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Analyst Coverage, Information, and Bubbles

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Abstract

We examine the 2007 stock market bubble in China. Using multiple measures of bubble intensity for each stock, we find significantly smaller bubbles in stocks for which there is greater analyst coverage. We further show that the abating effect of analyst coverage on bubble intensity is weaker when there is greater disagreement among analysts. This suggests that, in line with resale option theories of bubbles, one channel through which analyst coverage may mitigate bubbles is by coordinating investors' beliefs and thus reducing its dispersion. Stock turnover provides further evidence consistent with this particular information mechanism.

I. Introduction

> What is peculiar about China's stock market is that government officials, the People's Bank of China, the media, investment bankers, not to mention Li Ka-shing, Hong Kong's richest tycoon, and Alan Greenspan, the former chairman of the Federal Reserve, have all warned that it looks like a bubble. *The Economist*, May 24, 2007

> Many [Chinese investors] try to educate themselves, poring over analyst reports available free of charge at Web sites such as Hexun and Chinastock. *Business Week*, March 19, 2007

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Asset pricing bubbles are intriguing, large-scale economic phenomena. The distorted prices and potential resource misallocation associated with bubbles can lead to large societal costs. Bernanke (2002) notes the importance of understanding the factors that influence bubbles in order to design policies to mitigate such phenomena, and the recent boom and collapse in real estate prices has generated much debate among policy makers (Landau (2009), Bernanke (2010), and Dudley (2010)).

The anti-bubble policy prescriptions currently considered tend to be macro in nature. For example, discussions involve whether central banks should tighten monetary policy in response to perceived asset bubbles, or which kind of macro-prudential regulations (tightening of capital requirements, imposing transaction taxes or direct lending constraints, etc.) are likely to be most effective in deflating bubbles.[1] In contrast, this paper investigates whether a micro-level policy could potentially help mitigate asset pricing bubbles and thus complement macro-level policies. In particular, we study whether greater dissemination of public information about an asset could lower its susceptibility to bubbles.

Theory suggests that dissemination of public information could mitigate bubbles by coordinating investors' beliefs. In resale option theories, bubbles arise through the interaction of belief dispersion and short-sale constraints (Harrison and Kreps (1978), Scheinkman and Xiong (2003)).[2] In these theories, investors hold beliefs that are correct on average. Nonetheless, investors knowingly pay more for an asset than the present value of future dividends in hopes of selling the asset at yet higher prices to more optimistic investors in the future. In the resale option framework, public dissemination of information could coordinate beliefs as all investors update their beliefs toward the valuation implied by information being disseminated. Such coordination would thus lower bubble magnitude by reducing future belief dispersion and thereby the possibility that investors could sell in the future to more optimistic investors. In Appendix A, we add public dissemination of information to a two-period, two-state version of Scheinkman and Xiong's model in order to illustrate this bubble-mitigating mechanism. We show that the stronger is the public information signal, the smaller is the asset price bubble.

It is also possible that dissemination of public information mitigates bubbles by reducing investors' overoptimism. In contrast to resale option theories of bubbles, in which investors hold correct beliefs on average, bubbles may be caused by investors' "irrational exuberance" (Shiller (2005), Han and Kumar (2013)).

[1]For discussion of macro-level bubble-mitigating policies, see Allen and Carletti (2011), Christensson, Spong, and Wilkinson (2011), and Prasad (2010). Known drawbacks to such macro approaches include the need to recognize bubbles in real time in order to calibrate policy response and the potential to create distortions in regions or markets without bubbles. Moreover, even if an asset bubble is identified in real time, the effectiveness of macro approaches is still open to question. Allen (2011) notes that evidence from Korea, Hong Kong, and Singapore suggests that macro-prudential measures aiming at eliminating real estate bubbles may work in the short run but not in the long run.

[2]In addition to the dynamic resale option theories of bubbles, several static theories also feature a positive price bias due to the interaction between the dispersion of beliefs across investors and short-sale constraints (e.g., Miller (1977), Chen, Hong, and Stein (2002)). However, static models do not capture the speculative trading (buying in anticipation of capital gains, rather than buying and holding in order to receive long-term income streams) that is often ascribed to bubbles.

If that is the case, public information could serve as a "reality check" that anchors beliefs to fundamentals.[3]

To pursue our research question, we need a plausibly identified market-wide bubble and measures of the intensity of the bubble and of the degree of public dissemination of information in each individual asset in the bubble. The 2007 stock market in China provides an ideal setting. As we explain in Section II, the 2007 Chinese stock market displays classic features of a bubble, including a boom followed by a bust in asset prices, a dramatic surge in trading activity that is strongly correlated with price levels, and a documented flood of novice investors entering the market. Moreover, the Chinese setting allows us to construct unique measures of bubble intensity in individual assets, measures that are not available, for example, when studying the U.S. Internet bubble of the late 1990s.[4] These unique measures collectively alleviate concerns about measurement error.

Following an extensive literature, we use the number of security analysts covering a stock as a measure of the degree of public dissemination of information.[5] Analysts are specialized professionals who collect information about stocks and disseminate it to market participants in the form of periodic reports, earnings forecasts, and buy/sell/hold recommendations. To the extent that analyst research is at least partially independent and not released at the same time, a greater number of analysts producing and disseminating research about a given stock should result in a higher rate of information flow to market participants.

Figure 1 illustrates our key finding: Stocks with less analyst coverage develop significantly larger bubbles. On the vertical axis, we plot *Composite bubble measure*, one of our five measures of the intensity of the bubble in each individual stock. This measure is normalized to have a mean of 0 and a standard deviation (SD) equal to 1, and therefore a negative *Composite bubble measure* does not imply a negative bubble, just a bubble intensity that is below the cross-sectional average. On the horizontal axis, we plot *Analyst coverage,* the number of analysts following a stock. Figure 1 shows there is a strong negative correlation between each stock *Composite bubble measure* and its *Analyst coverage.* Results are similar when we use any of the other four bubble-intensity measures in our study.

We show that the negative correlation between *Analyst coverage* and bubble intensity remains after controlling for several stock-level characteristics. In particular, we provide compelling evidence that our key finding is *not* driven by the

[3] Note there is a subtle but important difference between these two bubble-mitigating mechanisms. The overoptimism reduction channel mechanism requires that the public information being disseminated is *truly* informative, whereas the belief coordination channel only requires that it is *perceived to be* informative. Hence, even though stock analyst research may suffer from an assortment of biases (e.g., De Bondt and Thaler (1990), Ertimur, Muslu, and Zhang (2011)), it could nevertheless mitigate bubbles as long as investors deem it credible.

