the number of media counts and first-day returns, an empirical finding consistently documented in prior research, but also provides additional evidence that the number of newspapers articles can predict low long-run abnormal returns, an empirical finding central to a behavioral explanation for post-IPO prices, and that the tone expressed in these newspapers articles can predict high IPO first-day returns and low long-term performance, even after controlling for the number of newspapers articles. To the best of our knowledge, none of previous studies provide consistent evidence on the negative relationship between media and post-IPO long-term performance.

The rest of this article is organized as follows. Section II provides a brief description of institutional background and develops our empirical hypothesis. Section III describes our data, sample and variables of interest. Section IV presents main results and Section V concludes.

II. Institutional Background and Hypothesis Development

Prior studies document that new shares of Chinese IPOs are priced in a way fundamentally different from

IPOs elsewhere, including Su and Fleisher (1999), Chan et al. (2004), Shen et al. (2013). The sample IPOs used in these studies are drawn from those issued in years before 2005, subject to different pricing mechanisms, thus empirically it can be rather difficult to separate the impact of different IPO pricing approaches from that of other explanations on post-IPO performance. We focus on IPOs over the 2005-2012 period primarily to rule out the potential impact of institutional arrangements across years on first-day returns and long-term stock performance, because they are priced following the same approach and new shares are allocated among institutional (retail) investors using the same method. This section provides a brief description of institutional features relevant to our empirical hypothesis.

1. The Pricing Mechanism

Since 2005, Chinese IPOs are done following a double tranche book-building approach. While the offline tranche is restricted only for institutional investors to subscribe for new shares, the online tranche is open for retail investors to subscribe. When a firm makes an announcement of its public listing, several important dates will be determined therein. The underwriter will invite subscription orders from institutional investors over a certain period of time, typically one working day. Institutional investors can submit multiple subscription orders, which carry information on the quantity to purchase and the price at which they are willing to pay. Towards the end of the day, the underwriter will collect subscription information and decide on the offer price for this particular IPO. This IPO price obtained from the offline tranche will then be used as the fixed price at which retail investors subscribe for new shares of IPO stocks in the following online tranche. In contrast to the offline tranche which allows multiple subscriptions, retail investors are only permitted to submit one subscription order from their registered stock accounts. Further subscription orders placed by the same account will be deemed invalid and no shares will be given thereafter.

2. The Allocation Mechanism

Two different tranches have their own arrangements to allocate new shares when they are oversubscribed. For the offline tranche, new shares will be allocated among institutional investors on a pro rata basis. No matter how much large of their subscription orders, each successful institutional investor will receive the same proportion of new shares allocated relative to new shares subscribed. For the online tranche, new shares will be allocated among retail investors on a pure lottery basis. Retail investors are required to submit their subscription orders in a unit of 1,000 shares or its multiple. Each subscription unit of 1,000 shares will be given a unique lottery number to decide whether this particular unit of subscription is successful or not. The rate of allocation among retail investors is defined as the number of new shares available to retail investors divided by the number of new shares subscribed by retail investors in the online tranche. Information on allocation in two tranches will be released as soon as they become available. We use allocation rates in the offline tranche to measure participation by institutional investors while allocation rates in the online tranche to measure participation by retail investors.

3. Empirical Hypothesis

Previous studies has demonstrated both theoretically and empirically that there is a negative relationship between investor recognition and stock returns. Building upon the behavioral assumption that investors can only buy securities that they know about to construct their optimal portfolio, Merton (1987) theoretically show that stock returns must be higher for those stocks that few investors know about. If few investors know about a particular stock, these investors can only construct and hold a suboptimally diversified portfolio taking on more idiosyncratic risks which will be priced in equilibrium. Subsequent empirical studies such as Lehavy and Sloan (2008), Bodnaruk and Ostberg (2009), and Fang and Peress (2009) provide consistent evidence that returns are negatively related to the number of investors who know about a particular stock. Indeed, Barber and Odean (2008) provide direct evidence that individual investors are more like to buy those attention-grabbing stocks, in other words stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns.

We argue that the media can influence investor recognition through two different channels: the attention channel and the tone channel. As to the first channel, other things being equal, a larger number of newspapers articles that appear in popular media outlets will enhance investor recognition by increasing the chance that retail investors know about a particular IPO stock. Thus the attention-based explanation should predict that there is a negative relationship between the number of newspapers articles and post-IPO abnormal returns in the long run. As for the tone channel which is more of a behavioral explanation, a larger number of positive (negative) newspapers articles can influence the judgement of retail investors, leading them to become more (less) over-optimistic about the future of a particular IPO stock, thus there will be a larger (smaller) number of retail investors who subscribe to new issues in the IPO market and buy shares of new issues on the first day of trading. This implies that there is a positive relationship between first-day returns and media tone, since media tone attracts the presence of retail investors who are irrational in general. This also implies that there is a negative relationship between long-run stock performance and media tone since high first-day closing prices driven by investor irrationality tend to reverse in the long run.

Hypothesis 1 (short-term): First-day returns tend to increase with pre-IPO media tone;

Hypothesis 2 (long-term): Long-term abnormal return tends to decrease with pre-IPO media tone.

III. Data, Sample and Variables

1. Data and Sample

We obtain our IPO sample from CSMAR and WIND. We start with a sample of IPO firms issued during the period between January 2005 and December 2012. We do not include IPOs issued before this period because it is not until the year of 2005 are Chinese IPOs priced using the book-building approach. We exclude IPOs after this period because we need a three-year window to calculate the long-term stock performance post IPOs. Following the literature, we do not include IPO firms that operate in the financial industry. We end up with 1,126 Chinese A-share book-built IPOs over this period. For these IPOs, we retrieve offer characteristics and firm characteristics from CSMAR, WIND and CVSource, including firm age, issue size, leverage, underwriter information, auditor information, VC backing, and rate of allocation among retail investors. We also retrieve daily price data and high frequency data from the CSMAR and WIND.

Our media data are drawn from the CNKI Archive of National Newspapers. CNKI is the China National Knowledge Infrastructure, a key project of national information construction dedicated to the mass digitalization of China Knowledge Resources. With supported from the Ministry of Education, the Ministry of Science and Technology, the Ministry of Publicity, and the General Administration of Press and Publications, the CNKI project was launched in June 1999 by Tsinghua University and Tsinghua Tongfang Holding Group. According to its introduction, the CNKI Archive of National Newspapers provides online access to a wide range of newspaper articles from more than 500 national news media dating back to the year of 2000. The total number of newspapers articles included in the archive has reached 7,950,000 by 2010. Previous studies, such as You and Wu (2012) and You et al. (2014), use the most influential eight newspapers in mainland China to construct their measures of media coverage.

2. Main Variables

2.1 First-day Return and Long-term Performance

We follow the literature and define first-day return as the percentage difference between the offer price and the first-day closing price:

$$IR_j = \left[\frac{P_{j,1} - P_{j,0}}{P_{j,0}}\right] \times 100\% \quad (1)$$

where $P_{j,1}$ is the first-day closing price and $P_{j,0}$ is the offer price.

