

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

Zhe Shen

School of Management, Xiamen University

z.shen@xmu.edu.cn

Jiaying You

School of Management, Xiamen University

jxyou@xmu.edu.cn

Abstract

Using word frequency analysis, we define media bias as the number of positive in excess of negative news articles in the pre-IPO period and examine whether media bias can account for post-IPO market performance. We find robust evidence that media bias is positively related to IPO first-day returns while negatively related to long-run abnormal returns. We also find a negative relation between media bias and the rate of allocation among retail investors, indicating that positive media bias can bring more retail investors to the primary market. Further analysis suggest that media bias is positively associated with retail trading in the immediate aftermarket, post-IPO liquidity, analyst coverage, and institutional shareholdings, which implies that media bias can improve investor participation in the secondary market. Taken together, these findings are consistent with the view that media is an important channel through which sentiment drives retail demand for IPOs in the primary and secondary markets, causing post-IPO prices to deviate from fundamentals in the short run.

Keywords: IPO, Media Bias, Investor Sentiment, China

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

Abstract

Using word frequency analysis, we define media bias as the number of positive in excess of negative news articles in the pre-IPO period and examine whether media bias can account for post-IPO market performance. We find robust evidence that media bias is positively related to IPO first-day returns while negatively related to long-run abnormal returns. We also find a negative relation between media bias and the rate of allocation among retail investors, indicating that positive media bias can bring more retail investors to the primary market. Further analysis suggest that media bias is positively associated with retail trading in the immediate aftermarket, post-IPO liquidity, analyst coverage, and institutional shareholdings, which implies that media bias can improve investor participation in the secondary market. Taken together, these findings are consistent with the view that media is an important channel through which sentiment drives retail demand for IPOs in the primary and secondary markets, causing post-IPO prices to deviate from fundamentals in the short run.

Keywords: IPO, Media Bias, Investor Sentiment, China

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

I. Introduction

Several recent studies report evidence that sentiment can drive the retail demand for IPOs (Dorn, 2009) and irrational behavior among retail investors appears to drive post-IPO prices (Cornelli et al., 2006). The empirical literature also shows that increasing pre-IPO publicity by more headline stories can attract the presence of investor sentiment (Cook et al., 2006), leading to improvements in long-term value, liquidity, analyst coverage, and institutional ownership (Liu et al., 2014). However, due to the IPO quiet period restrictions in the US, media are prohibited from containing any hard information which is previously unknown in the IPO prospectus thus over 99% of news articles included in Cook et al. (2006) is non-negative and primarily descriptive stories. Thus even if evidence suggests that media slant can have significant effects on political attitudes and outcomes (Stromberg, 2004; Gentzkow, 2006; DellaVigna and Kaplan, 2007), it is unexplored how media bias, the tendency of the media in the selection of news that are reported and how they are covered (Groseclose and Milyo, 2005; Gentzkow and Shapiro, 2010; Gurun and Butler, 2012), drives the presence of investor sentiment relative to media counts in the IPO context.

This article attempts to complement the literature by using a sample of Chinese IPOs to address this important question. There are at least two reasons that Chinese IPOs is more suited for testing the relation between media bias and post-IPO returns. First, if the presence of investor sentiment can be expected ex ante and rationally incorporated into the offer price in ways similar to Derrien (2005) and Ljungqvist et al. (2006), the relation between pre-IPO media bias and first-day returns is likely to be understated. In sharp contrast to the US practice that underwriter can allocate shares by their discretion to reward aggressive institutional investors, the beauty of Chinese data is that there is no adequate incentive in place to ensure the information transmitted from institutional investors to underwriters. Oversubscribed shares will be strictly allocated on a pro ration basis and Chinese underwriters cannot motivate institutional investors who reveal their value-relevant private information, as assumed in accepted theories of IPO underpricing such as Benveniste and Spindt (1989). Second, if the media follow the quiet period restriction and provide only plain description of previously known stories, then one might not be able to figure out

whether and how the content of pre-IPO media coverage on the presence of investor sentiment. To our best of knowledge, the only exception is Bhattacharya et al. (2009), which use positive news items net of negative news items to proxy for media sentiment and explore the role of media bias in the Internet IPO bubble. In contrast to the US setting, the added dimension of the Chinese one is that there is no similar restrictions in China so media can present information previously unknown and choose its positive or negative languages in their reports where appropriate. Our preliminary analysis reveals that less than 5% of pre-IPO media coverage is neutral, and the remaining news articles are positive and optimistic most of time, though they can go negative and pessimistic in some occasions.

We hypothesize that there is a positive relation between pre-IPO media bias and first-day returns, while there is a negative relation between pre-IPO media bias and long-term stock performance. 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 risk that they might not be able to sell 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 are a good predictor of first-day aftermarket prices and later reversals. To the extent that the presence of investor sentiment which causes IPO stocks to be overvalued in the short term is driven by media bias at the firm level, we expect that pre-IPO media bias can boost IPO first-day prices, leading to high first-day returns but low long-term abnormal returns when overvaluation tends to reverse in a longer period of time.

We also hypothesize that pre-IPO media bias can induce retail investors to participate in the primary market. Using a model of capital market equilibrium with incomplete information, Merton (1987) shows that stocks about which not all investors are informed should have lower investor recognition and a

smaller shareholder base, which leads to a lower stock price and yields a return premium. Consistent with Merton (1987), Leavy and Sloan (2008) provide evidence that investor recognition can explain more variation in stock returns than investment fundamentals. Using a comprehensive dataset of Swedish shareholdings, Bodnaruk and Ostberg (2009) show that stock returns are positively related to shareholder base, even after controlling for relative market size and idiosyncratic risks, the other two recognized shadow cost of incomplete information according to Merton (1987). More relatedly, Fang and Peress (2009) find that stocks with no media coverage earn higher stock returns than stocks with high media coverage, even after controlling for accepted risk characteristics, indicating that the breadth of information dissemination matters. To the extent that pre-IPO media bias can have positive impacts on attitudes and decision making, we expect more retail investors to participate in those IPO stocks which are mentioned more positively in the media.

Our third hypothesis is that pre-IPO media bias can increase retail trading in the secondary market. Our argument rests on the premise that retail investors drive post-IPO prices. Ofek and Richardson (2003) show that high initial returns occur when institutions sell IPO shares to retail investors on the first day, and such high initial returns are followed by sizable reversals to the end of 2000, when the bubble had burst. Barber and Odean (2008) demonstrate that individual investors are net buyers of attention-grabbing stocks, e.g., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns. Using the unique feature that only retail investors can trade shares in the grey market for European IPOs on a forward basis, Cornelli et al., (2006) separate the retail demand from the institutional demand and find that the valuation by retail investors appears to drive the post-IPO prices. Using actual when-issued trades made by a sample of clients at a large German retail broker during the 1999 and 2000 period, Dorn (2009) document evidence that retail investors overpay for IPO stocks that are in the news. To provide a micro foundation for our argument, our final analysis examines whether pre-IPO media coverage drives retail trading in the post-IPO market. To the extent that individual investors tend to buy attention-grabbing stocks including stocks in the news (Barber and Odean, 2008), we expect that retail investors tend to overpay by a greater extent for IPO stocks that are more positively covered in the news and thus there should be a positive relation between pre-IPO media bias and post-IPO retail trading.

We manually collect all news articles three months before the offer date and analyze the content of these news items. Using word frequency analysis, we define positive (negative) news articles as those that include a larger number of positive (negative) than negative (positive) words. News articles that do not include any positive or negative words or the same amount of positive and negative words are defined as neutral ones. Following the literature, we construct two measures of media coverage: 1) media count, defined as the simple count of news articles over the 3-month period prior to the offer date of an IPO in which the name or the stock ID of a particular IPO firm is mentioned; and 2) media bias, defined as the number of positive news articles in excess of the number of negative ones. Following the literature, we define initial returns as first-day returns after going public, while long-term performance as BHAR over the 36 event months using IPO firms and their otherwise comparable non-IPO firms.

Using 1,126 Chinese book-built IPOs issued over the 2005-2012 period, we find evidence consistent with our three hypotheses that positive media bias in the pre-IPO period can attract more retail investors in the IPO market, increase retail trading in the immediate aftermarket, and lead to high first-day returns and lower long-term performance. Specifically, consistent with our first hypothesis, we find that first-day returns tend to increase with positive media bias, even after controlling for the number of news articles over the three-month period before the offer date or when we alternatively define media bias using news articles over the period between the offer date and the first-trading date. We also find that BHARs, estimated using a non-IPO comparable firms over three years following IPOs, are significantly lower for IPOs with more positive media bias. We obtain qualitatively similar results when we consider 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.

Consistent with our second hypothesis, we find that the rate of allocation for retail investors is significantly lower for IPOs with more positive media bias, even after controlling for the number of news articles. We also find that the rate of allocation for institutional investors tends to decrease with positive media bias. These findings suggest that media bias brings to the IPO market not only retail investors but also institutional investors. Furthermore, we examine whether positive pre-IPO media bias can affect aftermarket liquidity, post-IPO analyst coverage and institutional holdings. We find evidence that illiquidity

ratios estimated over the 1-month period after going public are significantly lower for IPO stocks that are more positively mentioned in the pre-IPO period, and that these media-favored IPOs tends to have more analysts providing coverage and more institutional shareholdings in their 6-month post-IPO period.