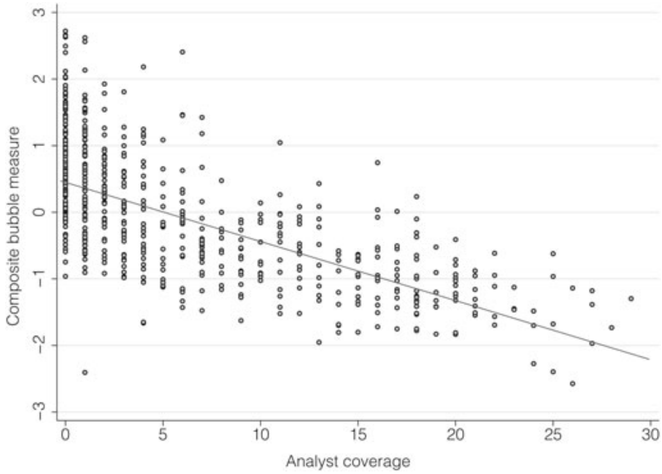
[4] In preliminary results we apply a similar research design to the U.S. Internet bubble of the late 1990s and find similar results: All else being equal, bubbles are smaller when there is more analyst coverage. Results are available from the authors.

[5] A partial list of papers using analyst coverage as a measure of the quality of the information environment includes Brennan, Jegadeesh, and Swaminathan (1993), Hong, Lim, and Stein (2000), Hou and Moskowitz (2005), Chan and Hameed (2006), Duarte, Han, Harford, and Young (2008), Kumar (2009), Hong and Kacperczyk (2010), and Kelly and Ljungqvist (2012). Ganguli and Yang (2009) and Angeletos and Werning (2006) investigate other dimensions of how the supply of information affects financial markets.

FIGURE 1

Bubble Intensity and Analyst Coverage

Figure 1 shows a scatter plot of *Composite bubble measure*, one of our measures of the bubble intensity for each stock, and *Analyst coverage*. *Composite bubble measure* is normalized to have a mean of 0 and a variance equal to 1. The R^2 of the best fit line is equal to 0.46. The sample consists of 623 Shanghai A-shares.



well-known fact that larger stocks tend to attract more analyst coverage coupled with the possibility that larger stocks also develop smaller bubbles for reasons unrelated to analyst coverage.

The results also show that analyst coverage is less effective in reducing bubble intensity when there is greater disagreement among analysts, measured by the dispersion of earnings forecasts or dispersion of buy/sell recommendations (or their first principal component).[6] This finding is important for two reasons. First, it alleviates concerns that *Analyst coverage* is correlated with bubble intensity solely because both variables are determined by a third, stock-specific variable orthogonal to all our control variables. If that was the case, then *how* analysts disseminate the information (with more or less disagreement) should be irrelevant.[7] Second, it provides insight as to *why* analyst coverage mitigates bubbles. Specifically, it supports the idea that analyst coverage mitigates bubbles by coordinating investors' beliefs. This is because analyst coverage should be less

[6]Note that disagreement among *analysts* is not necessarily a good proxy for disagreement among *investors* in China. This market is dominated by retail investors who are more likely to display overconfidence in the Scheinkman and Xiong (2003) sense (i.e., focusing on a limited, idiosyncratic information set, and overestimating the validity of the approaches they use to value stocks). Nonetheless, disagreement among *analysts* is useful in our analysis because it plausibly regulates the degree to which a given amount of analyst coverage is able to coordinate *investors'* beliefs. For a given number of analysts following a stock, the information that they disseminate should be less effective in coordinating investors' beliefs (and hence mitigating bubbles) when analysts themselves disagree more.

[7]Three additional exercises further address endogeneity concerns. First, in Section IV.B.1 we show that analyst coverage in 2005 (well before the bubble developed) is also negatively correlated with bubble intensity during 2007. Second, instrumental variables regressions in Section IV.B.2 corroborate the negative association between bubble intensity and analyst coverage. Third, in Section VI.B we explicitly provide evidence against three specific alternative stories based on endogenous analyst coverage.

effective in coordinating investors' beliefs when stock analysts themselves have more dispersed beliefs.

We provide further evidence consistent with analyst coverage mitigating bubbles by coordinating beliefs and thus reducing belief dispersion across investors. Even though we cannot directly observe the dispersion of beliefs across *investors* (as opposed to dispersion among *analysts*), several theories indicate that it is positively related to stock turnover. We show that *Analyst coverage* is negatively associated with stock turnover, consistent with analyst research coordinating beliefs across investors. Furthermore, analogous to our empirical analysis explaining bubble intensities, we find that the abating effect of *Analyst coverage* on stock turnover is weaker when there is more disagreement among analysts. This is an additional result one would expect if analyst coverage is indeed less effective in coordinating beliefs when there is more disagreement among analysts themselves.

For completeness, we investigate the possibility that analyst coverage mitigates bubbles by reducing investor overoptimism, in addition to reducing belief dispersion. We find that there is very little time-series variation in the average analyst recommendation before, during, and after the bubble. If anything, the average recommendation becomes slightly more optimistic as the bubble inflates. This indicates that analysts do not lean against high valuations during the bubble, and that analyst coverage does not mitigate bubbles by reducing investor overoptimism in our setting.

Overall, we find that stocks with more analyst coverage are much less affected by the spectacular boom and bust of the Chinese stock market in 2007. Multiple findings support an information-based channel in which analyst coverage mitigates bubbles by coordinating investors' beliefs. Thus, our results suggest that policies that increase public information dissemination to market participants may help mitigate asset pricing bubbles.

II. Why Study China?

There are at least three reasons why the 2007 Chinese stock market provides a good empirical setting in which to study asset pricing bubbles. First, the Chinese stock market has institutional characteristics that are conducive to bubbles. Specifically, like residential real estate markets around the world, the Chinese stock market is dominated by retail investors and has very strict short-selling constraints. Bailey, Cai, Cheung, and Wang (2009) document that individual investors accounted for 92% of the trading volume in 198 large Chinese stocks from Oct. 2003 to March 2004. Moreover, during 2007 short sales were forbidden, and the ability of pessimistic investors to indirectly affect equity prices through a derivatives market was extremely limited.[8]

Second, the 2007 Chinese stock market displays classic features of a bubble: a boom followed by a bust in asset prices, a dramatic surge in trading activity that is strongly correlated with asset price levels, and a flood of novice investors

[8]There were put warrants during our sample period, but these contracts only existed for a tiny subset of stocks.

entering the market (Kindleberger and Aliber (2005), Cochrane (2003), Hong and Stein (2007), and Greenwood and Nagel (2009)). Note that the *Economist* quote opening our paper shows that many recognized the 2007 bubble even before it crashed. Thus, any ex post rationalization for the boom and bust in asset prices and trading activity has to contend with such pre-crash views.

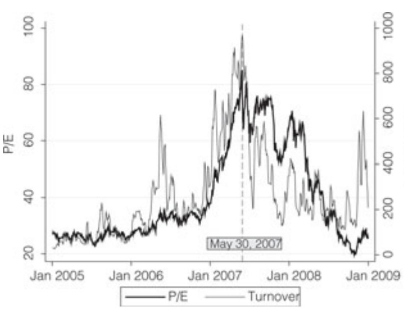
Figure 2 illustrates key elements of the bubble. Graph A plots the evolution of the median price/earnings (P/E) ratio and the median daily turnover across Shanghai A-shares in our sample. During the 6-month period from Nov. 29, 2006, to May 29, 2007, the median stock in our sample has its P/E ratio increase from 35 to 85, and its annualized daily turnover increases from 230% to 950%. As the figure shows, both P/E ratios and turnover decline after May 30, 2007, eventually falling to 20 and 150%, respectively, by Oct. 2008. The correlation between P/E ratios and turnover over the entire Jan. 2005 to Dec. 2008 period is 0.70. Graph B plots cumulative returns of the value-weighted Shanghai stock market index in rolling 6-month windows. During the 6-month period from Nov. 29, 2006, to May 29, 2007, the Shanghai stock index has a cumulative return equal to 178%, which is the highest 6-month return in the 2000–2010 period (Figure 2 only shows 2005–2009).