Following Lyon et al. (1999), we consider both the event-time BHAR and the calendar-time abnormal return estimated using factor regressions to measure long-term IPO performance. First, we estimate the event-time BHAR as the difference between the buy-and-hold return for IPO firms over the 36 post-IPO event months and the buy-and-hold return for otherwise comparable non-IPO firms over the same period:

$$BHAR_j = \prod_{t=1}^{n}\left(1 + r_{j,t}^{IPO}\right) - \prod_{t=1}^{n}\left(1 + r_{j,t}^{non-IPO}\right) \quad (2)$$

where $r_{j,t}^{IPO}$ and $r_{j,t}^{non-IPO}$ are the returns for IPO firm j and for its matching non-IPO firm on day t respectively. Following Chan et al. (2004) and Shen et al. (2013), we select non-IPO matching firms based on size and B/M characteristics, and use both tradable and non-tradable shares to calculate market capitalization and B/M ratio[2]. We require that these matching non-IPO firms should have a trading record of at least 2 years in the stock market. Second, we use Jensen's alpha estimated from the Fama and French three-factor model as an alternative measure of long-run stock performance. Specifically, we regress the monthly returns in excess of the risk-free rate for IPO firms in their 36 calendar months on three monthly risk factors. We define the intercept estimated from time-series regressions as the monthly abnormal return after adjusting for risk compensation:

$$r_{j,\tau} - r_{f,\tau} = \alpha + b \cdot \left(r_{m,\tau} - r_{f,\tau} \right) + s \cdot SMB_{\tau} + h \cdot HML_{\tau} + \varepsilon \tag{3}$$

where $r_{j,\tau}$, $r_{m,\tau}$ and $r_{f,\tau}$ are the returns to the IPO firm *j*, to the market portfolio *m*, and to the risk-free assets *f*, respectively, in the calendar month τ; $\left(r_{m,\tau} - r_{f,\tau} \right)$ is the monthly market risk factor; *SMB* and *HML* are the other two monthly factors constructed in a way similar to Fama and French (1993).

2.2 Media Tone and Media Count

In this article, we use both the counts and the tone of newspapers articles contained in 46 financial newspapers in the archive to construct our media-based variables. There are about 240,000 newspapers articles over the 2005-2012 period. First, we first relevant newspapers articles for each IPO firm. Specifically, we search among newspapers articles over the three-month period before its offer date for those that have its firm name or stock ID in the headline or body of an article. We also search among newspapers articles over the period between its offer date and the first-trading date for those that have its firm name and stock ID in the headline or body of an article. We exclude those newspapers articles if they are listing announcements or IPO prospectus. This initial screening procedure yields 4,818 relevant newspapers articles.

Second, using these newspapers articles, we construct our four media-based variables to measure the quantity and the tone of media news. Specifically, following Fang and Peress (2009) and Liu et al. (2014), we define *MediaCount* as the number of newspapers articles over the 3-month period before the offer date that are related to each IPO stock. We use word frequency to analyze the content of these

[2] Regression results are similar when we use tradable shares only to calculate market capitalization and B/M.

newspapers articles and classify them into three groups based on their tone: positive, neutral or negative. More specifically, we use a pre-defined word list to count the number of positive and negative words in each newspapers article. Our word list is based on the dictionary prepared by Loughran and McDonald (2011) and Loughran and McDonald (2013). We translate the original dictionary from English to Chinese and also supplement the word list with a number of positive and negative words which are widely used in China. The modified word list includes 181 positive words and 308 negative words. We define positive (negative) newspapers articles as those that include a larger number of positive (negative) than negative (positive) words. Newspapers articles that do not include any positive or negative words, or they include the same amount of positive and negative words are defined as neutral ones. Based on this objective judgement, we count the number of positive, neutral, and negative newspapers articles for each IPO stock respectively, and define *MediaTone* as the difference between the number of positive newspapers articles and the number of negative newspapers articles.

Third, to the extent that the information on newspapers articles before the offer date can be incorporated into the offer price as public information which undermines the power of our tests, we define *MediaCount2* as the number of newspapers articles for each IPO for the period between its offer date and its first trading date, and *MediaTone2* as the number of positive in excess of negative newspapers articles over the same period.

2.3 Control Variables

We include a wide range of deal, firm and market characteristics to control for other explanations in our multivariate analysis. Previous studies report evidence that these variables are found to be associated with either first-day returns or long-term abnormal returns, or both, including Chan et al. (2004), Fan et al. (2007), Kao et al. (2009), Gao (2010), Tian (2011), Shen et al. (2013), Chen et al. (2015). Specifically, we include *ROA*, net incomes over total assets in the pre-IPO year; *Leverage*, the leverage ratio estimated as total liabilities over total assets prior to listing; *Profitability*, the percentage difference between the offering P/E and the industry P/E; *IssueSize*, measured as the offer price multiplied by the number of new shares offered; *Assets*, the number of total assets in the pre-IPO year; *Underwriter*, a dummy equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters at least two times over the past three years, and 0 otherwise; *Big4*, a dummy equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed*, a dummy equal to 1 if the firm has been supported by venture capital; *State*, the proportional of state holdings in the firm; *Tradable*, the proportion of tradable shares at the time of IPO; *Age*, the firm age since establishment; *TimeLag*, the time elapsed between offering and listing; *Analysts_std*, the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias*, defined as the average difference between median EPS of analyst forecast and the realized EPS; *HighTech*, a dummy variable for new issues from high-tech industries; *MktSent1*, defined as the number of IPOs in the same calendar month; *MktSent2*, defined as the average first-day return in the same calendar month; *MktSent3*, defined as the market return in the same calendar month.

IV. Main Results

1. Descriptive Statistics

Table 1 provides descriptive statistics for main variables used in this study.

***** Insert Table 1 around here *****

Inspection of Table 1 has some interesting observations. First, while the average first-day return for these 1,126 book-built IPOs is as high as 60.2%, the average post-IPO abnormal return, measured as *BHAR* in the three subsequent years, is as low as -14.5%, or -1.6% measured on a monthly basis using calendar-time factor regressions. This pattern of high first-day returns followed by low long-run abnormal returns is consistent with previous findings in China and other countries. Second, four media-based measures seem to have considerable variations across firms. The average number of times that a typical IPO firms is mentioned in the newspapers articles over the three-month period before the offer date is 2.69. This number is 1.589 for the period between the offer date and the first trading date. Note that in some extreme cases, the name of an IPO firm can appear in the media very frequently, 24 times in the former period and 13 times in the latter period, respectively, as demonstrated in the table. Media tone also varies dramatically over these two different pre-IPO periods. Media tone can range from -4 to 11 for the three-month pre-IPO period, while this number can range also widely from -4 to 10 over a much shorter period prior to the listing, typically two weeks given that the average time lag between offering and listing is 12 days. Third, we find that it is very difficult to obtain an allocation as retail investors. The average rate of allocation for retail investors is 1.056%, indicating a very strong retail demand for IPOs throughout our sample period. Forth, this table also provides summary statistics for other variables. One might find that it usually takes 7.6 years for these sample firms to go public. They are usually profitable before going public because they have a positive *ROA* on average. They are underpriced on average since the mean value of *Profitability* is -0.184, implying that the offer price is generally lower than the intrinsic value. Tradable shares account for about 20% of total number of shares outstanding.