Consistent with our third hypothesis, we find robust evidence that positive media bias in the pre-IPO period can increase retail trading in the immediate aftermarket. Following Ofek and Richardson (2003) and Barber et al. (2009) among others, we assume that retail investors tend to trade in small RMB amounts. We follow the procedure outlined in Lee and Radhakrishna (2000) and obtain 6,700 RMB as the appropriate cutoff point. We define trades less than RMB6,700 as retail trades. We also follow the procedure outlined in Lee and Ready (1991) and identify whether a trade is buyer- or seller-initiated. We find that buyer-initiated retail trades is significantly higher for IPO stocks with more positive media bias, even after controlling for the impact of the number of news articles during the three-month period before the offer date and the number of news articles during the period between the offer date and the first-trading date. We also consider RMB26,800 as an alternative trade-based cutoff, because the proportion of retail trading under RMB6,700 account for only 1.05% of total trades in RMB volume while the proportion of trades completed by retail investors using RMB26,800 cutoff is much closer to 7.58% reported in Chan (2010). Regression analysis, based on this alternative retail trading definition, yields very similar results that there is a positive relation between pre-IPO media bias and retail trading.

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 assume 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. However, some contemporaneous studies suggest that this is not necessarily the case. 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 these studies by documenting a significant power of media in driving the presence of investor sentiment. Contrary to the exogenous nature of investor sentiment assumed in prior studies, we identify a new channel through which the media can play an important role, showing that the media can drive the presence of investor sentiment.

Second, we document an important role of the media in driving retail demand for IPOs through not only the number of news articles but also the tone of these news articles. Liu et al. (2009) report a positive relation 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 similar result between the number of news articles and IPO underpricing, using a sample of 86 Chinese IPOs. More recently, Bajo and Raimondo (2014) examine the relation 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 the finding of a positive relation between the number of media counts and IPO underpricing reported in prior research, but also provides additional evidence that the tone of media coverage can influence IPO first-day returns and long-term performance via driving the presence of retail investors. The impacts of positive media bias on first-day returns, long-run abnormal returns and investor participation are statistically significant even after controlling for the number of news articles.

The rest of this article is organized as follows. Section II provides a brief description of institutional background and develops our three empirical hypotheses. Section III explains how we obtain our IPO sample, our news sample, and how we define variables of interest used in this study. 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 regions. We focus on IPOs over the 2005-2012 period primarily because they are priced following the same approach and allocated among institutional (retail) investors using the same method. This section provides a brief description of institutional features relevant to our empirical hypotheses.

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 ration 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 1000 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 offline 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 hypotheses*

We drive our first hypothesis from the literature which focuses on the effects of investor sentiment on market performance. Miller (1977) proposes that short sales constraints can prevent the short-term equilibrium price from reflecting the average opinion of investors, leaving the first-day closing price biased towards the opinion of optimistic investors in an IPO market. Building upon this idea, both Derrien (2005) and Ljungqvist et al. (2006) develop their own theoretical models in which underwriters take advantage of these irrational investors by setting the offer price above a firm's intrinsic value and IPO underpricing can be justified as compensation for institutional investors taking on uncertainty arising from the presence of investor sentiment. The empirical literature seems to lend strong support to their predictions. 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. (2006) report evidence that the investor sentiment can predict both post-IPO price run-ups and long-run price reversals. Using actual when-issued trades for German IPOs during 1999 and 2000, Dorn (2009) find that investor sentiment appears to drive the retail demand in the IPO market.

We argue that pre-IPO media bias can drive the presence of investor sentiment, leading up to high first-day returns and low long-term stock performance.

Hypothesis 1a (short-term): First-day return tends to increase with pre-IPO media bias;

Hypothesis 1b (long-term): Long-term abnormal return tends to decrease with pre-IPO media bias;

We motivate our second hypothesis from the literature which focuses on the impact of investor recognition on stock returns, and from the literature which looks at the role of limited attention on stock returns. Building on the behavioral assumption that investors can only use securities that they know about

to construct their optimal portfolio, Merton (1987) theoretically demonstrates 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 studies such as Lehavy and Sloan (2008), Bodnaruk and Ostberg (2009), and Fang and Peress (2009) provide consistent evidence that returns are positively related to the number of investors who know about a particular stock.

There is another strand of literature which looks at the effects of investor inattention on stock returns, including Huberman and Rev (2001), Daniel et al. (2002), DellaVigna and Pollet (2007), Barber and Odean (2008), DellaVigna and Pollet (2009), Hirshleifer et al. (2009) among others. Drawing from cognitive psychology, these studies assume that investors have limited attention and find that limited attention can have significant impacts on stock returns. For example, consistent with psychological evidence, Barber and Odean (2008) find that individual investors are more likely 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. Consistent with the intuition that investor attention is more likely to be distracted over the weekend, Dellavigna and Pollet (2009) report evidence that Friday announcements are associated with less immediate price response and more drift compared to announcements in other weekdays. These studies suggest that limited attention affect stock returns.

We argue pre-IPO media bias can enhance investor recognition with a greater number of news articles. Given the fact that investors know about only a subset of securities in the market, investors are more likely to know about stocks that appear in the news more often. Given the fact that investor attention is limited thus they cannot search all stocks, investors are more likely to buy new shares of IPO stocks mentioned in the news more often.

Hypothesis 2 (Investor participation): investor participation tends to increase with pre-IPO media bias.

Our third hypothesis is motivated from the empirical literature which shows retail demand drives post-IPO prices. Ofek and Richardson (2003) explore a model in which agents with heterogeneous beliefs face short sales constraints. Using data on internet holdings, they find evidence of heterogeneity across

investors in the sense that the level of institutional holdings in internet stocks is significantly lower than it is for a sample of control firms. Consistent with their model prediction, they find that high initial returns occur when institutional investors sell IPO shares to retail investors on the first day, and such high initial returns are followed by sizable reversals to the end of 2000, when the bubble had burst. Using investor trading data, Barber and Odean (2008) demonstrate that individual investors are net buyers of stocks in the news. They interpret this results as being consistent with their hypothesis that many investors consider buying only stocks that have first caught their attention. Using actual when-issued trades to identify individual investor sentiment in the German IPO market, Dorn (2009) document evidence that retail investors consistently overpay for IPO stocks that are in the news, and that IPO stocks especially sought after by retail investors in the when-issued market or in the aftermarket experience negative long-run abnormal returns.

Hypothesis 3 (retail trading): buyer-initiated retail trade order tends to increase with pre-IPO media bias.

III. Data, Sample and Variables

1. Data

We start with a sample of IPO firms issued during the period between January 2005 and December 2012. Before the year of 2005, Chinese IPOs are not priced using the book-building approach. After excluding IPO firms that operate in the financial sector, we end up with 1,126 Chinese A-share book-built IPOs. 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, rate of allocation among institutional investors, and rate of allocation among retail investors, among others. We also retrieve daily price data and high frequency data from the CSMAR and WIND.

2. News Sample

Our media data are drawn from the CNKI Archive of National Newspapers. CNKI is the China Knowledge Resource Database, providing access to journal articles, doctoral theses, master theses, conference proceedings and newspaper articles. The CNKI archive of National Newspaper collects news

articles from more than 500 national print media dating back to 2000. According to the introduction of the archive, the total number of news 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. In this article, we extend the scope of newspapers by searching relevant news articles among 46 newspapers available in the archive to construct our media variables. Over the 2005-2012 period, there are about 240,000 new articles contained in the database. For each IPO firm, we search among news articles over the three-month before its offer date for those that have its firm name and stock ID. We also search among news articles over the period between its offer date and the first-trading date for those that have its firm name and stock ID. We exclude listing announcements and IPO prospectus. This initial screening procedure yields 4,818 relevant news articles.

3. Main Variables

3.1 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 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:

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

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 the tradable shares to calculate market capitalization and B/M ratio. We require that these matching non-IPO firms should have at least 2 years of trading record in the stock

market. Second, we use Jensen's alpha estimated from the Fama and French (1993) 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:

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

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 ; SMB and HML are two monthly factors constructed in a way similar to Fama and French (1993).

3.2 Media Coverage and Media Bias

We rely on four variables to measure the quantity and the content of media coverage over two different periods of time. First, following Fang and Peress (2009) and Liu et al. (2014), we define *MediaCount* as the number of news articles over the 3-month period before the offer date that refer to each IPO stock. Second, following Bhattacharya et al. (2009), we read all these news articles over the 3-month pre-offering period for each IPO and classify them into three types based on their contents: positive, neutral or negative. To analyze the content, we do not use human judgement as Bhattacharya et al. (2009) did but rely on word frequency analysis instead. Specifically, we use a pre-defined word list to count the number of positive and negative words in each news article. Our word list is based on the dictionary prepared by Loughran and McDonald (2011) and Loughran and McDonald (2013). We translate the dictionary from English to Chinese and also supplement its 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) news articles as those that include a larger number of positive (negative) than negative (positive) words. News 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 news, neutral, and negative news articles for each IPO stock respectively, and define *MediaBias* as the difference between the number of positive news articles and the number of negative news articles. Third, to the extent that media coverage before the offer date can be

incorporated into the offer price as public information and undermine the power of our tests, we define *MediaCount2* as the number of news articles for each IPO for the period between its offer date and its first trading date, and *MediaBias2* as the number of positive in excess of negative news articles over the same period.

3.3 Investor Participation in the Primary Market

We use allocation rates among retail investors who participate in the online fixed-price subscription (*Allocation_Retail*) to measure retail participation in the IPO market. A low rate of allocation implies a strong retail demand for IPOs in the primary market. We use allocation rates among institutional investors who participate in the offline book-building subscription (*Allocation_Insti*) to measure institutional participation in the IPO market. Likewise, a low rate of allocation also implies a strong institutional demand for IPOs in the primary market.