FIGURE 2

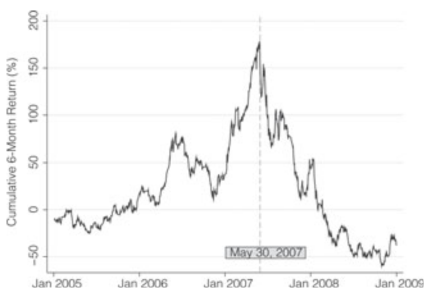
The Chinese Stock Market Bubble of 2007

Figure 2 illustrates key elements of the Chinese stock market bubble of 2007. All graphs show variables over the Jan. 2005–Jan. 2009 time period. Graph A has the median P/E ratio (left axis) and the median daily annualized stock turnover (right axis) of the 623 Shanghai A-shares in our sample. Graph B has the cumulative stock returns over the previous 6-month period of our sample stocks. Graph C shows a weekly index that tracks the relative level of Google searches for the terms "stock" or "stock market" (in Chinese) relative to overall Google searches in China. Graph D shows the monthly number of new (A-share) trading accounts opened in the Shanghai Stock Exchange.

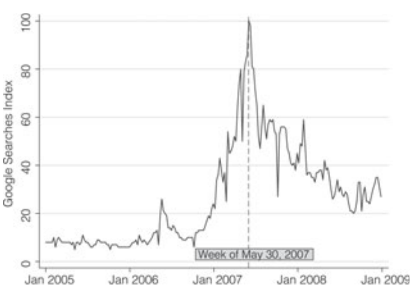
Graph A. Median P/E and Turnover



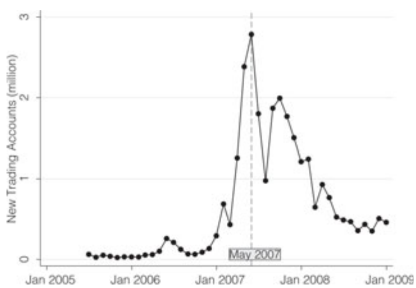
Graph B. Value-Weighted 6-Month Returns



Graph C. Google Searches in China



Graph D. New Trading Accounts



Alongside soaring asset prices and trading activity, from Dec. 2006 to May 2007 a total of 7.8 million new retail-investor A-share trading accounts were created at brokerages trading on the Shanghai Stock Exchange (see Graph D of Figure 2). These data are from the Shanghai Stock Exchange. The new accounts represent a 21% increase in the *total* number of retail A-share accounts during just 6 months. Because individual investors were not allowed to open accounts in multiple brokerages, the surge in new accounts is overwhelmingly due to new individual investors venturing into a booming equity market.

Graph C of Figure 2 plots a weekly index measuring the number of Google searches that originate in China for the terms "stock" or "stock market" (in Chinese), relative to overall Google search volume originating in China. The index is provided by Google Insights for Search and is normalized to 100 at the sample period peak. The plot shows a fivefold increase in Google searches from Dec. 2006 to May 2007, with a peak in the week of May 30, 2007, and almost monotonic decline thereafter. Google search data thus confirm that the 2007 Chinese stock market was marked by unusually high retail-investor interest, consistent with the flood of novice investors opening A-share trading accounts.

The third and arguably most important reason that the 2007 Chinese stock market offers an attractive setting is because it allows us to construct several stock-specific bubble-intensity measures (some of them unique) that collectively help overcome measurement error concerns. These measures, discussed in detail in Section III, are cumulative returns, P/E ratios, announcement returns following a sudden tripling of China's security transaction tax, the first principal component of these aforementioned metrics (labeled *Composite bubble measure*), and the ratios of prices in China over prices in Hong Kong for a subsample of stocks listed in both markets. Although none of these bubble-intensity measures is perfect, they are all reasonable proxies and at least to some extent provide conceptually independent measures of overvaluation. Thus, finding consistent results using all of these proxies would increase confidence in our conclusions.

III. Data and Variables

Our sample consists of the 623 Shanghai A-share stocks that traded on at least 90% of the trading days during the 6-month period from Nov. 29, 2006, to May 29, 2007. All of our data are from RESSET, a major provider of Chinese financial data.[9] RESSET obtains its stock market data directly from the stock exchanges. Similar to Institutional Brokers' Estimate System (IBES), RESSET collects its analyst forecast data from brokerage firms, except that the RESSET analyst database is much more comprehensive than the IBES data set for China.[10] The brokerage firms in the RESSET data issuing reports and earnings per share

[9]RESSET is headquartered at Tsinghua University. For more information, please see http://www.resset.cn/en/.

[10]Specifically, 250 of our sample stocks are reported with at least one analyst in the IBES data, whereas 453 stocks have at least one analyst covering them according to the RESSET data. The correlation between IBES analyst coverage and RESSET analyst coverage is 0.78. The Online Appendix (http://moya.bus.miami.edu/∼sandrade/research.html) shows that our results are robust to using IBES analyst coverage for China rather than the RESSET analyst coverage.

(EPS) forecasts for our sample stocks are listed in the Online Appendix. Tables 1 and 2 report summary statistics for the main variables in this study.

TABLE 1

Summary Statistics

Table 1 reports summary statistics for the main variables in the study. The variables are described in Table B1 of Appendix B. The sample consists of 623 Shanghai A-shares, selected by requiring that shares be traded on at least 90% of the trading days in the reference period. The reference period is from Nov. 29, 2006, to May 29, 2007.

Variables	Mean	Median	Std. Dev.
Cumulative return (%)	204.4	187.6	95.2
P/E ratio	94.2	56.7	79.2
Announcement return (%)	−23.9	−25.2	10.4
Composite bubble measure	0.000	−0.065	1.000
China-HK premium (%)	66.2	37.7	63.4
Analyst coverage	6.07	3.00	7.07
Market capitalization (billions of yuans)	11.92	2.84	70.54
Log of market capitalization	1.271	1.045	1.077
Turnover (daily, in %)	2.700	2.716	1.239
Lagged return volatility (annualized, %)	45.7	43.7	12.9
Lagged P/E ratio	75.4	34.3	81.5
Effective spread (bp)	20.65	20.00	5.45
Depth (millions of yuans)	0.256	0.172	0.450
Market beta	0.963	0.984	0.218
Liquidity beta	−0.116	−0.129	0.295
ΔTurnover (daily, in %)	−0.697	−0.641	0.638
ΔEffective spread (bp)	−1.519	−1.598	4.306

A. The Reference Period

Our analysis requires us to define a period over which to compute bubble-intensity measures, analyst coverage, and the control variables. In our baseline results we adopt a 6-month reference period from Nov. 29, 2006, to May 29, 2007. Figure 2 suggests a reference period ending May 29, 2007, based on P/E ratios, turnover, cumulative returns, and two measures of retail-investor enthusiasm (Google searches and account openings). Moreover, on May 30, 2007, the Chinese government implemented a previously unannounced tripling of China's security transaction tax, which seemingly marked a regime change in the Chinese stock market. We show later that our results are robust to using different window lengths ending on May 29, 2007, and that our results do not obtain in placebo 6-month periods far from May 30, 2007. For completeness, our Online Appendix plots price indices levels for our sample stocks.