2. Media Tone, First-day Returns and Long-term Performance

To examine whether media tone can account for IPO anomalies in the short and long run, we estimate the following two regression specifications:

$$IR = \beta_0 + \beta_1 \cdot Media\text{Tone} + \beta_2 \cdot Media\text{Tone2} + \beta_3 \cdot Media\text{Count} + \beta_4 \cdot Media\text{Count2} + \beta_5 \cdot X + \varepsilon \tag{5}$$

$$BHAR = \beta_0 + \beta_1 \cdot Media\text{Tone} + \beta_2 \cdot Media\text{Tone2} + \beta_3 \cdot Media\text{Count} + \beta_4 \cdot Media\text{Count2} + \beta_5 \cdot X + \varepsilon \tag{6}$$

where *IR* is the first-day return defined as the percentage difference between the first-day closing price and the offer price; *BHAR* is the buy-and-hold abnormal return defined as the buy-and-hold returns for IPO stocks over three post-IPO years in excess of the buy-and-hold returns for otherwise comparable non-IPO stocks over the same period; *MediaTone* is the tone of the media, defined as the number of positive newspapers articles in excess of the number of negative newspapers articles over the 3-month period before the offer date; *MediaTone2* is the number of positive newspapers articles in excess of the number of negative newspapers articles over the period between offering and listing; *MediaCount* is the number of newspapers articles that appear in the 46 national business media over the 3-month period before the offer date; *MediaCount2* is the number of newspapers articles that appear in the 46 national business media over the period between offering and listing; *X* is a vector of control variables which are found to be associated with first-day returns and long-term stock performance.

***** Insert Table 2 about here *****

Table 2 reports regression results for the relationship between first-day returns and media tone. In Column (1), we do not include any media variable in the regression since we wish to examine the relationship between first-day returns and non-media variables. We add in *MediaCount* and *MediaCount2* in Columns (2) and (3), respectively, and we find that first-day returns tend to increase with the number of newspapers articles over two different periods, consistent with the findings documented in Liu et al. (2009) and Huang and Chen (2013). Specifically, we find that one newspapers article in the three-month period before the offer date can increase first-day returns by 5.15 percentage points (=0.013∗3.962) while one newspapers article that appears in the media over the period between offering and listing can lead to an increase of 11.58 percentage points (=0.042∗2.758) in first-day returns. We further include *MediaTone* and *MediaTone2*, our measures for the content of newspapers articles in Columns (4) and (5), respectively. We find that there is a positive relationship between pre-IPO media tone and first-day returns even after controlling for those deal-level, firm-level and market-level determinants of IPO underpricing documented in the literature. One positive newspapers article in the first period can translate into an increase of 4.44 percentage points (=0.014∗3.168) in first-day returns. More dramatically, one positive newspapers articles in the second period can cause first-day returns to increase by 11.17 percentage points (=0.045∗2.483). More importantly, we find that this positive relationship between media tone and first-day returns remains significant even after we control for the number of newspapers articles in Column (6). A positive newspapers article can lead to an increase of 3.80 (=0.012∗3.168) and 6.95 (0.028∗2.483) percentage points if it appears in the media over the first and second periods, respectively. These findings seem to suggest that the media can influence first-day returns through a new channel other than attention as we claim.

***** Insert Table 3 about here *****

Table 3 reports regression results for the relationship between long-run abnormal returns and media tone. The dependent variable for long-run abnormal returns in Panel A is *BHAR*, defined as the buy-and-hold returns of IPO stocks in the 36 post-IPO event months relative to the buy-and-hold returns of non-IPO matching firms over the same period of time. We do not include any media variable in Column (1), and we find that *BHAR* is negatively related to *IR* in Panel A and that three-factor alpha is also negatively related to *IR* in Panel B, consistent with previous findings in the US such as Ritter (1991) and in Mainland China including Shen et al. (2013) among others. We add in two variables for media counts in Columns (2) and (3), respectively. We find that the coefficients on both *MediaCount* and *MediaCount2* are negative at the 1% significance level, indicating that media tone over two different periods can predict low long-run abnormal returns. A newspapers article during the three-month period before the offer date can predict a decrease of 7.92 percentage points (= −0.020∗3.962) in BHARs, while a newspapers article during the period between the offer date and the first-trading date can predict a decrease of 9.10 percentage points (= −0.033∗2.758) in BHARs. These findings are important for behavioral explanations for IPO underpricing, including this media-driven bias. Given that behavioral bias will be corrected in the long run, we should be able observe return reversals predicted by the source of behavioral bias. However, to the best of our knowledge, none of previous studies report similar evidence in this regard, including Liu et al. (2009), Huang and Chen (2013), and Bajo and Raimondo (2014).

We include two variables of media tone in Columns (4) and (5), respectively. We find that the coefficients on *MediaTone* in Column (4) and *MediaTone2* in Column (5) are negative at the 1% significance level, indicating that there is a strong negative relationship between pre-IPO media tone and long-run performance following IPOs, as predicted by our hypothesis. A positive newspapers article during the three-month period before the offer date can predict a decrease of 10.14 percentage points (= −0.032∗3.168) in BHARs, while a positive newspapers articles during the period between the offer date and the first-trading date can predict a decrease of 11.67 percentage points (= −0.047∗2.483) in BHARs. More importantly, the negative relationship between media tone and long-run abnormal returns remain significant even after we control for the number of newspapers articles in Column (6). A positive newspapers article can lead to a decrease of 8.87 (= −0.028∗3.168) and 10.93 (= −0.044∗2.483) percentage points in BHARs if it appears in the media over the first and second periods, respectively. These findings provide long-run evidence that the media can predict post-IPO abnormal returns through the tone channel.

Our regression results for long-term stock performance is robust to alternative specification.

Using Jensen's alpha in Panel B as the measure for long-term abnormal returns yields very similar results to those using *BHAR* in Panel A. This robustness check shows that there also is a negative relationship between alpha and media tone, even after controlling for the number of newspapers articles and other firm characteristics. More specifically, a positive newspapers article can lead to a decrease of 31.68 (= −0.001∗3.168) and 24.83 (= −0.001∗2.483) basis points in monthly abnormal returns if it appears in the media over the first and second periods, respectively.

Taken together, evidence in this section shows that media tone in the pre-IPO period can explain high first-day returns and low long-run abnormal returns. We attribute the ups and down in post-IPO prices to the presence of investor sentiment driven by media tone. In the next section, we provide additional tests for this claim.

V. Additional Tests: the Presence of Retail Investors

1. First-day Retail Trading

We first examine whether pre-IPO media tone can affect the presence of retail investors in the secondary market by estimating the following regression model:

$$SmallTrade\_buy = \beta_0 + \beta_1 \cdot MediaTone + \beta_2 \cdot MediaTone2 + \beta_3 \cdot MediaCount$$
$$+\beta_4 \cdot MediaCount2 + \beta_5 \cdot X + \varepsilon \qquad (7)$$

SmallTrade_buy is the proportion of buyer-initiated small trades on the first trading day of an IPO stock. We use the Lee and Ready (1991) algorithm, the standard approach in the market microstructure literature, to identify whether a trade is buyer- or seller-initiated. Specifically, a trade is classified as a buy (sell) if it is executed at a price below (above) the midpoint of bid/ask quotes. Following Ofek and Richardson (2003) and Barber et al. (2009) among others, we assume that retail investors tend to trade in small RMB amounts. Trades less than RMB6,700 are classified as small in our analysis following Lee and Radhakrishna (2000), Hvidkjaer (2006), and Hvidkjaer (2008). Table 4 summarizes regression results for the relationship between buyer-initiated small trades and pre-IPO media tone.