3.4 Retail Trading

We analyze the tick-by-tick transaction data for our sample IPO stocks over the first-trading day. CSMAR dataset has identified traders as buyer- and seller- initiated so we do not have to follow the procedure outlined in Lee and Ready (1991). Following the literature, we assume that retail investors tend to trade in smaller amounts. For robustness, we use two different cutoff points to define trade orders placed by retail investors. First, following the procedure outlined in Lee and Radhakrishna (2000), we partition trades into five groups based on their trade size. We find that the upper cutoff point for the bottom quintile bin is 6,700 RMB and thus we define trades less than RMB6, 700 as retail trades. Second, when we use 6,700 RMB as the cutoff point to define retail trades, we find that the proportion of retail trades relative to the total number of trades in the market is as low as 1.05%, which is far below the level documented in the literature. Some unofficial statistics show that retail trading dominates the Chinese stock markets and it can account for some 70% to 80% of total trading. We thus ask what cutoff point will give us an estimate of retail trading that takes up about 70% of total trades in the market. Working reversely, we find RMB26, 800 fits the purpose well and we define trades orders less than RMB26, 800 as retail trades for robustness checks.

3.5 Investor Participation in the Secondary Market

In addition to retail trading, we also use another three variables to measure the extent to which different market participants are involved in the secondary market. First, following Amihud (2002), we use the price impact ratio (*PriceImpact*) to measure illiquidity in the immediate aftermarket, defined as the daily return over trading volume in the first post-IPO event month:

$$PI_j = \frac{1}{n} \sum_{t=1}^n \frac{|r_{j,t}|}{V_{j,t}} \quad (4)$$

where n is the number of days over which we take the PI ratio; $|r_t|$ is the absolute value of the return on event day t ; V_t is trading volume on day t . If the stock is illiquid, the price tends to move a lot when trading volume is high. Thus the larger the price impact, the more illiquid the stock and the stronger investor participation in the aftermarket.

Second, we use the number analysts providing coverage over the 6-month post-IPO period to measure analyst participation. Finally, we use institutional shareholdings 6 months after going public to measure institutional participation in the secondary market.

3.6 Control Variables

We control for other explanations for investor participation, first-day returns, long-term performance and retail trading by including a number of variables in our multivariate analysis: *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; *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 analyst's forecasting EPS and 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 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 abnormal return in three subsequent years is as low as -14.5% measured as BHAR, 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 measures of media coverage seem to have considerable variations across observations. The average number of times that a typical IPO firms is mentioned in the news 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 media can refer to an IPO firms very frequently, 24 times in the former period and 13 times in the latter period, respectively, as demonstrated in the table. Media bias also varies dramatically over these two periods. Media bias can range from -4 to 11 for the three-month pre-offering period, while the number of positive news articles can also range from -4 to 10 over a much shorter period prior to the listing, typically two weeks. Third, we find that it is more difficult to obtain an allocation as retail investors, indicating a very strong retail demand for IPOs throughout our sample period. The average rate of allocation for retail investors is 1.056% while the average rate of allocation for institutional investors is around 6%. We also find that there are two analysts, on average, providing coverage for an IPO firm over 6 months after going public. Institutional shareholdings for IPO firms can vary a lot, from 7.22% to 52.40%. The average price impact ratio is -0.84 and its standard deviation is 0.485. Forth, this table also provides summary statistics for other variables. One might find that these firms usually spend 7.6 years before going public. They are usually profitable because they have a positive ROA on average. Tradable

shares account for about 20% of total number of shares outstanding. The average time lag between offering and listing is 12 days.

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

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

$$IR = \beta_0 + \beta_1 \cdot MediaCount + \beta_2 \cdot MediaCount2 + \beta_3 \cdot MediaBias + \beta_4 \cdot MediaBias2 + \beta_5 \cdot Control + \varepsilon \quad (5)$$

$$BHAR = \beta_0 + \beta_1 \cdot MediaCount + \beta_2 \cdot MediaCount2 + \beta_3 \cdot MediaBias + \beta_4 \cdot MediaBias2 + \beta_5 \cdot Control + \varepsilon \quad (6)$$

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.

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

Table 2 reports regression results for the relation between first-day returns and media bias. In Column (1), we do not include any media variable in the regression since we wish to examine the relation between first-day returns and non-media variables. When we add in *MediaCount* and *MediaCount2* in Columns (2) and (3), respectively, we find that first-day returns tend to increase with the number of new articles over two different periods, consistent with prior studies such as Liu et al. (2009) and Huang and Chen (2013). Regression results in Columns (4) and (5), when we include *MediaBias* and *MediaBias2*, respectively, reveal a positive relation between pre-IPO media bias and first-day returns, even after controlling for those deal-level, firm-level and market-level determinants of IPO returns documented in the literature. This positive relation between media bias and first-day returns remains significant when we further control for the number of news articles in Column (6).

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

Table 3 reports regression results for the relation between long-run abnormal returns and media

bias. 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. The dependent variable in Panel B is Jensen's alpha estimated from Fama-French three-factor regressions using the calendar-time approach. 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. Columns (2) and (3) add in two variables of media coverage in, and we find that the coefficients on *MediaCount* and *MediaCount2* are negative at the 1% significance level, respectively. Columns (4) and (5) includes another two variables of media bias, and we find that the coefficients on *MediaBias* in the form case and *MediaBias2* in the latter case are also negative at the 1% significance level, indicating that there is a strong negative relation between pre-IPO media bias and long-run performance following IPOs, as predicted by our first hypothesis. The negative relation between media bias and long-run abnormal returns remain significant even when we control for the number of new articles in Colum (6). Using three-factor alpha in Panel B as measure for long-term abnormal returns yields very similar results to those using *BHAR* in Panel A. Alpha is negatively related to *MediaBias* and *MediaBias2*, even after controlling for the number of news articles and other firm characteristics.

Taken together, evidence in this section strengthens our belief that investor sentiment drives post-IPO prices and media bias can account for the presence of investor sentiment, at least partly.

3. *Media Bias and Investor Participation in the Primary Market*

To investigate whether pre-IPO media bias affects investor participation, we estimate the following regression models:

$$\begin{aligned}
 \text{InvestorPar} = & \beta_0 + \beta_1 \cdot \text{MediaCount} + \beta_2 \cdot \text{MediaCount2} + \beta_3 \cdot \text{MediaBias} \\
 & + \beta_4 \cdot \text{MediaBias2} + \beta_5 \cdot \text{Control} + \varepsilon
 \end{aligned} \tag{7}$$

where, *InvestorPar* is a vector which includes our two measures for investor participation; *MediaCount* is the simple count of news articles over the 3-month period before the offer date; *MediaCount2* is another simple count of news articles for the period between offering and listing; *MediaBias* is the tone of

relevant news articles over the 3-month period before the offer date; *MediaBias2* is another measure for the tone of relevant news articles for the period between offering and listing; *Control* is a vector which includes a number of variables which potentially influence investor participation.

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

Table 4 reports regression results on the relation between pre-IPO media bias and investor participation in the primary market. The dependent variable in Panel A is *Allocation_Retail*, defined as the allocation rate among retail investors. Consistent with our investor participation hypothesis that media bias can attract more investors to the primary market, we find that the probability of retail investors receiving an allocation is smaller for IPOs with more positive news articles. More specifically, Column (1) does not include any media 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 relation between the number of pre-IPO news articles and retail participation, we find a negative relation between pre-IPO media bias and the rate of allocation for retail investors in Columns (3) and (4). We interpret this finding being consistent with our investor hypothesis that pre-IPO media bias can attract more retail investors to the IPO market.

We also explore whether pre-IPO media bias can attract more institutional investors in Panel B. where the dependent variable is *Allocation_Insti*, defined as the allocation rate among institutional investors. Likewise, we find a negative relation between allocation to institutional investors and IPO's profitability in Column (1) where we do not include any media variable. We do not find evidence that the number of news articles in the pre-IPO period can attract more institutional investors. However, we find strong evidence in Columns (3) and (4) that the proportion of shares allocated to institutional investors is smaller on average for IPO stocks that have more positive news articles in the pre-IPO period. This finding seems to suggest that media bias drives not only retail but institutional demand for IPOs.

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

Table 5 reports regression results on the relation between pre-IPO media bias and investor participation in the secondary market. The dependent variable in Panel A is *PriceImpact*, which is the

price impact ratio defined as the daily return over trading volume in the first post-IPO event month. Column (1) does not include any media variable. In Columns (2) and (3) where we add in two media variables using information before the offer date, we find no evidence that both the number of news articles and the number of positive news articles have any significant impact on liquidity in the immediate aftermarket. However, regression results in Column (5) reveal a negative relation between the number of positive news articles and aftermarket illiquidity. This negative relation remains significant even after we control of the number of news articles over the same period in Column (6), which appears to indicate that pre-IPO media bias can drive post-IPO liquidity. The dependent variable in Panel B is *Analyst_Cov*, defined as the number of analysts providing coverage. We do not include any media variable in Column (1), before including one of our four media variables in Columns (2) to (5), respectively, and all four variables in Column (6). We find a positive relation between pre-IPO media coverage and the number of analysts providing coverage in the post-IPO period, even after controlling for the number of news articles for the three-month pre-IPO period and for the period between the offering date and the first trading date, which suggests that pre-IPO media bias can attract the attention of analysts and their coverage. The dependent variable in Panel C is *Shareholding_Insti*, defined as the proportion of institutional holdings into the firm. Regression results in Columns (2) and (3) show that institutional shareholding is not related to the number of news articles for the three-month period before the offer date, or the number of positive news articles over the same period. However, Columns (5) and (6) report a positive relation between institutional holding and pre-IPO media bias for the period between the offer date and the first trading date, indicating that media bias can attract institutional demands for IPOs over a relatively longer period of time.