B. Measures of Bubble Intensity

Cumulative Return. This variable is the cumulative stock return during the 6-month reference period from Nov. 29, 2006, to May 29, 2007. As reported in Table 1, the mean and median of *Cumulative return* are 204.4% and 187.6%, respectively, implying that the average stock roughly tripled in price over the 6-month reference period. Of the 623 sample stocks, 567 (91%) have *Cumulative return* exceeding 100%, 275 (44%) have returns exceeding 200%, and 73 (12%) have returns exceeding 300%. The smallest *Cumulative return* is 53%.

P/E Ratio. This variable is the average ratio of each stock's price to its earnings during the 6-month reference period from Nov. 29, 2006, to May 29, 2007. Each day, we calculate this ratio using the total earnings reported over the

TABLE 2

Correlation Matrix

Table 2 reports correlation coefficients between the main variables of this study. The variables are described in Table B1 of Appendix B. The sample consists of 623 Shanghai A-shares, selected by requiring that shares be traded on at least 90% of the trading days in the reference period. The reference period is from Nov. 29, 2006, to May 29, 2007.

	Comp. Bubble Meas.	Cumulative Return	P/E Ratio	Announcement Return	China-HK Premium	Analyst Coverage	Log of Market Cap.	Turnover	Lagged Return Vol.	Lagged P/E Ratio	Effective Spread	Depth	Market Beta	Liquidity Beta	ΔTurnover	ΔEffective Spread
Comp. bubble meas.	1.000															
Cumulative return	0.721	1.000														
P/E ratio	0.760	0.316	1.000													
Announcement return	–0.771	–0.334	–0.390	1.000												
China-HK premium	0.679	0.482	0.661	–0.481	1.000											
Analyst coverage	–0.685	–0.400	–0.455	0.679	–0.691	1.000										
Log of market cap.	–0.484	–0.186	–0.347	0.547	–0.499	0.754	1.000									
Turnover	0.506	0.353	0.265	–0.518	0.434	–0.514	–0.504	1.000								
Lagged return vol.	0.167	0.010	0.315	–0.048	0.551	–0.189	–0.156	0.066	1.000							
Lagged P/E ratio	0.676	0.269	0.923	–0.318	0.607	–0.403	–0.304	0.220	0.320	1.000						
Effective spread	0.516	0.349	0.518	–0.295	0.225	–0.418	–0.443	0.057	0.115	0.478	1.000					
Depth	–0.135	–0.056	–0.081	0.163	–0.270	0.342	0.575	–0.097	–0.162	–0.062	–0.073	1.000				
Market beta	–0.047	0.127	–0.237	–0.013	–0.261	0.111	0.195	0.196	–0.051	–0.219	–0.349	0.096	1.000			
Liquidity beta	0.053	0.169	–0.053	–0.012	–0.380	0.099	0.213	0.004	–0.090	–0.025	–0.050	0.217	0.529	1.000		
ΔTurnover	–0.138	–0.071	–0.059	0.179	–0.348	0.116	0.155	–0.632	–0.072	–0.053	0.082	–0.015	–0.161	0.030	1.000	
ΔEffective spread	–0.286	–0.488	–0.115	0.058	0.194	0.029	–0.197	–0.071	0.124	–0.011	–0.323	–0.186	–0.108	–0.157	–0.168	1.000

four most recent available quarterly earnings prior to the calculation date. We cap daily P/E ratios at 250 and assign a P/E ratio of 250 to stocks with negative earnings. We then compute the average ratio for each stock throughout the reference period. The mean and median *P/E ratios* are 94.2 and 56.7, respectively.

Announcement Return. Even though *Cumulative return* and *P/E ratio* are intuitive measures that capture cross-sectional differences in bubble intensities, both are noisy. As an alternative stock-specific measure of bubble intensity, we exploit our unique setting to construct a third metric that we label *Announcement return.* We argue that this measure should be less affected by unobservable cross-sectional variation in the evolution of fundamentals and in earnings growth rates.

Announcement return is each stock's 5-day cumulative return following the announcement of the tripling of China's security transaction tax on May 30, 2007. Before the market's open on this day, the Chinese government announced and implemented a sudden increase in the security transaction tax from 0.1% to 0.3%. News reports suggest the tax increase was motivated by concerns over an overheating stock market.

We argue that stocks with larger bubbles would have had stronger price reactions to this sudden tax increase. This bubble-intensity identification strategy is anchored on Scheinkman and Xiong's (2003) theory of bubbles, which implies that prices of stocks in larger bubbles will have more negative price reactions to an increase in trading costs.[11] In their theory, asset prices have two components: a fundamental value given by the expected present value of future dividends (averaged across different investors' beliefs), plus the value of the option to resell to potential future investors at greater prices. Scheinkman and Xiong show that an increase in trading costs instantly decreases the value of the resale option (which depends on expected after-tax cash flows of future stock trading). This implies that stocks in which the resale option is a larger fraction of the stock price should have larger percentage price decreases in response to the transaction tax increase announcement.[12]

The 5-day period in the calculation of *Announcement return* starts on May 30, 2007, because the tax tripling announcement was made early that day before the market opened. We use 5-day returns because China has a price change limit of 10% per day, and many stocks hit the limit on one or more of the first 4 days following the tax increase announcement (as detailed later, results are robust to shorter and longer windows). For example, 122 stocks have −10% returns on all of the first 3 days following the tax increase. The mean and median *Announcement*

[11] Mei, Scheinkman, and Xiong (2009) and Xiong and Yu (2011) find evidence supporting the resale option theory of bubbles in Chinese securities markets. However, our strategy of identifying bubble intensities through *Announcement return* is also consistent with investors viewing the sudden tax tripling as a strong, public signal from the Chinese government that the market was overvalued, which could also reduce bubble magnitudes.

[12] Suppose that stocks H and L are priced at $100, and that the fundamental values of H and L are $50 and $90, respectively. Thus, the bubble intensity of stock H is five times larger than the bubble intensity of stock L. A common security transaction tax increase levied on both stocks implies that the value of the option to resell decreases by a similar proportion in both stocks, say, 50%. Such a decrease would imply post-tax-increase announcement prices of about $75 and $95 for stocks H and L, respectively, leading to announcement returns of −25% and −5%. Note that these announcement returns are proportional to bubble intensities in this simple example.

return are −23.9% and −25.2%, respectively. To help put the −23.9% mean *Announcement return* in perspective, we note that the lowest and highest mean cumulative returns over any 5 consecutive trading days during the previous year were −8.5% and 13.5%, respectively.[13] Note that *Announcement return* has an SD of 10.4%, and hence this measure has substantial cross-sectional variation that our analysis can exploit.