***** Insert Table 4 about here *****

We do not include any media-based variable in Column (1). We find that retail trading is positively related to *ROA* and *VC-backed* dummy while negatively related to issue size. In Columns (2) to (5) where we progressively add in four media-based variables, we find that coefficients on these variables are significantly positive, even after controlling for firm characteristics. The coefficients on *MediaCount* and *MediaCount2* are 0.004 and 0.007 in Columns (2) and (3), indicating that a newspapers article over two different periods can increase first-day retail trading by 1.58% (=0.004*3.962) and 1.93% (=0.007*2.758), respectively. The coefficients on *MediaTone* and *MediaTone2* are 0.012 and 0.014 in Columns (4) and (5), indicating that a positive newspapers article over two different periods can increase first-day retail trading by 3.80% (= 0.012*3.168) and 3.48% (=0.014*2.483), respectively. The regression in Column (6) includes four media –based variables and the positive coefficients on *MediaTone* and *MediaTone2* after controlling for the attention channel suggest that the media can influence first-day retail trading, as predicted, through the tone channel. A positive newspapers article over two different periods can increase first-day retail trading by 4.12% (= 0.013*3.168) and 3.48% (=0.014*2.483), respectively.

2. Media Tone and Investor Participation in the Primary Market

If media tone can attract more investors to a particular IPO event, more retail investors should be observed not only on the first day of trading but also in the IPO market where they subscribe to new issues. To investigate whether pre-IPO media tone can affect the subscribing decision of retail investors in the primary market, we estimate the following regression model:

$$Allocation\_Retail = \beta_0 + \beta_1 \cdot MediaCount + \beta_2 \cdot MediaCount2 + \beta_3 \cdot MediaTone + \beta_4 \cdot MediaTone2 + \beta_5 \cdot X + \varepsilon \quad (8)$$

where *Allocation_Retail* is the rate of allocation among retail investors who subscribe to a new issue at a fixed price. Table 5 reports regression results on the relationship between pre-IPO media tone and investor participation in the primary market.

***** Insert Table 5 about here *****

Consistent with our expectation, we find evidence of a positive relationship between retail investor participation and media tone. Note that the dependent variable is *Allocation_Retail*, defined as the rate of allocation among retail investors. A smaller value in *Allocation_Retail* indicates a smaller probability of receiving an allocation when shares are oversubscribed, thus strong retail investor participation. In Column (1), we do not include any media-based variable and we find that the rate of allocation for retail investor is negatively related to IPO's profitability, consistent with Rock's (1986) prediction that new issues are underpriced to attract more investors to participate. Although regression results in Column (2) do not lend support to a positive relationship between the number of pre-IPO newspapers articles and retail investor participation, we find a negative relationship between pre-IPO media tone and the rate of allocation for retail investors in Column (3). A newspapers article before the offer date can lead to a decrease of 12.36% (= −0.039∗3.168) in the rate of allocation among retail investors. In fact, after we control for the number of newspapers articles in Column (4), the coefficient on *MediaTone* remains negative and significant. One more newspapers article before the offer date can lead to a further decrease of 19.64% (= −0.062∗3.168) in the probability of receiving an allocation by retail investors. We interpret this finding as being consistent with our media tone hypothesis that pre-IPO media tone can attract more retail investors around an IPO event.

VI. Conclusion

Accepted theories of IPO pricing usually assume the random presence of investor sentiment. In this paper, we identify a channel through which pre-IPO media tone as well as media counts can drive the presence of investor sentiment. Using a sample of Chinese book-built IPOs where private information on the presence of investor sentiment cannot be incorporated into the offer price, we empirically examine the relationship between pre-IPO media tone and post-IPO prices. Consistent with our hypothesis, we find that media tone is positively related to first-day returns while negatively related to long-run abnormal returns, even after controlling for other firm characteristics and the number of newspapers articles over the same period. One positive newspapers article can predict an increase of 6.95 percentage points in first-day returns and a decrease of 10.93 percentage points in BHARs, which is economically significant given that the average first-day return is about 60.2% while the average BHAR is 14.5%. Further analysis suggests that media tone in the pre-IPO period can increase first-day retail trading. One more positive newspapers articles can lead to an increase of 8.5%-10.1% in the proportion of first-day retail trading. We also find a negative relationship between pre-IPO media tone and allocation rates among retail investors, which seems to suggest that media tone can attract more retail investors to participate in the primary market, making it more difficult for them receive an allocation on average. Taken together, these findings are consistent with the view that the media plays an important role in driving the presence of investor sentiment around the IPO event through the tone channel.

Reference

Bajo, E., Raimondo, C., 2014. Media sentiment and the pricing of IPOs. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2531373

Barber, B.M., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 21, 785-818.

Barber, B.M., Odean, T., Zhu, N., 2009. Do retail trades move markets? *Review of Financial Studies* 22, 151-186.

Benveniste, L.M., Spindt, P.A., 1989. How investment bankers determine the offer price and allocation of new issues? *Journal of Financial Economics* 24, 343 – 361.

Bodnaruk, A., Ostberg, P., 2009. Does investor recognition predict returns? *Journal of Financial Economics* 91, 208-226.

Chan, K., Wang, J., Wei, K., 2004. Underpricing and long-term performance of IPOs in China. *Journal of Corporate Finance* 10, 409 – 430.

Chen, Y., Wei, S., Li, W., Sun, Q., Tong, W., 2015. Institutional environment, firm ownership, and IPO first-day returns: Evidence from China. *Journal of Corporate Finance* 32, 150-168.

Cook, D., Kieschnick, R., Van Ness, R., 2006. On the marketing of IPOs. *Journal of Financial Economics* 82, 35-61.

Cornelli, F., Goldreich, D., Ljungqvist, A., 2006. Investor sentiment and pre-IPO market. *Journal of Finance* 61, 1187-1216.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. *Journal of Finance* 66, 1461-1499.

Derrien, F., 2005. IPO pricing in 'hot' market conditions: who leaves money on the table. *Journal of Finance* 60, 487-521.

Dorn, D., 2009. Does sentiment drive the retail demand for IPOs? *Journal of Financial and Quantitative Analysis* 44, 85-108.

Fan, J., Wong, T.J., Zhang, T., 2007. Politically-connected CEO, corporate governance, and post-IPO performance of China's newly partially privatized firms. *Journal of Financial Economics* 84, 330-357.

Fang, L., Peress, J., 2009. Media coverage and the cross-section of stock returns. *Journal of Finance* 64, 2023-2052.

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

Gao, Y., 2010. What comprises IPO initial returns: evidence from the Chinese market. *Pacific-Basin Finance Journal* 18, 77-89.

Huang, J., Chen, X., 2013. Media coverage and IPO underpricing: Evidence from the ChiNext Board.

Journal of Management Science 16, 83-94. (in Chinese)

Hvidkjaer, S., 2006. A trade-based analysis of momentum. *Review of Financial Studies* 19, 457-491.

Hvidkjaer, S., 2008. Small trades and the cross-section of stock returns. *Review of Financial Studies* 21, 1123-1151.

Kao, J., Wu, D., Yang, Z., 2009. Regulations, earnings management and post-IPO performance: the Chinese evidence. *Journal of Banking and Finance* 33, 63-76.

Lehavy, R., Sloan, R.G., 2008. Investor recognition and stock returns. *Review of Accounting Studies* 13, 327-361.

Lee, C.M.C., Radhakrishna, B., 2000. Inferring investor behavior: Evidence from TORQ data. *Journal of Financial Markets* 3, 83–111.

Lee, C.M.C., Ready, M.J., 1991. Inferring trade direction from intraday data. *Journal of Finance* 46, 733–746.

Liu, L.X., Sherman, A.E., Zhang, Y., 2009. Media coverage and IPO underpricing. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=890602

Liu, L.X., Sherman, A.E., Zhang, Y., 2014. The long run role of the media: Evidence from Initial Public Offerings. *Management Science* 60, 1945-1964.