4. *Media Bias and Retail Trading*

Prior studies has shown that retail demand appears to drive the IPO market (Derrien 2005), and that retail trading seems to drive post-IPO prices (Dorn 2009). In previous sections, we show that pre-IPO media bias is positively related to first-day returns while negatively related to long-term abnormal returns. We also show that investor participation is stronger for IPOs which are more positively covered by the media before going public. To complement our previous analysis, we further investigate retail trading on the first day in

this section by examining whether pre-IPO media bias can affect retail trading:

$$\begin{aligned}
 \text{SmallTrade_buy} = & \beta_0 + \beta_1 \cdot \text{MediaCount} + \beta_2 \cdot \text{MediaCount2} + \beta_3 \cdot \text{MediaTone} \\
 & + \beta_4 \cdot \text{MediaTone2} + \beta_5 \cdot \text{Control} + \varepsilon
 \end{aligned}
 \tag{8}$$

where, *SmallTrade_buy* is defined as the total RMB trading volume of those smallest 20% of trade orders placed on the first day of trading.

***** Insert Table 6 about here *****

Table 6 summarizes relevant regression results for the relation between buyer-initiated small trades and pre-IPO media bias. The dependent variable of retail trading in Panel A is *SmallTrade_buy*, defined as defined as the total RMB trading volume of those smallest 20% of trade orders placed on the first trading day, worth less than RMB6,700. We do not include any variable for media coverage or media bias 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 our four media variables, we find that the coefficients on these measures for media coverage are significantly positive, even after controlling for those firm characteristics. Further analysis in Column (6) shows that media bias seems to have greater explanatory power of retail trading than media coverage. While the coefficients on *MediaCount* and *MediaCount2* become insignificant in Column (6), the coefficients on *MediaBias* and *MediaBias2* remain positive and significant at the 5% level. The dependent variable of retail trading in Panel B is *SmallTrade_buy2*, defined alternatively as the total RMB trading volume of those trade orders worth less than RMB28,400. Panel B presents a very similar picture on the relation between pre-IPO media bias and retail trading, since the coefficients on buyer-initiated small trade defined in an alternative way are significantly positive in Columns (3) to (5), except for *MediaCount* in Column (2). After controlling for four measures, we end up with a similar result that pre-IPO media bias appears to influence retail trading to a greater extent than media counts does. Overall, results in these two panels provide consistent evidence that buyer-initiated orders placed by retail investors on the first-trading day tend to increase in pre-IPO media bias.

V. 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 bias 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 role of media bias on investor participation, retail trading and market performance post IPOs. Consistent with our hypotheses, we find that the number of positive news articles is positively related to first-day returns while negatively related to long-run abnormal returns. We also find that pre-IPO media bias attracts not only retail investors but also institutional investors to the primary markets, and that pre-IPO media bias increases aftermarket liquidity, attracts more analysts coverage, and leads to a greater institutional shareholding in the IPO firms. Further analysis suggests that the number of positive news article can increase retail trading on the first trading date. Overall, our findings are consistent with the view that media can drive retail demand and account for the presence of investor sentiment, which causes post-IPO prices to deviate temporarily from fundamentals in the short run.

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.
- Bhattacharya, U., Galpin, N., Ray, R., Yu, X., 2009. The role of the media in the Internet IPO bubble. *Journal of Financial and Quantitative Analysis* 44, 657 – 682.
- Bodnaruk, A., Ostberg, P., 2009. Does investor recognition predict returns? *Journal of Financial Economics* 91, 208-226.
- Chan, Y., 2010. Retail trading and IPO returns in the aftermarket. *Financial Management* 39, 1475-1495.
- Chan, K., Wang, J., Wei, K., 2004. Underpricing and long-term performance of IPOs in China. *Journal of Corporate Finance* 10, 409 – 430.
- 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.
- Daniel, K., Hirshleifer, D., Teoh, S.H., 2002. Investor psychology in capital markets: Evidence and policy implications. *Journal of Monetary Economics* 49, 139–209.
- DellaVigna, S., Kaplan, E., 2007. The Fox News effect: media bias and voting. *Quarterly Journal of Economics* 122, 1187 – 1234.
- DellaVigna, S., Pollet, J., 2009. Investor inattention and Friday earnings announcements. *Journal of Finance* 64, 709–749.
- 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.
- 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.
- Frieder, L, Subrahmanyam, A., 2005. Brand perceptions and the market for common stock. *Journal of Financial and Quantitative Analysis* 40, 57-85.
- Gentzkow, M., 2006. Television and voter turnout. *Quarterly Journal of Economics* 121, 931 – 972.
- Gentzkow, M., Shapiro, J., 2010. What derives media slant? Evidence from U.S. daily newspapers. *Econometrica* 78, 35 – 71.
- Groseclose, T., Milyo, J., 2005. A measure of media bias. *Quarterly Journal of Economics*, 120, 1191–1237.
- Gurun, U., Butler, A., 2012. Don't believe the hype: local media slant, local advertising, and firm value. *Journal of Finance* 67, 561–597.
- Hirshleifer, D., Lim, S., Teoh, S.H., 2009. Driven to distraction: Extraneous events and underreaction to earnings news. *Journal of Finance* 64, 2289–2325.
- Huang, J., Chen, X., 2013. Media coverage and IPO underpricing: Evidence from the ChiNext Board. *Journal of Management Science in China* 16, 83-94.
- Huberman, G., Regev, T. 2001. Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. *Journal of Finance* 56, 387–396.
- 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.
- Mullainathan, S., Shleifer, A., 2005. The market for news. *American Economic Review* 95, 1031 – 1053.
- Ofek, E., Richardson, M., 2003. DotCom mania: the rise and fall of internet stock prices. *Journal of Finance* 58, 1113-1138.
- Purnanandam, A., Swaminathan, B., 2004. Are IPOs really underpriced? *Review of Financial Studies* 17, 811-848
- 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.
- Su, D., Fleisher, B., 1999. An empirical investigation of underpricing in Chinese IPOs. *Pacific-Basin Finance Journal* 7, 173 – 202.
- Shen, Z., Coakley, J., Instefjord, N., 2013. Investor participation and underpricing in lottery-allocated Chinese IPOs. *Pacific-Basin Finance Journal* 25, 294-314.
- Stromberg, D., 2004. Radio's impact on public spending. *Quarterly Journal of Economics* 119, 189 – 221.
- 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](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. *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; *MediaBias* 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; *MediaBias2* is the number of positive news items in excess of the number of negative news items over the period between offering and listing; *Allocation_Insti* is defined as the allocation rate among institutional investors; *Allocation_Retail* is defined as the allocation rate among retail investors; *Analyst_Cov* is defined as the number of analysts providing coverage; *Shareholding_Insti* is defined as the proportion of institutional holdings into the firm; *PriceImpact* is the price impact ratio defined as the daily return over trading volume in the first post-IPO event month; *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 defined as the total RMB trading volume of those smallest 20% of trade orders placed on the first trading day, worth less than RMB6,700; *SmallTrade_buy2* is defined as defined as the total RMB trading volume of those trade orders worth less than RMB26,800.

Variable	Obs	Mean	St dev	Min	P10	P25	P50	P75	P90	Max
<i>IR</i>	1126	0.602	0.745	-0.137	-0.032	0.126	0.366	0.797	1.522	3.807
<i>BHAR</i>	865	-0.145	0.712	-1.905	-1.087	-0.592	-0.137	0.315	0.718	1.763
<i>Alpha</i>	865	-0.016	0.013	-0.046	-0.033	-0.024	-0.016	-0.008	0	0.024
<i>MediaCount</i>	1126	2.69	3.962	0	0	0	1	4	9	24
<i>MediaCount2</i>	1126	1.589	2.758	0	0	0	0	2	5	13
<i>MediaBias</i>	1126	1.042	3.168	-4	-1	0	0	1	5	11
<i>MediaBias2</i>	1126	0.777	2.483	-4	-1	0	0	1	2	10
<i>Allocation_Insti</i>	1126	5.983	9.532	0.257	0.43	0.885	2.012	6.296	16.667	53.571
<i>Allocation_Retail</i>	1126	1.056	1.523	0.027	0.103	0.329	0.627	1.122	2.24	9.695
<i>Analyst_Cov</i>	1126	2.143	0.433	0	1.792	1.946	2.197	2.398	2.565	2.944
<i>Shareholding_Insti</i>	1126	15.84	11.601	0.722	4.193	7.469	12.631	20.64	33.7	52.396
<i>PriceImpact</i>	1126	-0.84	0.485	-3.012	-1.32	-1.002	-0.753	-0.541	-0.368	-0.079
<i>SmallTrade_buy</i>	1126	0.566	0.21	0.077	0.31	0.445	0.548	0.665	0.837	1.268