Composite Bubble Measure. Our fourth bubble-intensity measure is the first principal component of *Cumulative return*, *P/E ratio*, and *Announcement return*. We normalize the first principal component to have zero mean and unit variance. *Composite bubble measure* has the same orientation as *Cumulative return* and *P/E ratio*. That is, higher values of *Composite bubble measure* are associated with larger bubble intensities. As reported in Table 2, the correlations between *Composite bubble measure* and *Cumulative return*, *P/E ratio*, and *Announcement return* are 0.721, 0.760, and −0.771, respectively.

China-HK Premium. Our fifth bubble-intensity metric is only available for a subsample of 23 stocks that are dual-listed in Shanghai and Hong Kong. Because Hong Kong's market is more developed and allows short selling, prices in Hong Kong are relatively less prone to severe pricing bubbles than are prices in China. Therefore, similar to Mei et al. (2009), Chan, Kot, and Yang (2010), and Liu and Seasholes (2011), we define *China-HK premium* as the Chinese stock price divided by the corresponding exchange-rate-adjusted Hong Kong price minus 1. We average the resulting values across the 6-month reference period from Nov. 29, 2006, to May 29, 2007. The mean and median *China-HK premiums* are 66.2% and 37.7%, respectively.

The top left corner of Table 2 shows that our five cross-sectional measures of bubble intensity are significantly correlated with each other. The average absolute value of the correlations among our bubble-intensity measures (excluding *Composite bubble measure*) is 0.44. The signs of all correlations are as expected, as smaller values of *Announcement return* and larger values of *Cumulative return, P/E ratio, Composite bubble measure*, and *China-HK premium* signify larger bubbles. All 10 correlations among the five bubble-intensity metrics are statistically significant.

C. Analyst Coverage

Following Brennan et al. (1993) and others, we use the number of security analysts following a stock as our firm-level measure of the degree of information dissemination. We define *Analyst coverage* as the number of brokerage firms providing EPS reports during the 6-month reference period from Nov. 29, 2006, to May 29, 2007. To the extent that analyst reports are (at least partially) independent and not released on the same dates, it follows that a greater number of analysts will result in a higher rate of information flow to market participants. Later in the paper we address the concern that *Analyst coverage* is endogenous. We also

[13]It is hard to attribute the large negative returns to events other than the tax increase. We cannot find other major macroeconomic announcements on May 30, 2007, or the subsequent 4 trading days.

present evidence consistent with an information channel explaining the link we find between *Analyst coverage* and bubble intensity.

In line with Chan and Hameed (2006), we argue that analyst coverage is a particularly good cross-sectional measure of information dissemination in China. Compared to markets such as the United States, the corporate environment in China has a relatively low degree of voluntary disclosure and transparency. It is presumably more difficult for Chinese investors to observe and analyze relevant firm information on their own, and such investors are likely to seek guidance from analyst reports, as the paper's second opening quote indicates.

Chinese investors can obtain analyst reports from the brokerage firms in which they have stock brokerage accounts. Moreover, a few popular Web sites serve as repositories for analyst reports from different brokerage firms (e.g., www.cnstock.com and www.prnews.cn/rating). Analyst reports are even available in the finance sections of popular Web portals such as www.sina.com.cn and www.sohu.com. Finally, summaries of analyst reports and recommendations are also available in nationally circulated financial newspapers such as *Shanghai Securities News* and *China Securities Journal*.

Consistent with the notion that analyst reports matter for Chinese investors, Moshirian, Ng, and Wu (2009) find that between 1996 and 2005, Chinese stock prices react to changes in analyst buy/sell recommendations. In our sample, we find that the average 3-day market-adjusted reaction to a strong upward revision (e.g., from hold to strong buy) exceeds that to a strong downgrade by an average of 2.9%, with the average reaction to an upgrade statistically different than the reaction to a downgrade (p-value = 0.0002).[14]

Table 1 shows that the mean and median *Analyst coverage* are 6.07 and 3.00, respectively, and Table 2 shows that *Analyst coverage* is smaller when any of our five bubble-intensity metrics implies larger bubbles. The correlations between *Analyst coverage* and *Cumulative return*, *P/E ratio*, *Announcement return, Composite bubble measure*, and *China-HK premium* are −0.400, −0.455, 0.679, −0.685, and −0.691, respectively.

D. Control Variables

We include several control variables in our regressions explaining bubble-intensity measures. Although some of our control variables are more justified than others depending on the bubble-intensity measure under study, for simplicity the regression analyses include all of them regardless of the bubble-intensity metric used.

Market capitalization is the most important control variable in our analysis, because presumably larger firms are expected to attract more analysts, and yet size may be correlated with stock characteristics that are orthogonal to information dissemination. We use the average market capitalization throughout the 6-month reference period from Nov. 29, 2006, to May 29, 2007. The mean and median

[14]If we consider the reaction to *any* upgrade or downgrade, the announcement reaction to upgrades exceeds that to downgrades by 0.9%, on average, and the average reactions to upgrades and downgrades are statistically different, with a p-value of 0.010.

Market capitalization in billions of yuan are 11.92 and 2.84, respectively. We use the log of *Market capitalization* in our empirical work due to the highly skewed nature of raw market capitalization. Our additional control variables are *Turnover, Lagged return volatility, Lagged P/E ratio, Industry effects, Effective spread, Depth, Market beta, Liquidity beta, ΔTurnover*, and *ΔEffective spread.*

Turnover is the daily number of shares traded divided by the number of tradable shares, averaged across all trading days in the 6-month reference period from Nov. 29, 2006, to May 29, 2007. The mean and median *Turnover* are 2.700% and 2.716%, respectively. *Turnover* is an important control variable in *Announcement return* regressions because exogenous increases in trading costs may differentially affect stocks with different levels of trading activity.

Lagged return volatility is the annualized square root of the average squared daily return in the 6-month period immediately before the 6-month reference period from Nov. 29, 2006, to May 29, 2007. This variable is included because resale option theories imply larger bubbles in stocks with more volatile fundamentals, regardless of the degree of dispersion of information among investors. We use lagged volatility rather than contemporaneous volatility in the baseline regressions because contemporaneous volatility is mechanically associated with *Cumulative return* in our sample period, as the median stock returns 188% in only 6 months. As we show in a robustness check, our conclusions are unchanged if we use contemporaneous rather than lagged volatility. The average *Lagged return volatility* is 45.7%.

Lagged P/E ratio is the average ratio of each stock's price to its earnings during the 6-month period immediately before the reference period from Nov. 29, 2006, to May 29, 2007. We calculate lagged P/E ratios the same way we calculate *P/E ratio*, one of our bubble measures. The mean and median *Lagged P/E ratio* are 75.4 and 34.3, respectively. This variable is included because some stocks may have permanently higher P/E ratios than others.

Industry effects are indicator variables allowing for industry-specific intercept terms. We group the 623 sample stocks into 13 industries based on China Securities Regulatory Commission (CSRC) industry classifications. In regressions explaining *Cumulative return,* as well as those explaining *Announcement return,* controlling for *Industry effects* helps control for news about fundamental values because such news often has a strong industry structure. In regressions explaining *P/E ratio*, the *Industry effects* indicator variables control for industry-level differences in expected earnings growth rates.