Loughran, T., McDonald, B., 2011. When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance* 66, 35-65.

Loughran, T., McDonald, B., 2013. IPO first-day returns, offer price revisions, volatility, and Form S-1 language. *Journal of Financial Economics* 109, 307-326.

Ljungqvist, A., Nanda, V.K., Singh, R., 2006. Hot market, investor sentiment and IPO pricing. *Journal of Business* 79, 1667-1702.

Lyon, J., Barber, B., Tsai, C., 1999. Improved methods for tests of long-run abnormal stock returns. *Journal of Finance* 54, 165–201.

Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42, 483-510.

Miller, E., 1977. Risk, uncertainty, and divergence of opinion. *Journal of Finance* 32, 1151–1168.

Ofek, E., Richardson, M., 2003. DotCom mania: the rise and fall of internet stock prices. *Journal of Finance* 58, 1113-1138.

Ritter, J., 1991. The long-run performance of initial public offerings. *Journal of Finance* 45, 365-394.

Rock, K., 1986. Why new issues are underpriced. *Journal of Financial Economics* 15, 187-212.

Shen, Z., Coakley, J., Instefjord, N., 2013. Investor participation and underpricing in lottery-allocated Chinese IPOs. *Pacific-Basin Finance Journal* 25, 294-314.

Tetlock, P.C., 2007. Giving content to investor sentiment: the role of media in the stock market. Journal of

Finance 62 (3), 1139 – 1168.

Tian, L., 2011. Regulatory underpricing. *Journal of Empirical Finance* 18, 78-90.

You, J., Wu, J., 2012. The spiral of silence: media sentiment and mispricing. *Economic Research Journal* 7, 141-152. (in Chinese)

You, J., Zhang, B., Zhang, L., 2014. Who captures the power of the pen? MIT Asian conference in Accounting, available at http://mitsloan.mit.edu/international/images/uploads/MITAsiaAccounting14-105(3).pdf

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48, 817-838.

Table 1: Descriptive Statistics

This table provides descriptive statistics for variables used in this study. *IR* is the first-day return; *BHAR* is defined as the buy-and-hold returns of IPO stocks in the 36 event months relative to the buy-and-hold returns of non-IPO matching firms over the same period of time; *Alpha* is estimated from calendar-time Fama-French three-factor regression model; *MediaTone* is defined as the number of positive news items in excess of the number of negative news items over the 3-month period before the offer date; *MediaTone2* is the number of positive news items in excess of the number of negative news items over the period between offering and listing; *MediaCount* is the number of news items that appear in the 46 national business media over the 3-month period before the offer date; *MediaCount2* is the number of news items that appear in the 46 national business media over the period between offering and listing; *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; *Profitability* is the percentage difference between the offering P/E and the industry P/E; *IssueSize* is IPO proceeds, measured as the offer price multiplied by the number of new shares offered; *Assets* is the number of total assets in the pre-IPO year; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters, at least two times over the past three years, and 0 otherwise; *Big4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportional of state holdings in the firm; *Tradable* is the proportion of tradable shares; *Age* is the firm age since establishment; *TimeLag* is the time elapsed between offering and listing; *Analysts_std* is the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *HighTech* is a dummy variable for new issues from high-tech industries; *MktSent1* is the number of IPOs in the same calendar month; *MktSent2* is the average first-day return in the same calendar month; *MktSent3* is the market return in the same calendar month. *SmallTrade_buy* is defined as the fraction of buy trades initiated by retail investors on the first day of trading using the RMB6,700 specification.

Variable	Obs	Mean	St dev	Min	P10	P25	P50	P75	P90	Max
IR	1126	0.602	0.745	-0.137	-0.032	0.126	0.366	0.797	1.522	3.807
BHAR	865	-0.145	0.712	-1.905	-1.087	-0.592	-0.137	0.315	0.718	1.763
Alpha	865	-0.016	0.013	-0.046	-0.033	-0.024	-0.016	-0.008	0	0.024
MediaCount	1126	2.69	3.962	0	0	0	1	4	9	24
MediaCount2	1126	1.589	2.758	0	0	0	0	2	5	13
MediaTone	1126	1.042	3.168	-4	-1	0	0	1	5	11
MediaTone2	1126	0.777	2.483	-4	-1	0	0	1	2	10
Allocation_Retail (%)	1126	1.056	1.523	0.027	0.103	0.329	0.627	1.122	2.24	9.695
SmallTrade_buy (%)	1126	0.566	0.21	0.077	0.31	0.445	0.548	0.665	0.837	1.268
ROA	1126	0.099	0.072	0.002	0.025	0.044	0.082	0.135	0.197	0.371
Leverage	1126	0.473	0.179	0.074	0.217	0.343	0.486	0.607	0.694	0.85
Profitability	1126	-0.184	0.325	-0.764	-0.581	-0.403	-0.216	0	0.236	0.825
Log (IssueSize)	1126	11.067	0.831	9.552	10.112	10.522	10.986	11.484	12.073	14.145
Log(Assets)	1126	20.206	1.141	18.498	19.035	19.464	19.965	20.691	21.567	24.679
Underwriter	1126	0.353	0.478	0	0	0	0	1	1	1
Big4	1126	0.047	0.212	0	0	0	0	0	0	1

VC-backed	1126	0.396	0.489	0	0	0	0	1	1	1
State	1126	0.114	0.27	0	0	0	0	0	0.611	1
Tradable	1126	0.203	0.041	0.08	0.2	0.2	0.201	0.203	0.25	0.369
Age	1126	7.572	4.75	0.83	1.888	3.288	7.153	10.485	14.153	20.06
Timelag	1126	11.77	3.378	7	8	9	11	14	15	24
Analysts_std	1126	0.066	0.066	0.007	0.018	0.029	0.045	0.08	0.131	0.449
Analysts_bias	1126	0.017	0.291	-0.618	-0.337	-0.193	-0.005	0.212	0.451	0.71
HighTech	1126	0.121	0.326	0	0	0	0	0	1	1
MktSent1	1126	22.193	8.882	3	10	15	24	29	32	37
MktSent2	1126	0.603	0.631	0.016	0.066	0.176	0.375	0.75	1.484	3.346
MktSent3	1126	0.013	0.09	-0.218	-0.078	-0.056	0.009	0.059	0.138	0.342