<i>SmallTrade_buy2</i>	1126	3.429	1.207	-0.031	1.732	2.866	3.697	4.156	4.701	6.072
<i>MediaCount</i>	1126	2.69	3.962	0	0	0	1	4	9	24
<i>MediaCount2</i>	1126	1.589	2.758	0	0	0	0	2	5	13
<i>MediaBias</i>	1126	1.042	3.168	-4	-1	0	0	1	5	11
<i>MediaBias2</i>	1126	0.777	2.483	-4	-1	0	0	1	2	10
<i>ROA</i>	1126	0.099	0.072	0.002	0.025	0.044	0.082	0.135	0.197	0.371
<i>Leverage</i>	1126	0.473	0.179	0.074	0.217	0.343	0.486	0.607	0.694	0.85
<i>Profitability</i>	1126	-0.184	0.325	-0.764	-0.581	-0.403	-0.216	0	0.236	0.825
<i>Log (IssueSize)</i>	1126	11.067	0.831	9.552	10.112	10.522	10.986	11.484	12.073	14.145
<i>Log(Assets)</i>	1126	20.206	1.141	18.498	19.035	19.464	19.965	20.691	21.567	24.679
<i>Underwriter</i>	1126	0.353	0.478	0	0	0	0	1	1	1
<i>Big4</i>	1126	0.047	0.212	0	0	0	0	0	0	1
<i>VC-backed</i>	1126	0.396	0.489	0	0	0	0	1	1	1
<i>State</i>	1126	0.114	0.27	0	0	0	0	0	0.611	1
<i>Tradable</i>	1126	0.203	0.041	0.08	0.2	0.2	0.201	0.203	0.25	0.369
<i>Age</i>	1126	7.572	4.75	0.83	1.888	3.288	7.153	10.485	14.153	20.06
<i>Timelag</i>	1126	11.77	3.378	7	8	9	11	14	15	24
<i>Analysts_std</i>	1126	0.066	0.066	0.007	0.018	0.029	0.045	0.08	0.131	0.449
<i>Analysts_bias</i>	1126	0.017	0.291	-0.618	-0.337	-0.193	-0.005	0.212	0.451	0.71
<i>HighTech</i>	1126	0.121	0.326	0	0	0	0	0	1	1
<i>MktSent1</i>	1126	22.193	8.882	3	10	15	24	29	32	37
<i>MktSent2</i>	1126	0.603	0.631	0.016	0.066	0.176	0.375	0.75	1.484	3.346
<i>MktSent3</i>	1126	0.013	0.09	-0.218	-0.078	-0.056	0.009	0.059	0.138	0.342

Table 2: Media Bias and First-day Returns

This table reports regression results for the relation between pre-IPO media coverage and first-day returns. The dependent variable is *IR*, the first-day return. *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; *MediaBias* 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; *MediaBias2* is the number of positive news items in excess of the number of negative news items 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.

	<i>IR</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>MediaCount</i>		0.013*** (3.32)				-0.000 (-0.01)
<i>MediaCount2</i>			0.042*** (7.23)			0.024*** (2.76)
<i>MediaBias</i>				0.014*** (2.99)		0.012** (2.43)
<i>MediaBias2</i>					0.045*** (7.50)	0.028*** (3.11)
<i>ROA</i>	0.875*** (4.16)	0.845*** (4.07)	0.819*** (3.92)	0.839*** (4.06)	0.837*** (3.99)	0.790*** (3.85)
<i>Leverage</i>	-0.118 (-1.13)	-0.088 (-0.84)	-0.031 (-0.30)	-0.110 (-1.07)	-0.054 (-0.54)	-0.023 (-0.23)
<i>Profitability</i>	0.002 (0.05)	0.001 (0.03)	-0.016 (-0.37)	0.003 (0.07)	-0.027 (-0.61)	-0.025 (-0.57)
Log (<i>IssueSize</i>)	-0.377*** (-9.37)	-0.389*** (-9.82)	-0.371*** (-9.56)	-0.383*** (-9.63)	-0.347*** (-9.06)	-0.360*** (-9.49)
Log (<i>Assets</i>)	0.122*** (3.62)	0.114*** (3.35)	0.086*** (2.62)	0.121*** (3.63)	0.100*** (3.08)	0.088*** (2.68)
<i>Underwriter</i>	-0.012 (-0.52)	-0.013 (-0.54)	-0.009 (-0.38)	-0.012 (-0.52)	-0.013 (-0.56)	-0.011 (-0.47)
<i>Big4</i>	0.072 (1.06)	0.047 (0.68)	0.006 (0.09)	0.057 (0.86)	0.017 (0.27)	-0.010 (-0.16)
<i>VC-backed</i>	0.040* (1.71)	0.043* (1.86)	0.039* (1.70)	0.036 (1.58)	0.043* (1.91)	0.038* (1.71)
<i>State</i>	0.194*** (3.10)	0.173*** (2.84)	0.144** (2.53)	0.173*** (2.74)	0.158*** (2.59)	0.126** (2.17)
<i>Tradable</i>	0.005 (0.01)	-0.106 (-0.28)	0.050 (0.14)	-0.023 (-0.06)	0.114 (0.33)	0.072 (0.21)
Log (1+ <i>Age</i>)	-0.002 (-0.98)	-0.003 (-1.15)	-0.002 (-0.76)	-0.003 (-1.13)	-0.002 (-0.98)	-0.002 (-0.98)

<i>Timelag</i>	0.000 (0.12)	0.002 (0.47)	-0.002 (-0.42)	0.002 (0.40)	-0.001 (-0.15)	-0.000 (-0.11)
<i>Analysts_std</i>	0.150 (1.22)	0.194 (1.59)	0.227* (1.88)	0.196 (1.60)	0.245** (2.10)	0.291** (2.51)
<i>Analysts_bias</i>	-0.024 (-0.59)	-0.024 (-0.60)	0.002 (0.06)	-0.030 (-0.77)	0.011 (0.28)	0.006 (0.17)
<i>HighTech</i>	0.016 (0.45)	0.015 (0.41)	0.017 (0.48)	0.014 (0.40)	0.021 (0.59)	0.018 (0.51)
<i>MktSent1</i>	-0.000 (-0.13)	0.001 (0.29)	0.000 (0.21)	-0.000 (-0.12)	-0.001 (-0.28)	-0.000 (-0.02)
<i>MktSent2</i>	0.895*** (18.17)	0.875*** (17.93)	0.843*** (17.25)	0.883*** (17.88)	0.860*** (17.04)	0.834*** (17.10)
<i>MktSent3</i>	-0.162 (-0.82)	-0.187 (-0.95)	-0.273 (-1.42)	-0.196 (-0.99)	-0.260 (-1.36)	-0.315 (-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 Bias and Long-term Stock Performance

This table reports regression results for the relation between pre-IPO media coverage and initial returns. The dependent variable in Panel A is *BHAR*, 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. The dependent variable in Panel B is Jensen's alpha estimated from calendar-time Fama-French three-factor regression model. *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; *MediaBias* 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; *MediaBias2* is the number of positive news items in excess of the number of negative news items 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

	(1)	(2)	(3)	(4)	(5)	(6)
<i>MediaCount</i>		-0.020*** (-3.27)				-0.002 (-0.17)
<i>MediaCount2</i>			-0.033*** (-3.19)			-0.002 (-0.10)
<i>MediaBias</i>				-0.032*** (-4.18)		-0.028*** (-2.72)
<i>MediaBias2</i>					-0.047*** (-4.17)	-0.044*** (-2.83)
<i>IR</i>	-0.267*** (-5.07)	-0.244*** (-4.65)	-0.216*** (-4.09)	-0.240*** (-4.55)	-0.190*** (-3.55)	-0.166*** (-3.09)
<i>ROA</i>	-0.502 (-1.04)	-0.451 (-0.94)	-0.472 (-0.99)	-0.431 (-0.90)	-0.502 (-1.06)	-0.433 (-0.92)
<i>Leverage</i>	-0.124 (-0.66)	-0.190 (-1.03)	-0.188 (-1.00)	-0.152 (-0.83)	-0.204 (-1.09)	-0.232 (-1.26)
<i>Profitability</i>	-0.042 (-0.40)	-0.030 (-0.29)	-0.019 (-0.18)	-0.038 (-0.37)	-0.007 (-0.07)	-0.004 (-0.04)
Log (<i>IssueSize</i>)	-0.045 (-0.68)	-0.029 (-0.43)	-0.034 (-0.51)	-0.026 (-0.40)	-0.055 (-0.82)	-0.036 (-0.54)
Log (<i>Assets</i>)	-0.057 (-1.20)	-0.036 (-0.74)	-0.029 (-0.59)	-0.051 (-1.09)	-0.029 (-0.60)	-0.023 (-0.46)
<i>Underwriter</i>	-0.033 (-0.63)	-0.032 (-0.61)	-0.036 (-0.69)	-0.029 (-0.57)	-0.032 (-0.62)	-0.029 (-0.57)
<i>Big4</i>	-0.097 (-0.77)	-0.051 (-0.41)	-0.066 (-0.53)	-0.067 (-0.55)	-0.064 (-0.51)	-0.035 (-0.28)
<i>VC-backed</i>	-0.010 (-0.20)	-0.013 (-0.25)	-0.009 (-0.18)	-0.004 (-0.09)	-0.016 (-0.32)	-0.011 (-0.21)
<i>State</i>	0.121	0.153*	0.146	0.162*	0.134	0.174*

	(1.35)	(1.69)	(1.61)	(1.83)	(1.49)	(1.95)
<i>Tradable</i>	-0.119 (-0.22)	0.111 (0.21)	-0.048 (-0.09)	-0.030 (-0.06)	-0.075 (-0.14)	0.024 (0.04)
Log (1+Age)	0.002 (0.46)	0.003 (0.59)	0.003 (0.50)	0.004 (0.73)	0.003 (0.59)	0.004 (0.84)
<i>Timelag</i>	-0.002 (-0.24)	-0.004 (-0.52)	-0.000 (-0.01)	-0.004 (-0.58)	-0.000 (-0.04)	-0.003 (-0.36)
<i>Analysts_std</i>	0.723 (1.54)	0.632 (1.36)	0.600 (1.30)	0.607 (1.30)	0.551 (1.19)	0.445 (0.96)
<i>Analysts_bias</i>	-0.295*** (-3.18)	-0.297*** (-3.21)	-0.317*** (-3.44)	-0.279*** (-3.00)	-0.328*** (-3.59)	-0.312*** (-3.40)
<i>HighTech</i>	0.091 (1.35)	0.095 (1.42)	0.088 (1.32)	0.101 (1.50)	0.084 (1.28)	0.094 (1.42)
<i>MktSent1</i>	-0.003 (-0.57)	-0.004 (-0.85)	-0.003 (-0.70)	-0.003 (-0.60)	-0.002 (-0.40)	-0.002 (-0.45)
<i>MktSent2</i>	0.033 (0.42)	0.043 (0.56)	0.025 (0.33)	0.039 (0.51)	-0.001 (-0.02)	0.007 (0.10)
<i>MktSent3</i>	-0.116 (-0.42)	-0.084 (-0.31)	-0.043 (-0.16)	-0.031 (-0.11)	-0.025 (-0.09)	0.052 (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 regressions