Effective spread and *Depth* are two measures of liquidity calculated from intraday transaction data. *Effective spread,* measured in basis points (bp), is the absolute difference between the transaction price and the corresponding midpoint between the best bid and best ask quotes at the time of the trade, divided by the midpoint. For each stock, we calculate the effective spread for each transaction, then take the daily average across all transactions, and lastly take the mean across all days in the 6-month reference period from Nov. 29, 2006, to May 29, 2007. The mean *Effective spread* is 20.65 bp. *Depth*, measured in millions of yuan, is the best bid and ask monetary quantities at the time of each transaction, averaged first across all transactions at the stock-day level, and then averaged for each stock across the 6-month reference period. The mean *Depth* is 0.256.

Market beta and *Liquidity beta* are control variables capturing systematic factor loadings. All else being equal, stocks with higher betas should have lower values of *P/E ratio*, larger values of *Cumulative return*, and more negative values of *Announcement return.* To estimate *Market beta* and *Liquidity beta*, we regress daily stock returns during the 6-month reference period from Nov. 29, 2006, to May 29, 2007, against the aggregate value-weighted market return and an aggregate liquidity factor. All of our results are robust to regressing stock returns on the market and liquidity factors separately instead. For the liquidity factor, we use the innovation in the average daily effective spread across all stocks, where each day's innovation is defined as the residual in a regression of the average effective spread across stocks on its lagged value, similar to Acharya and Pedersen (2005). For the market factor, we use the value-weighted return on all tradable Shanghai A-shares. The mean *Market beta* is 0.963, and the mean *Liquidity beta* is −0.116.[15]

We use *ΔTurnover* and *ΔEffective spread* to control for changes in trading activity and trading costs following the tax increase on May 30, 2007.[16] These variables control for the possibility that each stock's *Announcement return* partially reflects changes in an illiquidity discount as implied by models such as Lo, Mamaysky, and Wang (2004) and Acharya and Pedersen (2005). *ΔTurnover* is the average daily turnover during the 6-month period immediately following the 6-month reference period from Nov. 29, 2006, to May 29, 2007, minus the average daily turnover in the reference period. The definition of *ΔEffective spread* is analogous. The mean *ΔTurnover* and *ΔEffective spread* are −0.697% and −1.519 bp, respectively.

IV. Analyst Coverage and Bubble Intensity

In Table 3 we report ordinary least squares (OLS) regressions of our four full-sample bubble-intensity measures onto *Analyst coverage* and various control variables (we defer analysis using *China-HK premium* until Section IV.C). Columns (1), (3), (5), and (7) show that bubble measures are strongly correlated with *Analyst coverage*. The signs of the correlations indicate that stocks with larger *Analyst coverage* experience smaller bubbles (i.e., lower *Cumulative return*, lower *P/E ratio,* higher (less negative) *Announcement return,* and lower *Composite bubble measure*). The adjusted R^2s of these univariate regressions range from 0.16 in column (1) to 0.46 in columns (5) and (7).

Columns (2), (4), (6), and (8) show that the negative association between *Analyst coverage* and bubble intensity remains after we add a battery of control variables. In all cases the coefficient on *Analyst coverage* is statistically significant at the 1% level. The coefficients in columns (2), (4), (6), and (8) are economically

[15]In robustness work available in our Online Appendix, we address the concern that *Market beta* and *Liquidity beta*, even though theoretically motivated, do not adequately represent true factor loadings in the data (Ross (1976)). We replace *Market beta* and *Liquidity beta* with three empirical factor loadings constructed from a factor analysis of returns. Our conclusions are unchanged when we use these empirical factor exposures in place of *Market beta* and *Liquidity beta*.

[16]In robustness work, we include a *ΔDepth* variable, and all of our conclusions are unchanged. We do not include *ΔDepth* in our baseline specifications because *ΔDepth* is very strongly correlated with *Depth* ($\rho = -0.95$).

TABLE 3

Regressions Explaining Bubble-Intensity Measures

Table 3 reports ordinary least squares regressions that explain four stock-level bubble-intensity measures. The sample consists of 623 Shanghai A-shares, selected by requiring that shares be traded on at least 90% of the trading days in the reference period. The reference period is from Nov. 29, 2006, to May 29, 2007. The variables are described in Table B1 of Appendix B. We report heteroskedasticity-robust *t*-statistics in parentheses below variable coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variables							
	Cumulative Return		P/E Ratio		Announcement Return		Composite Bubble Measure	
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Analyst coverage	–5.392***	–4.628***	–5.086***	–0.843***	0.997***	0.748***	–0.097***	–0.058***
	(–13.37)	(–7.56)	(–15.91)	(–3.59)	(21.46)	(9.88)	(–26.84)	(–12.00)
Log of market capitalization		28.228***		9.455***		0.592		0.154***
		(4.01)		(3.66)		(0.86)		(3.05)
Turnover		21.586***		8.954***		–1.951***		0.233***
		(4.48)		(4.03)		(–4.29)		(6.64)
Lagged return volatility		–0.296		0.098		0.060**		–0.003**
		(–1.44)		(1.23)		(2.36)		(–2.20)
Lagged P/E ratio		0.070		0.811***		–0.008*		0.005***
		(1.50)		(43.12)		(–1.75)		(16.62)
Effective spread		3.933***		1.911***		–0.063		0.031***
		(4.31)		(4.78)		(–0.64)		(4.22)
Depth		–29.630***		–7.023***		–1.867***		–0.090**
		(–4.65)		(–3.02)		(–2.94)		(–2.36)
Market beta		21.878		–7.100		–1.745		0.135
		(1.12)		(–0.68)		(–0.95)		(0.99)
Liquidity beta		41.564***		–0.227		–1.823		0.265***
		(3.04)		(–0.04)		(–1.33)		(2.68)
ΔTurnover		4.397		8.127***		–0.694		0.096**
		(0.67)		(2.80)		(–0.97)		(1.97)
ΔEffective spread		–6.733***		1.151**		–0.079		–0.020***
		(–6.17)		(2.37)		(–0.79)		(–2.65)
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Constant	237.1***		125.1***		–30.0***		0.588***	
	(47.42)		(–29.15)		(–77.13)		(–14.25)	
No. of obs.	623	623	623	623	623	623	623	623
Adj. R^2	0.160	0.477	0.206	0.870	0.461	0.532	0.468	0.757

significant as well, as they imply that a one-SD increase in *Analyst coverage* is associated with decreases of 0.34, 0.08, 0.51, and 0.41 SDs in each of the respective bubble-intensity measures.[17]

A. Robustness Checks

Our results are robust to several methodological changes. Table B2 in Appendix B shows that our results are robust to changing the length of the windows over which our bubble-intensity measures and independent variables are constructed. In Panel A we change the length of the window used in regressions that explain *Cumulative return, P/E ratio*, and *Composite bubble measure*. Instead of using the baseline 6-month period, we use 3-, 9-, and 12-month windows

[17] *Analyst coverage* is an economically and statistically significant determinant of bubble-intensity measures for all combination of control variables we tried. In the Online Appendix, we report some alternative regression specifications containing different combinations of control variables.

ending on May 29, 2007. We report the results of repeating regression columns (2), (4), and (8) of Table 3 while using each of these three alternative window lengths. We find that *Analyst coverage* remains strongly statistically significant in all nine regressions.