Table 2: Media Tone and First-day Returns

This table reports regression results for the relationship between pre-IPO media coverage and first-day returns. The dependent variable is *IR*, the first-day return; *MediaTone* is the tone of the media, defined as the number of positive news items in excess of the number of negative news items over the 3-month period before the offer date; *MediaTone2* is the number of positive news items in excess of the number of negative news items over the period between offering and listing; *MediaCount* is the number of news items that appear in the 46 national business media over the 3-month period before the offer date; *MediaCount2* is the number of news items that appear in the 46 national business media over the period between offering and listing; *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; *Profitability* is the percentage difference between the offering P/E and the industry P/E; *IssueSize* is IPO proceeds, measured as the offer price multiplied by the number of new shares offered; *Assets* is the number of total assets in the pre-IPO year; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters, at least two times over the past three years, and 0 otherwise; *Big4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportional of state holdings in the firm; *Tradable* is the proportion of tradable shares; *Age* is the firm age since establishment; *TimeLag* is the time elapsed between offering and listing; *Analysts_std* is the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *HighTech* is a dummy variable for new issues from high-tech industries; *MktSent1* is the number of IPOs in the same calendar month; *MktSent2* is the average first-day return in the same calendar month; *MktSent3* is the market return in the same calendar month. Year dummies and industry dummies are included in all regressions. The *t*-values are calculated using White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
MediaCount		0.013***				-0.000
		(3.32)				(-0.01)
MediaCount2			0.042***			0.024***
			(7.23)			(2.76)
MediaTone				0.014***		0.012**
				(2.99)		(2.43)
MediaTone2					0.045***	0.028***
					(7.50)	(3.11)
ROA	0.875***	0.845***	0.819***	0.839***	0.837***	0.790***
	(4.16)	(4.07)	(3.92)	(4.06)	(3.99)	(3.85)
Leverage	-0.118	-0.088	-0.031	-0.110	-0.054	-0.023
	(-1.13)	(-0.84)	(-0.30)	(-1.07)	(-0.54)	(-0.23)
Profitability	0.002	0.001	-0.016	0.003	-0.027	-0.025
	(0.05)	(0.03)	(-0.37)	(0.07)	(-0.61)	(-0.57)
Log (*IssueSize*)	-0.377***	-0.389***	-0.371***	-0.383***	-0.347***	-0.360***
	(-9.37)	(-9.82)	(-9.56)	(-9.63)	(-9.06)	(-9.49)
Log (*Assets*)	0.122***	0.114***	0.086***	0.121***	0.100***	0.088***
	(3.62)	(3.35)	(2.62)	(3.63)	(3.08)	(2.68)
Underwriter	-0.012	-0.013	-0.009	-0.012	-0.013	-0.011
	(-0.52)	(-0.54)	(-0.38)	(-0.52)	(-0.56)	(-0.47)
Big4	0.072	0.047	0.006	0.057	0.017	-0.010
	(1.06)	(0.68)	(0.09)	(0.86)	(0.27)	(-0.16)
VC-backed	0.040*	0.043*	0.039*	0.036	0.043*	0.038*
	(1.71)	(1.86)	(1.70)	(1.58)	(1.91)	(1.71)
State	0.194***	0.173***	0.144**	0.173***	0.158***	0.126**
	(3.10)	(2.84)	(2.53)	(2.74)	(2.59)	(2.17)
Tradable	0.005	-0.106	0.050	-0.023	0.114	0.072
	(0.01)	(-0.28)	(0.14)	(-0.06)	(0.33)	(0.21)
Log (1+*Age*)	-0.002	-0.003	-0.002	-0.003	-0.002	-0.002
	(-0.98)	(-1.15)	(-0.76)	(-1.13)	(-0.98)	(-0.98)
Timelag	0.000	0.002	-0.002	0.002	-0.001	-0.000

	(0.12)	(0.47)	(-0.42)	(0.40)	(-0.15)	(-0.11)
Analysts_std	0.150	0.194	0.227*	0.196	0.245**	0.291**
	(1.22)	(1.59)	(1.88)	(1.60)	(2.10)	(2.51)
Analysts_bias	-0.024	-0.024	0.002	-0.030	0.011	0.006
	(-0.59)	(-0.60)	(0.06)	(-0.77)	(0.28)	(0.17)
HighTech	0.016	0.015	0.017	0.014	0.021	0.018
	(0.45)	(0.41)	(0.48)	(0.40)	(0.59)	(0.51)
MktSent1	-0.000	0.001	0.000	-0.000	-0.001	-0.000
	(-0.13)	(0.29)	(0.21)	(-0.12)	(-0.28)	(-0.02)
MktSent2	0.895***	0.875***	0.843***	0.883***	0.860***	0.834***
	(18.17)	(17.93)	(17.25)	(17.88)	(17.04)	(17.10)
MktSent3	-0.162	-0.187	-0.273	-0.196	-0.260	-0.315
	(-0.82)	(-0.95)	(-1.42)	(-0.99)	(-1.36)	(-1.62)
Number of obs.	1,126	1,126	1,126	1,126	1,126	1,126
Adjusted R^2	0.741	0.744	0.759	0.744	0.760	0.765

Table 3: Media Tone and Long-term Stock Performance

This table reports regression results for the relationship between pre-IPO media coverage and long-term stock performance. The dependent variable in Panel A is *BHAR*, defined as the buy-and-hold returns of IPO stocks in the 36 post-IPO event months relative to the buy-and-hold returns of non-IPO matching firms over the same period of time. The dependent variable in Panel B is *Jensen's alpha* estimated from calendar-time Fama-French three-factor regression model. *MediaTone* is the tone of the media, defined as the number of positive news items in excess of the number of negative news items over the 3-month period before the offer date; *MediaTone2* is the number of positive news items in excess of the number of negative news items over the period between offering and listing; *MediaCount* is the number of news items that appear in the 46 national business media over the 3-month period before the offer date; *MediaCount2* is the number of news items that appear in the 46 national business media over the period between offering and listing; *IR* is the first-day return. *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; *Profitability* is the percentage difference between the offering P/E and the industry P/E; *IssueSize* is IPO proceeds, measured as the offer price multiplied by the number of new shares offered; *Assets* is the number of total assets in the pre-IPO year; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters, at least two times over the past three years, and 0 otherwise; *Big4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportional of state holdings in the firm; *Tradable* is the proportion of tradable shares; *Age* is the firm age since establishment; *TimeLag* is the time elapsed between offering and listing; *Analysts_std* is the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *HighTech* is a dummy variable for new issues from high-tech industries; *MktSent1* is the number of IPOs in the same calendar month; *MktSent2* is the average first-day return in the same calendar month; *MktSent3* is the market return in the same calendar month. Year dummies and industry dummies are included in all regressions. The *t*-values are calculated using White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: *BHAR* as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
MediaCount		-0.020***				-0.002
		(-3.27)				(-0.17)
MediaCount2			-0.033***			-0.002
			(-3.19)			(-0.10)
MediaBias				-0.032***		-0.028***
				(-4.18)		(-2.72)
MediaBias2					-0.047***	-0.044***
					(-4.17)	(-2.83)
IR	-0.267***	-0.244***	-0.216***	-0.240***	-0.190***	-0.166***
	(-5.07)	(-4.65)	(-4.09)	(-4.55)	(-3.55)	(-3.09)
ROA	-0.502	-0.451	-0.472	-0.431	-0.502	-0.433
	(-1.04)	(-0.94)	(-0.99)	(-0.90)	(-1.06)	(-0.92)
Leverage	-0.124	-0.190	-0.188	-0.152	-0.204	-0.232
	(-0.66)	(-1.03)	(-1.00)	(-0.83)	(-1.09)	(-1.26)
Profitability	-0.042	-0.030	-0.019	-0.038	-0.007	-0.004
	(-0.40)	(-0.29)	(-0.18)	(-0.37)	(-0.07)	(-0.04)
Log (*IssueSize*)	-0.045	-0.029	-0.034	-0.026	-0.055	-0.036
	(-0.68)	(-0.43)	(-0.51)	(-0.40)	(-0.82)	(-0.54)
Log (*Assets*)	-0.057	-0.036	-0.029	-0.051	-0.029	-0.023
	(-1.20)	(-0.74)	(-0.59)	(-1.09)	(-0.60)	(-0.46)
Underwriter	-0.033	-0.032	-0.036	-0.029	-0.032	-0.029
	(-0.63)	(-0.61)	(-0.69)	(-0.57)	(-0.62)	(-0.57)
Big4	-0.097	-0.051	-0.066	-0.067	-0.064	-0.035
	(-0.77)	(-0.41)	(-0.53)	(-0.55)	(-0.51)	(-0.28)
VC-backed	-0.010	-0.013	-0.009	-0.004	-0.016	-0.011
	(-0.20)	(-0.25)	(-0.18)	(-0.09)	(-0.32)	(-0.21)