	(1)	(2)	(3)	(4)	(5)	(6)
<i>MediaCount</i>		-0.000*** (-3.34)				-0.000 (-0.29)
<i>MediaCount2</i>			-0.001*** (-3.47)			-0.000 (-0.68)
<i>MediaBias</i>				-0.001*** (-4.01)		-0.000** (-2.45)
<i>MediaBias2</i>					-0.001*** (-3.64)	-0.001* (-1.82)
<i>IR</i>	-0.005*** (-5.47)	-0.005*** (-4.93)	-0.005*** (-4.49)	-0.005*** (-4.94)	-0.004*** (-4.27)	-0.004*** (-3.73)
<i>ROA</i>	0.009 (1.02)	0.010 (1.13)	0.010 (1.08)	0.011 (1.17)	0.009 (1.03)	0.011 (1.20)
<i>Leverage</i>	0.004 (1.25)	0.003 (0.85)	0.003 (0.90)	0.004 (1.11)	0.003 (0.89)	0.002 (0.68)
<i>Profitability</i>	-0.000 (-0.25)	-0.000 (-0.12)	-0.000 (-0.02)	-0.000 (-0.22)	0.000 (0.04)	0.000 (0.10)
Log (<i>IssueSize</i>)	-0.002 (-1.40)	-0.001 (-1.10)	-0.002 (-1.24)	-0.001 (-1.13)	-0.002 (-1.52)	-0.001 (-1.15)
Log (<i>Assets</i>)	-0.001 (-0.92)	-0.000 (-0.48)	-0.000 (-0.42)	-0.001 (-0.83)	-0.000 (-0.51)	-0.000 (-0.29)
<i>Underwriter</i>	0.001 (0.93)	0.001 (0.96)	0.001 (0.88)	0.001 (1.00)	0.001 (0.95)	0.001 (0.99)
<i>Big4</i>	-0.000 (-0.14)	0.001 (0.27)	0.000 (0.11)	0.000 (0.10)	0.000 (0.08)	0.001 (0.37)
<i>VC-backed</i>	-0.000 (-0.55)	-0.001 (-0.61)	-0.000 (-0.54)	-0.000 (-0.44)	-0.001 (-0.66)	-0.000 (-0.54)
<i>State</i>	0.005** (2.54)	0.005*** (2.85)	0.005*** (2.77)	0.005*** (2.98)	0.005*** (2.68)	0.006*** (3.13)
<i>Tradable</i>	0.003 (0.25)	0.007 (0.64)	0.004 (0.37)	0.004 (0.40)	0.003 (0.32)	0.006 (0.52)

<i>Log (1+Age)</i>	-0.000 (-0.26)	-0.000 (-0.12)	-0.000 (-0.23)	0.000 (0.00)	-0.000 (-0.16)	0.000 (0.08)
<i>Timelag</i>	0.000 (0.70)	0.000 (0.40)	0.000 (0.93)	0.000 (0.38)	0.000 (0.88)	0.000 (0.59)
<i>Analysts_std</i>	-0.001 (-0.09)	-0.002 (-0.32)	-0.003 (-0.37)	-0.003 (-0.35)	-0.003 (-0.41)	-0.005 (-0.69)
<i>Analysts_bias</i>	-0.010*** (-6.14)	-0.010*** (-6.21)	-0.010*** (-6.39)	-0.010*** (-5.98)	-0.010*** (-6.51)	-0.010*** (-6.36)
<i>HighTech</i>	0.002* (1.67)	0.002* (1.73)	0.002 (1.64)	0.002* (1.81)	0.002 (1.61)	0.002* (1.74)
<i>MktSent1</i>	-0.000 (-1.30)	-0.000 (-1.58)	-0.000 (-1.42)	-0.000 (-1.33)	-0.000 (-1.16)	-0.000 (-1.27)
<i>MktSent2</i>	0.001 (0.95)	0.002 (1.09)	0.001 (0.85)	0.001 (1.02)	0.001 (0.60)	0.001 (0.74)
<i>MktSent3</i>	-0.018*** (-3.24)	-0.017*** (-3.20)	-0.017*** (-3.05)	-0.016*** (-3.00)	-0.017*** (-3.04)	-0.015*** (-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 Bias and Investor Participation in the Primary Market

This table reports regression results for the relation between pre-IPO media bias and investor participation in the primary market. The dependent variable in Panel A is *Allocation_Retail*, defined as the allocation rate among retail investors. The dependent variable in Panel B is *Allocation_Insti*, defined as the allocation rate among institutional investors. *MediaCount* is the number of news items that appear in the 46 national business media over the 3-month period before the offer date; *MediaBias* 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; *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: Participation and Allocation for Retail Investors

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

	(3.86)	(3.84)	(3.81)	(3.88)
<i>Analysts_bias</i>	-0.101 (-0.66)	-0.101 (-0.66)	-0.082 (-0.55)	-0.072 (-0.49)
<i>HighTech</i>	0.085 (0.76)	0.085 (0.76)	0.090 (0.81)	0.090 (0.81)
<i>MktSent1</i>	-0.005 (-0.73)	-0.005 (-0.74)	-0.005 (-0.75)	-0.003 (-0.42)
<i>MktSent2</i>	-0.173** (-2.34)	-0.172** (-2.27)	-0.140* (-1.93)	-0.169** (-2.25)
<i>MktSent3</i>	1.186*** (3.33)	1.188*** (3.34)	1.283*** (3.56)	1.278*** (3.54)
Number of obs.	1,126	1,126	1,126	1,126
Adjusted R-squared	0.349	0.348	0.354	0.356

Panel B: Participation and Allocation for Institutional Investors

	(1)	(2)	(3)	(4)
<i>MediaCount</i>		0.001 (0.01)		0.192* (1.85)
<i>MediaBias</i>			-0.225*** (-2.90)	-0.364*** (-2.98)
<i>ROA</i>	4.191 (0.87)	4.189 (0.86)	4.765 (0.98)	4.681 (0.97)
<i>Leverage</i>	-0.305 (-0.16)	-0.303 (-0.15)	-0.425 (-0.22)	-0.063 (-0.03)
<i>Profitability</i>	-4.766*** (-5.30)	-4.766*** (-5.29)	-4.780*** (-5.35)	-4.803*** (-5.40)
Log (<i>IssueSize</i>)	0.367 (0.54)	0.366 (0.55)	0.459 (0.68)	0.342 (0.51)
Log (<i>Assets</i>)	2.130*** (3.29)	2.129*** (3.22)	2.143*** (3.34)	2.025*** (3.12)
<i>Underwriter</i>	1.261** (2.55)	1.261** (2.55)	1.262** (2.56)	1.256** (2.56)
<i>Big4</i>	-2.454 (-1.58)	-2.455 (-1.56)	-2.226 (-1.45)	-2.453 (-1.58)
<i>VC-backed</i>	-0.835* (-1.89)	-0.834* (-1.89)	-0.779* (-1.77)	-0.695 (-1.58)
<i>State</i>	-3.017*** (-3.11)	-3.018*** (-3.07)	-2.676*** (-2.72)	-2.783*** (-2.87)
<i>Tradable</i>	-6.918 (-0.78)	-6.926 (-0.76)	-6.464 (-0.73)	-7.818 (-0.88)
Log (1+ <i>Age</i>)	-0.071 (-1.31)	-0.071 (-1.31)	-0.066 (-1.21)	-0.068 (-1.27)
<i>Timelag</i>	0.163** (2.18)	0.163** (2.12)	0.146* (1.92)	0.155** (2.04)
<i>Analysts_std</i>	14.779*** (2.91)	14.782*** (2.90)	14.036*** (2.77)	14.228*** (2.82)
<i>Analysts_bias</i>	-0.343 (-0.37)	-0.343 (-0.37)	-0.236 (-0.26)	-0.177 (-0.19)
<i>HighTech</i>	0.081 (0.11)	0.080 (0.11)	0.113 (0.15)	0.111 (0.15)
<i>MktSent1</i>	0.015 (0.37)	0.015 (0.39)	0.015 (0.36)	0.028 (0.71)
<i>MktSent2</i>	-0.901* (-1.88)	-0.903* (-1.89)	-0.711 (-1.41)	-0.887* (-1.74)

<i>MktSent3</i>	6.781*** (3.37)	6.780*** (3.39)	7.337*** (3.62)	7.310*** (3.60)
Number of obs.	1,126	1,126	1,126	1,126
Adjusted R-squared	0.417	0.416	0.421	0.423

Table 5: Media Bias and Investor Participation in the Secondary Market

This table reports regression results for the relation between pre-IPO media coverage and investor participation in the secondary market. The dependent variable in Panel A is *PriceImpact*, which is the price impact ratio defined as the daily return over trading volume in the first post-IPO event month. The dependent variable in Panel B is *Analyst_Cov*, defined as the number of analysts providing coverage in the 6-month post-IPO period. The dependent variable in Panel C is *Shareholding_Insti*, defined as the proportion of institutional holdings into the firm in the 6-month post-IPO period. *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; *MediaBias* 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; *MediaBias2* is the number of positive news items in excess of the number of negative news items 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.