In Panel B of Table B2 we vary the length of the window over which *Announcement return* is defined (independent variables are measured over the 6-month reference period as before). Instead of the baseline 5 trading days, we use 1, 2, 3, 4, or 10 trading days, as well as 1, 2, and 3 calendar months. We report results of repeating the regression in column (6) of Table 3 while using each of these eight alternative lengths for *Announcement return*. Due to China's daily absolute return limit of 10%, the first four regressions are estimated using a Tobit model. This accommodates the fact that several stocks have returns hitting the limit on every day during the return window being used. We find that *Analyst coverage* remains strongly statistically significant in all eight regressions.

We pursue several additional robustness checks in the Online Appendix available on the author's Web site (http://moya.bus.miami.edu/∼sandrade/research.html). We show: i) additional evidence that our key finding is not driven by a positive correlation between analyst coverage and firm size; ii) results hold when we use IBES rather than RESSET data to define analyst coverage; iii) results are not driven by outliers; iv) results are robust to the inclusion of additional explanatory variables such as the ratio of nontradable to tradable shares and contemporaneous stock volatility; and v) results do not hold in placebo, nonbubble periods.

B. Addressing Endogeneity Concerns

The previous subsections document correlations between bubble-intensity measures and *Analyst coverage*, and show that these correlations are robust to including a myriad of control variables. It is possible, however, that *Analyst coverage* is an endogenous regressor in our OLS specifications, which would make the coefficient estimates biased and inconsistent. In this section we use traditional approaches to address this concern in two different and complementary ways. In addition, in Section V we report yet another set of results that help to alleviate concerns about endogeneity and other potential explanations for the negative correlation between *Analyst coverage* and bubble intensity.

1. Lagged *Analyst Coverage*

First, we address the possibility of reverse causality, namely, that brokerage firms choose to provide analyst coverage in stocks that are currently experiencing lower bubble intensities. To do so, we use analyst coverage measured during 2005 rather than our original *Analyst coverage* variable, which is measured during the 6-month reference period from Nov. 29, 2006, to May 29, 2007. Because there was no asset pricing bubble in 2005 (see Figure 2), using *Analyst coverage in 2005* mitigates concerns about reverse causality.

The mean of *Analyst coverage in 2005* is 6.079, and its correlation with *Analyst coverage* measured in the reference period from Nov. 29, 2006, to May 29, 2007, is 0.83. This high degree of correlation suggests that analyst coverage is not largely driven by the extent to which a stock is in a contemporaneous bubble. The downside of this approach, however, is that *Analyst coverage in 2005* does not as directly reflect the dissemination of information during the bubble period as our original *Analyst coverage* variable does.

The first two specifications of Table 4 report the results of regressing *Composite bubble measure* on *Analyst coverage in 2005* rather than on *Analyst coverage*. The results show that *Analyst coverage in 2005* is a statistically strong determinant of *Composite bubble measure* (t-statistic $= -7.44$ in the second specification). Even though its economic significance is lower than that of the contemporaneous *Analyst coverage*, as one would expect, *Analyst coverage in 2005* is nonetheless economically significant as well: A one-SD change in *Analyst coverage in 2005* is associated with a 0.22-SD change in *Composite bubble measure.*

TABLE 4

Robustness Regressions Addressing Endogeneity

Table 4 reports ordinary least squares (OLS) and two-stage least squares (2SLS) regressions that explain *Composite bubble measure* for a sample of 623 Shanghai A-shares. The 2SLS regressions use *Trading volume in 2005* (average daily trading volume in 2005) and *Mutual fund ownership in June 2005* (the percent of tradable shares owned by mutual funds at the end of June 2005) as instruments for *Analyst coverage.* The sample consists of 623 Shanghai A-shares, selected by requiring that shares be traded on at least 90% of the trading days in the reference period. The reference period is from Nov. 29, 2006, to May 29, 2007. The variables are described in Table B1 of Appendix B. We report heteroskedasticity-robust t-statistics in parentheses below variable coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Composite Bubble Measure			
	OLS		2SLS	
Explanatory Variables	(1)	(2)	(3)	(4)
Analyst coverage in 2005	–0.082***	–0.032***		
	(–19.28)	(–7.44)		
Analyst coverage			–0.092***	–0.064***
			(–18.25)	(–6.59)
Log of market capitalization		0.017		0.184***
		(0.35)		(2.81)
Turnover		0.277***		0.227***
		(7.49)		(6.47)
Lagged return volatility		–0.004*		–0.004**
		(–1.93)		(–2.30)
Lagged P/E ratio		0.006***		0.005***
		(16.79)		(15.93)
Effective spread		0.029***		0.031***
		(3.61)		(4.36)
Depth		–0.133**		–0.097**
		(–2.53)		(–2.27)
Market beta		0.105		0.136
		(0.71)		(1.02)
Liquidity beta		0.304***		0.261***
		(2.89)		(2.67)
ΔTurnover		0.136***		0.089*
		(2.65)		(1.84)
ΔEffective spread		–0.029***		–0.019**
		(–3.59)		(–2.45)
Industry effects	No	Yes	No	Yes
Constant	0.501***		0.561***	
	(10.58)		(12.25)	
No. of obs.	623	623	623	623
Adj. R^2	0.314	0.717	0.462	0.751
Sargan χ^2				0.183
(p-value)				(0.67)

2. Instrumental Variables

We also use instrumental variable estimation (two-stage least squares (2SLS)) to address the potential endogeneity of *Analyst coverage*. Instrumental variable estimation addresses the possibility that analyst coverage proxies for a slow-moving "bubble-proneness" stock characteristic that is orthogonal to all of our control variables.

We use two instruments for *Analyst coverage*: *Trading volume in 2005,* the average daily trading volume (in monetary terms) during 2005, and *Mutual fund ownership in June 2005*, the fraction of tradable shares owned by Chinese mutual funds on June 30, 2005.[18] Since brokerage firms earn commissions on stock trades, they have incentives to provide analyst services in stocks with higher trading volume in order to attract more trading business. Moreover, Chinese mutual funds are likely to be relatively important clients of brokerage firms, in which case brokerage firms have incentives to provide analyst services in stocks more heavily owned by mutual funds.

When we regress *Analyst coverage* on *Trading volume in 2005* and *Mutual fund ownership in June 2005* in the first stage, with or without all the remaining regressors, we find that the coefficients on both instruments are positive and statistically significant at the 1% level (see Online Appendix). The strong significance of our instruments in the first-stage regressions indicates that our estimation does not suffer from a weak instruments problem.

The last two columns of Table 4 report the results of 2SLS estimation of *Composite bubble measure* in which we use *Trading volume in 2005* and *Mutual fund ownership in June 2005* as instruments for *Analyst coverage.* Results in column (4) show that *Analyst coverage* remains a strongly significant determinant of *Composite bubble measure* in the instrumental variable estimation (t-statistic $=$ -6.59). A one-SD change in *Analyst coverage* is associated with a 0.45-SD change in *Composite bubble measure*. We find that the Sargan χ^2-statistic for the regression in column (4) is equal to 0.183, with a p-value of 0.67, which is well above conventional significance levels. Therefore, we cannot reject the null hypothesis that our instruments are uncorrelated with the residuals from the estimation equation, which implies that our instrumental variable estimation is valid.