State	0.121	0.153*	0.146	0.162*	0.134	0.174*
	(1.35)	(1.69)	(1.61)	(1.83)	(1.49)	(1.95)
Tradable	-0.119	0.111	-0.048	-0.030	-0.075	0.024
	(-0.22)	(0.21)	(-0.09)	(-0.06)	(-0.14)	(0.04)
Log (1+*Age*)	0.002	0.003	0.003	0.004	0.003	0.004
	(0.46)	(0.59)	(0.50)	(0.73)	(0.59)	(0.84)
Timelag	-0.002	-0.004	-0.000	-0.004	-0.000	-0.003
	(-0.24)	(-0.52)	(-0.01)	(-0.58)	(-0.04)	(-0.36)
Analysts_std	0.723	0.632	0.600	0.607	0.551	0.445
	(1.54)	(1.36)	(1.30)	(1.30)	(1.19)	(0.96)
Analysts_bias	-0.295***	-0.297***	-0.317***	-0.279***	-0.328***	-0.312***
	(-3.18)	(-3.21)	(-3.44)	(-3.00)	(-3.59)	(-3.40)
HighTech	0.091	0.095	0.088	0.101	0.084	0.094
	(1.35)	(1.42)	(1.32)	(1.50)	(1.28)	(1.42)
MktSent1	-0.003	-0.004	-0.003	-0.003	-0.002	-0.002
	(-0.57)	(-0.85)	(-0.70)	(-0.60)	(-0.40)	(-0.45)
MktSent2	0.033	0.043	0.025	0.039	-0.001	0.007
	(0.42)	(0.56)	(0.33)	(0.51)	(-0.02)	(0.10)
MktSent3	-0.116	-0.084	-0.043	-0.031	-0.025	0.052
	(-0.42)	(-0.31)	(-0.16)	(-0.11)	(-0.09)	(0.20)
Number of obs.	865	865	865	865	865	865
Adjusted R^2	0.101	0.110	0.112	0.117	0.124	0.136

Panel B: *Jensen's Alpha* Estimated from the Fama-French three-factor Model as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
MediaCount		-0.000***				-0.000
		(-3.34)				(-0.29)
MediaCount2			-0.001***			-0.000
			(-3.47)			(-0.68)
MediaBias				-0.001***		-0.000**
				(-4.01)		(-2.45)
MediaBias2					-0.001***	-0.001*
					(-3.64)	(-1.82)
IR	-0.005***	-0.005***	-0.005***	-0.005***	-0.004***	-0.004***
	(-5.47)	(-4.93)	(-4.49)	(-4.94)	(-4.27)	(-3.73)
ROA	0.009	0.010	0.010	0.011	0.009	0.011
	(1.02)	(1.13)	(1.08)	(1.17)	(1.03)	(1.20)
Leverage	0.004	0.003	0.003	0.004	0.003	0.002
	(1.25)	(0.85)	(0.90)	(1.11)	(0.89)	(0.68)
Profitability	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(-0.25)	(-0.12)	(-0.02)	(-0.22)	(0.04)	(0.10)
Log (*IssueSize*)	-0.002	-0.001	-0.002	-0.001	-0.002	-0.001
	(-1.40)	(-1.10)	(-1.24)	(-1.13)	(-1.52)	(-1.15)
Log (*Assets*)	-0.001	-0.000	-0.000	-0.001	-0.000	-0.000
	(-0.92)	(-0.48)	(-0.42)	(-0.83)	(-0.51)	(-0.29)
Underwriter	0.001	0.001	0.001	0.001	0.001	0.001
	(0.93)	(0.96)	(0.88)	(1.00)	(0.95)	(0.99)
Big4	-0.000	0.001	0.000	0.000	0.000	0.001
	(-0.14)	(0.27)	(0.11)	(0.10)	(0.08)	(0.37)
VC-backed	-0.000	-0.001	-0.000	-0.000	-0.001	-0.000
	(-0.55)	(-0.61)	(-0.54)	(-0.44)	(-0.66)	(-0.54)
State	0.005**	0.005***	0.005***	0.005***	0.005***	0.006***
	(2.54)	(2.85)	(2.77)	(2.98)	(2.68)	(3.13)
Tradable	0.003	0.007	0.004	0.004	0.003	0.006

	(0.25)	(0.64)	(0.37)	(0.40)	(0.32)	(0.52)
Log (1+*Age*)	-0.000	-0.000	-0.000	0.000	-0.000	0.000
	(-0.26)	(-0.12)	(-0.23)	(0.00)	(-0.16)	(0.08)
Timelag	0.000	0.000	0.000	0.000	0.000	0.000
	(0.70)	(0.40)	(0.93)	(0.38)	(0.88)	(0.59)
Analysts_std	-0.001	-0.002	-0.003	-0.003	-0.003	-0.005
	(-0.09)	(-0.32)	(-0.37)	(-0.35)	(-0.41)	(-0.69)
Analysts_bias	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(-6.14)	(-6.21)	(-6.39)	(-5.98)	(-6.51)	(-6.36)
HighTech	0.002*	0.002*	0.002	0.002*	0.002	0.002*
	(1.67)	(1.73)	(1.64)	(1.81)	(1.61)	(1.74)
MktSent1	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.30)	(-1.58)	(-1.42)	(-1.33)	(-1.16)	(-1.27)
MktSent2	0.001	0.002	0.001	0.001	0.001	0.001
	(0.95)	(1.09)	(0.85)	(1.02)	(0.60)	(0.74)
MktSent3	-0.018***	-0.017***	-0.017***	-0.016***	-0.017***	-0.015***
	(-3.24)	(-3.20)	(-3.05)	(-3.00)	(-3.04)	(-2.81)
Number of obs.	865	865	865	865	865	865
Adjusted R^2	0.136	0.146	0.146	0.151	0.151	0.164