Panel A: the Price Impact Ratio

	(1)	(2)	(3)	(4)	(5)	(6)
<i>MediaCount</i>		-0.003 (-0.73)				0.000 (0.00)
<i>MediaBias</i>			-0.005 (-0.76)			0.022** (2.44)
<i>MediaCount2</i>				-0.010** (-2.25)		-0.008 (-1.44)
<i>MediaBias2</i>					-0.026*** (-4.26)	-0.041*** (-4.45)
<i>ROA</i>	-0.222 (-1.00)	-0.215 (-0.97)	-0.215 (-0.97)	-0.195 (-0.88)	-0.200 (-0.91)	-0.196 (-0.89)
<i>Leverage</i>	0.068 (0.71)	0.061 (0.64)	0.058 (0.59)	0.062 (0.65)	0.031 (0.32)	0.051 (0.52)
<i>Profitability</i>	-0.012 (-0.22)	-0.011 (-0.22)	-0.009 (-0.19)	-0.012 (-0.24)	0.005 (0.11)	0.005 (0.09)
Log (<i>IssueSize</i>)	-0.044 (-1.22)	-0.041 (-1.15)	-0.045 (-1.24)	-0.040 (-1.11)	-0.061* (-1.74)	-0.065* (-1.85)
Log (<i>Assets</i>)	-0.077** (-2.55)	-0.075** (-2.46)	-0.073** (-2.38)	-0.077** (-2.54)	-0.064** (-2.18)	-0.075** (-2.50)
<i>Underwriter</i>	-0.012 (-0.47)	-0.012 (-0.46)	-0.013 (-0.48)	-0.012 (-0.47)	-0.012 (-0.46)	-0.010 (-0.38)
<i>Big4</i>	0.025 (0.37)	0.031 (0.44)	0.032 (0.46)	0.035 (0.52)	0.057 (0.80)	0.048 (0.70)
<i>VC-backed</i>	-0.029 (-1.06)	-0.030 (-1.09)	-0.029 (-1.06)	-0.026 (-0.97)	-0.031 (-1.14)	-0.031 (-1.13)
<i>State</i>	0.004	0.008	0.009	0.019	0.025	0.023

	(0.05)	(0.13)	(0.14)	(0.28)	(0.37)	(0.35)
<i>Tradable</i>	0.084	0.109	0.080	0.105	0.022	0.026
	(0.27)	(0.35)	(0.25)	(0.34)	(0.07)	(0.08)
Log (1+Age)	0.001	0.001	0.000	0.001	0.000	0.001
	(0.17)	(0.20)	(0.15)	(0.25)	(0.14)	(0.31)
<i>Timelag</i>	-0.004	-0.005	-0.004	-0.005	-0.004	-0.005
	(-0.98)	(-1.04)	(-0.92)	(-1.15)	(-0.84)	(-1.14)
<i>Analysts_std</i>	0.156	0.147	0.148	0.123	0.101	0.083
	(0.82)	(0.77)	(0.78)	(0.64)	(0.53)	(0.43)
<i>Analysts_bias</i>	0.127***	0.127***	0.124***	0.132***	0.107**	0.113**
	(2.75)	(2.75)	(2.67)	(2.87)	(2.34)	(2.49)
<i>HighTech</i>	0.008	0.008	0.007	0.009	0.005	0.005
	(0.20)	(0.21)	(0.20)	(0.25)	(0.13)	(0.14)
<i>MktSent1</i>	-0.002	-0.003	-0.002	-0.002	-0.002	-0.002
	(-0.96)	(-1.03)	(-1.00)	(-0.97)	(-0.91)	(-0.72)
<i>MktSent2</i>	-0.067	-0.062	-0.061	-0.058	-0.046	-0.055
	(-1.55)	(-1.43)	(-1.41)	(-1.35)	(-1.08)	(-1.31)
<i>MktSent3</i>	-0.522**	-0.516**	-0.510**	-0.497**	-0.465**	-0.470**
	(-2.54)	(-2.52)	(-2.47)	(-2.45)	(-2.29)	(-2.34)
Number of obs.	1,126	1,126	1,126	1,126	1,126	1,126
Adjusted R ²	0.189	0.188	0.188	0.191	0.204	0.211

Panel B: the Number of Analysts Providing Coverage

	(1)	(2)	(3)	(4)	(5)	(6)
<i>MediaCount</i>		-0.001				-0.011**
		(-0.31)				(-2.05)
<i>MediaBias</i>			0.009**			0.002
			(1.97)			(0.32)
<i>MediaCount2</i>				0.008**		0.015***
				(1.96)		(2.82)
<i>MediaBias2</i>					0.018***	0.016**
					(3.28)	(1.97)
<i>ROA</i>	-0.099	-0.096	-0.111	-0.119	-0.113	-0.128
	(-0.45)	(-0.44)	(-0.51)	(-0.54)	(-0.52)	(-0.59)
<i>Leverage</i>	-0.071	-0.074	-0.052	-0.067	-0.046	-0.059
	(-0.74)	(-0.75)	(-0.54)	(-0.69)	(-0.48)	(-0.60)
<i>Profitability</i>	0.060	0.060	0.056	0.060	0.048	0.050
	(1.14)	(1.14)	(1.06)	(1.15)	(0.91)	(0.94)
Log (<i>IssueSize</i>)	0.015	0.016	0.016	0.012	0.026	0.030
	(0.44)	(0.48)	(0.48)	(0.35)	(0.78)	(0.87)
Log (<i>Assets</i>)	-0.006	-0.005	-0.014	-0.007	-0.015	-0.010
	(-0.21)	(-0.18)	(-0.48)	(-0.23)	(-0.52)	(-0.34)
<i>Underwriter</i>	-0.043	-0.043	-0.042	-0.043	-0.043	-0.042
	(-1.56)	(-1.55)	(-1.53)	(-1.56)	(-1.57)	(-1.56)
<i>Big4</i>	0.031	0.034	0.017	0.023	0.010	0.014
	(0.46)	(0.50)	(0.25)	(0.34)	(0.15)	(0.20)
<i>VC-backed</i>	0.010	0.009	0.010	0.008	0.011	0.005
	(0.38)	(0.37)	(0.37)	(0.30)	(0.44)	(0.18)
<i>State</i>	0.059	0.061	0.048	0.047	0.045	0.039
	(0.94)	(0.95)	(0.76)	(0.74)	(0.71)	(0.59)
<i>Tradable</i>	-0.915***	-0.904***	-0.905***	-0.931***	-0.873***	-0.813**
	(-2.79)	(-2.71)	(-2.74)	(-2.85)	(-2.63)	(-2.40)
Log (1+Age)	0.001	0.001	0.001	0.001	0.001	0.001
	(0.35)	(0.37)	(0.41)	(0.28)	(0.38)	(0.39)

<i>Timelag</i>	-0.011** (-2.29)	-0.011** (-2.32)	-0.011** (-2.40)	-0.010** (-2.17)	-0.011** (-2.38)	-0.011** (-2.40)
<i>Analysts_std</i>	0.177 (0.96)	0.173 (0.94)	0.194 (1.04)	0.203 (1.10)	0.214 (1.14)	0.228 (1.23)
<i>Analysts_bias</i>	-0.042 (-1.00)	-0.042 (-1.00)	-0.036 (-0.86)	-0.046 (-1.10)	-0.029 (-0.68)	-0.035 (-0.83)
<i>HighTech</i>	0.025 (0.72)	0.025 (0.72)	0.026 (0.72)	0.024 (0.68)	0.027 (0.77)	0.026 (0.74)
<i>MktSent1</i>	-0.003 (-1.44)	-0.003 (-1.46)	-0.003 (-1.37)	-0.003 (-1.43)	-0.003 (-1.50)	-0.004* (-1.77)
<i>MktSent2</i>	0.206*** (4.99)	0.208*** (5.09)	0.194*** (4.74)	0.199*** (4.97)	0.192*** (4.71)	0.194*** (4.87)
<i>MktSent3</i>	-0.250 (-1.40)	-0.248 (-1.37)	-0.274 (-1.54)	-0.270 (-1.50)	-0.288 (-1.62)	-0.307* (-1.69)
Number of obs.	1,126	1,126	1,126	1,126	1,126	1,126
Adjusted R ²	0.076	0.075	0.078	0.078	0.084	0.087

Panel C: the Proportion of Institutional Holdings into the Firm

	(1)	(2)	(3)	(4)	(5)	(6)
<i>MediaCount</i>		0.152 (1.61)				0.054 (0.40)
<i>MediaBias</i>			0.151 (1.12)			-0.208 (-1.10)
<i>MediaCount2</i>				0.260** (2.25)		0.197 (1.32)
<i>MediaBias2</i>					0.389*** (2.79)	0.509*** (2.80)
<i>ROA</i>	-3.936 (-0.65)	-4.284 (-0.70)	-4.135 (-0.68)	-4.599 (-0.75)	-4.253 (-0.70)	-4.705 (-0.78)
<i>Leverage</i>	2.987 (1.10)	3.332 (1.23)	3.296 (1.22)	3.125 (1.15)	3.535 (1.30)	3.506 (1.30)
<i>Profitability</i>	6.007*** (4.87)	5.996*** (4.90)	5.943*** (4.83)	6.024*** (4.90)	5.758*** (4.68)	5.779*** (4.70)
<i>Log (IssueSize)</i>	6.143*** (6.47)	6.005*** (6.30)	6.163*** (6.52)	6.037*** (6.35)	6.400*** (6.68)	6.321*** (6.44)
<i>Log (Assets)</i>	-2.994*** (-4.00)	-3.095*** (-4.24)	-3.122*** (-4.15)	-3.010*** (-4.02)	-3.186*** (-4.22)	-3.118*** (-4.18)
<i>Underwriter</i>	0.823 (1.15)	0.817 (1.15)	0.835 (1.17)	0.822 (1.16)	0.819 (1.15)	0.797 (1.12)
<i>Big4</i>	-1.431 (-0.80)	-1.722 (-0.95)	-1.663 (-0.92)	-1.694 (-0.93)	-1.895 (-1.05)	-2.022 (-1.09)
<i>VC-backed</i>	0.909 (1.31)	0.949 (1.36)	0.905 (1.30)	0.845 (1.22)	0.938 (1.35)	0.918 (1.31)
<i>State</i>	-1.201 (-0.84)	-1.452 (-1.01)	-1.379 (-0.96)	-1.594 (-1.11)	-1.513 (-1.06)	-1.753 (-1.21)
<i>Tradable</i>	-16.655** (-2.02)	-17.954** (-2.20)	-16.498** (-2.00)	-17.181** (-2.06)	-15.727* (-1.88)	-16.516** (-1.98)
<i>Log (1+Age)</i>	-0.126* (-1.75)	-0.131* (-1.81)	-0.124* (-1.72)	-0.132* (-1.84)	-0.125* (-1.73)	-0.134* (-1.84)
<i>Timelag</i>	0.021 (0.21)	0.037 (0.36)	0.014 (0.13)	0.041 (0.40)	0.012 (0.12)	0.040 (0.39)
<i>Analysts_std</i>	6.590 (1.15)	7.107 (1.23)	6.865 (1.18)	7.449 (1.30)	7.407 (1.28)	8.117 (1.41)
<i>Analysts_bias</i>	-5.122***	-5.127***	-5.029***	-5.246***	-4.827***	-4.959***

	(-4.03)	(-4.02)	(-3.93)	(-4.13)	(-3.78)	(-3.87)
<i>HighTech</i>	0.138	0.121	0.142	0.101	0.178	0.151
	(0.13)	(0.12)	(0.14)	(0.10)	(0.17)	(0.15)
<i>MktSent1</i>	-0.062	-0.051	-0.059	-0.061	-0.065	-0.065
	(-1.10)	(-0.89)	(-1.06)	(-1.10)	(-1.15)	(-1.12)
<i>MktSent2</i>	0.974	0.740	0.789	0.754	0.672	0.582
	(1.02)	(0.77)	(0.81)	(0.78)	(0.69)	(0.58)
<i>MktSent3</i>	-6.478	-6.773	-6.876	-7.121	-7.323	-7.631*
	(-1.43)	(-1.50)	(-1.51)	(-1.57)	(-1.61)	(-1.67)
Number of obs.	1,126	1,126	1,126	1,126	1,126	1,126
Adjusted R ²	0.135	0.136	0.135	0.138	0.140	0.142

Table 6: Media Bias and First-day Retail Trading

This table reports regression results for the relation between pre-IPO media coverage and first-day retail trading. The dependent variable of retail trading in Panel A is *SmallTrade_buy*, defined as defined as the total RMB trading volume of those smallest 20% of trade orders placed on the first trading day, worth less than RMB6,700. The dependent variable of retail trading in Panel B is *SmallTrade_buy2*, defined as defined as the total RMB trading volume of those trade orders worth less than RMB26,800. *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; *MediaBias* 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; *MediaBias2* is the number of positive news items in excess of the number of negative news items 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.

Panel A: Buyer-initiated Trade RMB Volume for Trade Orders Worth RMB6,700 and Less

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

<i>Tradable</i>	-0.180 (-1.17)	-0.218 (-1.39)	-0.173 (-1.12)	-0.204 (-1.32)	-0.147 (-0.96)	-0.147 (-0.95)
Log (1+Age)	0.000 (0.15)	0.000 (0.05)	0.000 (0.23)	-0.000 (-0.05)	0.000 (0.19)	0.000 (0.02)
<i>Timelag</i>	0.003 (1.31)	0.003 (1.52)	0.002 (1.14)	0.003* (1.76)	0.002 (1.15)	0.003 (1.52)
<i>Analysts_std</i>	-0.010 (-0.10)	0.005 (0.05)	0.002 (0.02)	0.028 (0.28)	0.019 (0.19)	0.049 (0.50)
<i>Analysts_bias</i>	0.129*** (6.07)	0.128*** (6.07)	0.133*** (6.23)	0.123*** (5.89)	0.139*** (6.61)	0.132*** (6.37)
<i>HighTech</i>	0.112** (5.18)	0.111** (5.19)	0.112*** (5.19)	0.110** (5.20)	0.113** (5.30)	0.112*** (5.30)
<i>MktSent1</i>	0.000 (0.32)	0.001 (0.62)	0.000 (0.44)	0.000 (0.36)	0.000 (0.24)	0.000 (0.01)
<i>MktSent2</i>	0.030 (1.56)	0.023 (1.21)	0.022 (1.11)	0.020 (1.08)	0.019 (1.04)	0.015 (0.80)
<i>MktSent3</i>	0.533*** (6.80)	0.525*** (6.68)	0.515*** (6.51)	0.505*** (6.53)	0.503*** (6.50)	0.480*** (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

Panel B: Buyer-initiated Trade RMB Volume for Trade Orders Worth RMB28,400 and Less

	(1)	(2)	(3)	(4)	(5)	(6)
<i>MediaCount</i>		0.001 (0.06)				-0.035** (-2.46)
<i>MediaCount2</i>			0.041*** (3.20)			0.005 (0.24)
<i>MediaBias</i>				0.035*** (3.30)		0.056*** (3.82)
<i>MediaBias2</i>					0.077*** (6.44)	0.074*** (4.10)
<i>ROA</i>	3.474*** (6.11)	3.473*** (6.11)	3.420*** (6.05)	3.385*** (5.99)	3.411*** (6.10)	3.344*** (6.01)
<i>Leverage</i>	-0.216 (-0.80)	-0.215 (-0.80)	-0.132 (-0.49)	-0.198 (-0.73)	-0.107 (-0.40)	-0.151 (-0.57)
<i>Profitability</i>	0.149 (1.19)	0.149 (1.19)	0.131 (1.05)	0.151 (1.21)	0.099 (0.80)	0.105 (0.85)
Log (<i>IssueSize</i>)	-0.266** (-2.46)	-0.267** (-2.44)	-0.261** (-2.41)	-0.281*** (-2.60)	-0.215** (-2.01)	-0.208** (-2.00)
Log (<i>Assets</i>)	0.122 (1.39)	0.121 (1.39)	0.087 (0.97)	0.120 (1.37)	0.084 (0.96)	0.101 (1.22)
<i>Underwriter</i>	0.044 (0.61)	0.044 (0.61)	0.048 (0.67)	0.044 (0.61)	0.044 (0.61)	0.045 (0.63)
<i>Big4</i>	-0.064 (-0.32)	-0.066 (-0.33)	-0.128 (-0.65)	-0.100 (-0.50)	-0.156 (-0.82)	-0.150 (-0.78)
<i>VC-backed</i>	0.427*** (6.10)	0.427*** (6.11)	0.426*** (6.10)	0.418*** (5.98)	0.433*** (6.28)	0.409*** (5.95)
<i>State</i>	0.264* (1.70)	0.263* (1.67)	0.215 (1.39)	0.211 (1.37)	0.202 (1.34)	0.171 (1.14)
<i>Tradable</i>	1.254 (1.30)	1.249 (1.31)	1.297 (1.36)	1.184 (1.23)	1.439 (1.51)	1.621* (1.79)
Log (1+Age)	0.004 (0.51)	0.004 (0.51)	0.005 (0.60)	0.003 (0.41)	0.004 (0.56)	0.004 (0.54)
<i>Timelag</i>	0.008	0.008	0.006	0.011	0.006	0.007

	(0.83)	(0.82)	(0.63)	(1.10)	(0.65)	(0.68)
<i>Analysts_std</i>	-1.008*	-1.006*	-0.933*	-0.893*	-0.846*	-0.777
	(-1.95)	(-1.93)	(-1.79)	(-1.75)	(-1.66)	(-1.54)
<i>Analysts_bias</i>	0.628***	0.628***	0.653***	0.611***	0.686***	0.662***
	(5.04)	(5.04)	(5.26)	(4.94)	(5.60)	(5.48)
<i>HighTech</i>	0.583***	0.583***	0.584***	0.578***	0.591***	0.586***
	(6.93)	(6.92)	(6.94)	(6.91)	(7.04)	(7.06)
<i>MktSent1</i>	-0.004	-0.004	-0.004	-0.004	-0.005	-0.007
	(-0.71)	(-0.70)	(-0.60)	(-0.71)	(-0.82)	(-1.22)
<i>MktSent2</i>	0.134	0.133	0.084	0.105	0.074	0.077
	(1.58)	(1.53)	(0.97)	(1.24)	(0.92)	(0.95)
<i>MktSent3</i>	2.498***	2.497***	2.390***	2.412***	2.330***	2.253***
	(4.99)	(4.98)	(4.76)	(4.88)	(4.69)	(4.56)
Number of obs.	1,126	1,126	1,126	1,126	1,126	1,126
Adjusted R ²	0.147	0.147	0.153	0.153	0.168	0.177