Table 4: Media Tone and First-day Retail Trading

This table reports regression results for the relationship between pre-IPO media tone and first-day retail trading. The dependent variable is *SmallTrade_buy*, defined as the fraction of buy trades initiated by retail investors on the first day of trading using the RMB6,700 specification. *MediaTone* is the tone of the media, defined as the number of positive news items in excess of the number of negative news items over the 3-month period before the offer date; *MediaTone2* is the number of positive news items in excess of the number of negative news items over the period between offering and listing; *MediaCount* is the number of news items that appear in the 46 national business media over the 3-month period before the offer date; *MediaCount2* is the number of news items that appear in the 46 national business media over the period between offering and listing; *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; *Profitability* is the percentage difference between the offering P/E and the industry P/E; *IssueSize* is IPO proceeds, measured as the offer price multiplied by the number of new shares offered; *Assets* is the number of total assets in the pre-IPO year; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters, at least two times over the past three years, and 0 otherwise; *Big4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportional of state holdings in the firm; *Tradable* is the proportion of tradable shares; *Age* is the firm age since establishment; *TimeLag* is the time elapsed between offering and listing; *Analysts_std* is the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *HighTech* is a dummy variable for new issues from high-tech industries; *MktSent1* is the number of IPOs in the same calendar month; *MktSent2* is the average first-day return in the same calendar month; *MktSent3* is the market return in the same calendar month. Year dummies and industry dummies are included in all regressions. The *t*-values are calculated using White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
MediaCount		0.004**				-0.003
		(2.53)				(-1.56)
MediaCount2			0.007***			-0.002
			(3.15)			(-0.52)
MediaBias				0.012***		0.013***
				(6.03)		(5.77)
MediaBias2					0.014***	0.014***
					(6.50)	(4.65)
ROA	0.585***	0.575***	0.576***	0.555***	0.573***	0.549***
	(5.79)	(5.71)	(5.71)	(5.61)	(5.77)	(5.61)
Leverage	-0.027	-0.017	-0.013	-0.021	-0.007	-0.010
	(-0.62)	(-0.38)	(-0.29)	(-0.48)	(-0.16)	(-0.23)
Profitability	0.015	0.014	0.012	0.015	0.006	0.007
	(0.66)	(0.65)	(0.53)	(0.71)	(0.26)	(0.33)
Log (*IssueSize*)	-0.042***	-0.046***	-0.041**	-0.047***	-0.033**	-0.035**
	(-2.60)	(-2.82)	(-2.53)	(-2.92)	(-2.03)	(-2.21)
Log (*Assets*)	0.022*	0.019	0.016	0.021	0.015	0.018
	(1.66)	(1.41)	(1.19)	(1.62)	(1.13)	(1.31)
Underwriter	0.006	0.006	0.007	0.006	0.006	0.006
	(0.50)	(0.49)	(0.54)	(0.50)	(0.49)	(0.49)
Big4	-0.006	-0.014	-0.016	-0.017	-0.022	-0.027
	(-0.20)	(-0.51)	(-0.59)	(-0.64)	(-0.82)	(-1.03)
VC-backed	0.060***	0.062***	0.060***	0.058***	0.061***	0.057***
	(4.94)	(5.04)	(4.93)	(4.77)	(5.11)	(4.84)
State	0.012	0.004	0.004	-0.006	0.001	-0.012
	(0.48)	(0.18)	(0.15)	(-0.24)	(0.02)	(-0.53)
Tradable	-0.180	-0.218	-0.173	-0.204	-0.147	-0.147
	(-1.17)	(-1.39)	(-1.12)	(-1.32)	(-0.96)	(-0.95)

Log (1+*Age*)	0.000	0.000	0.000	-0.000	0.000	0.000
	(0.15)	(0.05)	(0.23)	(-0.05)	(0.19)	(0.02)
Timelag	0.003	0.003	0.002	0.003*	0.002	0.003
	(1.31)	(1.52)	(1.14)	(1.76)	(1.15)	(1.52)
Analysts_std	-0.010	0.005	0.002	0.028	0.019	0.049
	(-0.10)	(0.05)	(0.02)	(0.28)	(0.19)	(0.50)
Analysts_bias	0.129***	0.128***	0.133***	0.123***	0.139***	0.132***
	(6.07)	(6.07)	(6.23)	(5.89)	(6.61)	(6.37)
HighTech	0.112***	0.111***	0.112***	0.110***	0.113***	0.112***
	(5.18)	(5.19)	(5.19)	(5.20)	(5.30)	(5.30)
MktSent1	0.000	0.001	0.000	0.000	0.000	0.000
	(0.32)	(0.62)	(0.44)	(0.36)	(0.24)	(0.01)
MktSent2	0.030	0.023	0.022	0.020	0.019	0.015
	(1.56)	(1.21)	(1.11)	(1.08)	(1.04)	(0.80)
MktSent3	0.533***	0.525***	0.515***	0.505***	0.503***	0.480***
	(6.80)	(6.68)	(6.51)	(6.53)	(6.50)	(6.29)
Number of obs.	1,126	1,126	1,126	1,126	1,126	1,126
Adjusted R^2	0.189	0.193	0.194	0.212	0.211	0.233

Table 5: Media Tone and Retail Investor Participation in the Primary Market

This table reports regression results for the relationship between pre-IPO media tone and investor participation in the primary market. The dependent variable is *Allocation_Retail*, defined as the allocation rate among retail investors. *MediaTone* is the tone of the media, defined as the number of positive news items in excess of the number of negative news items over the 3-month period before the offer date; *MediaCount* is the number of news items that appear in the 46 national business media over the 3-month period before the offer date; *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; *Profitability* is the percentage difference between the offering P/E and the industry P/E; *IssueSize* is IPO proceeds, measured as the offer price multiplied by the number of new shares offered; *Assets* is the number of total assets in the pre-IPO year; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters, at least two times over the past three years, and 0 otherwise; *Big4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportional of state holdings in the firm; *Tradable* is the proportion of tradable shares; *Age* is the firm age since establishment; *TimeLag* is the time elapsed between offering and listing; *Analysts_std* is the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *HighTech* is a dummy variable for new issues from high-tech industries; *MktSent1* is the number of IPOs in the same calendar month; *MktSent2* is the average first-day return in the same calendar month; *MktSent3* is the market return in the same calendar month. Year dummies and industry dummies are included in all regressions. The *t*-values are calculated using White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
MediaCount		-0.001		0.031*
		(-0.09)		(1.67)
MediaTone			-0.039***	-0.062***
			(-3.66)	(-3.09)
ROA	-1.061	-1.059	-0.961	-0.975
	(-1.43)	(-1.42)	(-1.30)	(-1.32)
Leverage	0.054	0.051	0.033	0.092
	(0.18)	(0.17)	(0.11)	(0.31)
Profitability	-0.409***	-0.409***	-0.411***	-0.415***
	(-2.72)	(-2.72)	(-2.75)	(-2.80)
Log (*IssueSize*)	0.698***	0.699***	0.714***	0.695***
	(6.55)	(6.56)	(6.70)	(6.68)
Log (*Assets*)	0.018	0.019	0.021	0.001
	(0.21)	(0.21)	(0.23)	(0.01)
Underwriter	-0.037	-0.037	-0.037	-0.038
	(-0.48)	(-0.48)	(-0.48)	(-0.49)
Big4	-0.297	-0.295	-0.257	-0.295
	(-1.23)	(-1.20)	(-1.07)	(-1.20)
VC-backed	0.046	0.046	0.056	0.070
	(0.59)	(0.59)	(0.71)	(0.88)
State	-0.550***	-0.548***	-0.491***	-0.508***
	(-3.53)	(-3.45)	(-3.11)	(-3.23)
Tradable	1.303	1.312	1.382	1.160
	(1.06)	(1.07)	(1.12)	(0.94)
Log (1+*Age*)	-0.009	-0.009	-0.008	-0.008
	(-0.96)	(-0.95)	(-0.87)	(-0.91)
Timelag	0.034***	0.034***	0.031**	0.033**
	(2.67)	(2.62)	(2.40)	(2.56)
Analysts_std	4.520***	4.516***	4.390***	4.422***
	(3.86)	(3.84)	(3.81)	(3.88)
Analysts_bias	-0.101	-0.101	-0.082	-0.072

	(-0.66)	(-0.66)	(-0.55)	(-0.49)
HighTech	0.085	0.085	0.090	0.090
	(0.76)	(0.76)	(0.81)	(0.81)
MktSent1	-0.005	-0.005	-0.005	-0.003
	(-0.73)	(-0.74)	(-0.75)	(-0.42)
MktSent2	-0.173**	-0.172**	-0.140*	-0.169**
	(-2.34)	(-2.27)	(-1.93)	(-2.25)
MktSent3	1.186***	1.188***	1.283***	1.278***
	(3.33)	(3.34)	(3.56)	(3.54)
Number of obs.	1,126	1,126	1,126	1,126
Adjusted R-squared	0.349	0.348	0.354	0.356