In the Online Appendix we repeat the 2SLS analysis in this section and the lagged dependent variable analysis of previous section, using the other bubble measures (*Cumulative return, P/E ratio*, and *Announcement return)* rather than *Composite bubble measure*. We find that our results are robust. The Online Appendix also contains 2SLS regressions using one instrumental variable at a time (either *Trading volume in 2005* or *Mutual fund ownership in June 2005*). We find that *Analyst coverage* remains significant in 7 of the 8 additional 2SLS regressions. Based on all results of instrumental variable estimations, we conclude that it is unlikely that our results are driven by an omitted, slow-moving bubble-proneness variable with which *Analyst coverage* is endogenously correlated.

[18]Because these variables are measured during 2005, they are relatively unlikely to be economically correlated with 2007 bubble magnitudes. The mean *Trading volume in 2005* is 3.699 million yuan, and the mean *Mutual fund ownership in June 2005* is 7.28%.

C. Explaining the China-Hong Kong Premium

In this subsection we discuss regressions in which *China-HK premium* is the measure of bubble intensity. This analysis is limited to only the 23 stocks (from the broader sample of 623) that are also listed in Hong Kong during the period we study. An important caveat is that the small sample size reduces statistical power and reduces our ability to make solid inferences.[19]

Table 5 reports the results. Column (1) shows that *Analyst coverage* is negatively related to the China-Hong Kong premium, consistent with information dissemination reducing bubble magnitudes. Columns (2) and (3) show that the negative association between *Analyst coverage* and *China-HK premium* is robust to the inclusion of *Log of market capitalization* and *Daily turnover*.

TABLE 5

Regressions Explaining the China-Hong Kong Premium of Dual-Listed Stocks

Table 5 reports ordinary least squares regressions that explain *China-HK premium* for a subsample of 23 stocks with dual trading in Shanghai and in Hong Kong. The sample consists of 623 Shanghai A-shares, selected by requiring that shares be traded on at least 90% of the trading days in the reference period. The reference period is from Nov. 29, 2006, to May 29, 2007. The variables are described in Table B1 of Appendix B. We report heteroskedasticity-robust *t*-statistics in parentheses below variable coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: China-HK Premium					
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Analyst coverage	–6.015***	–6.182**	–6.022**	–3.652	–3.000	–4.709***
	(–4.31)	(–2.71)	(–2.14)	(–1.06)	(–0.93)	(–3.24)
Log of market capitalization		0.975	3.242	–11.290	–1.962	
		(0.11)	(0.46)	(–0.70)	(–0.09)	
Turnover			–21.337	–4.300	14.091	
			(–0.96)	(–0.32)	(0.21)	
Lagged return volatility			2.059	1.053	0.541	
			(1.12)	(0.46)	(0.24)	
Lagged P/E ratio				0.682*	0.829*	0.474***
				(2.02)	(2.15)	(5.75)
Effective spread				–1.682	0.615	
				(–0.53)	(0.18)	
Depth				10.333	6.533	
				(1.01)	(0.51)	
Market beta				69.4	109.4	
				(0.59)	(0.78)	
Liquidity beta				13.780	–10.870	
				(0.25)	(–0.20)	
ΔTurnover					23.125	
					(0.24)	
ΔEffective spread					5.795	
					(0.84)	
Constant	163.7***	163.0***	90.6	55.8	–44.165	123.6
	(5.55)	(5.47)	(0.99)	(0.33)	(–0.24)	(3.82)
No. of obs.	23	23	23	23	23	23
Adj. R^2	0.45	0.43	0.44	0.50	0.46	0.58

[19]In addition to the small sample size concern, it is possible that inferences made with this sample may not be representative of the entire universe of Chinese stocks because the listing of firms in Hong Kong is not likely to be random. Yet another caveat is that the twin share premiums may reflect information asymmetry between Chinese and foreign investors, as discussed in Chan, Menkveld, and Yang (2008).

The coefficient on *Analyst coverage* is statistically significant at the 5% level in columns (1), (2), and (3) with the predicted negative sign, but not in columns (4) and (5). Note, however, that the small sample size severely reduces the power of all specifications. In columns (4) and (5) we have 10 or more regressors but only 23 observations. In column (6) we include only the regressor *Analyst coverage* and *Lagged P/E ratio* (the only significant regressors in columns (4) and (5)). We find that the coefficient on *Analyst coverage* is strongly statistically significant, and note that the adjusted R^2 of column (6) is the highest among all specifications in Table 5. We compute three formal information criteria (Akaike, Schwartz, and Bozdogan), and all three indicate that the specification in column (6) is superior to those in the other columns. We conclude that the China-HK premium analysis is consistent with the analyses of the other bubble-intensity metrics.

V. Exploring the Mechanism: Analyst Coverage and Analyst Disagreement

Results in the previous section indicate that greater dissemination of information, as measured in our setting by greater analyst coverage, mitigates the formation of price bubbles. In light of the resale option theories of bubbles (Harrison and Kreps (1978), Scheinkman and Xiong (2003)), we conjecture that one channel by which information dissemination mitigates bubbles is by coordinating investors' beliefs, which reduces belief dispersion. The simple model in Appendix A illustrates such a bubble-mitigating mechanism.

It is not possible, however, to directly test whether greater information dissemination reduces the dispersion of beliefs across investors because the latter is not directly observable. Therefore, in this section we explore two alternative ways to investigate whether the evidence is consistent with this particular bubble-abating channel. In doing so, we also provide additional evidence that helps to alleviate the concern that our main finding is due to analyst coverage being determined by an omitted variable that is orthogonal to all of our control variables.

A. Disagreement among Analysts and Bubble Mitigation

First, if *Analyst coverage* mitigates bubbles because it coordinates investors' beliefs, we should observe less bubble mitigation when there is higher dispersion of beliefs across analysts themselves. To investigate, we construct the variable *Dispersion among analysts,* which is defined only for a subsample of 364 firms with at least two analysts. *Dispersion among analysts* is defined as the first principal component of two variables, *Dispersion of analysts' earnings forecasts* and *Dispersion of analysts' recommendations* (we also use each one separately in the Online Appendix). We normalize the first principal component to have zero mean and unit variance.

Dispersion of analysts' earnings forecasts is the SD of 2007 EPS forecasts (scaled by stock prices at the end of the reference period), normalized to have zero mean and unit variance.[20] To define *Dispersion of analysts' recommendations*, we first map the five possible buy/sell recommendations (strong buy, buy, hold, sell, and strong sell) into one of five integer values ranging from -2 (strong sell) to +2 (strong buy). Then we compute the SD across analysts' recommendations for the stock using the last recommendation made by each analyst during the reference period, and we normalize the variable to have zero mean and unit variance.[21] Note that because both *Dispersion of analysts' earnings forecasts* and *Dispersion of analysts' recommendations* are normalized variables and are positively correlated, their first principal component is equal to their sum. Hence, one can think of *Dispersion among analysts* as the (normalized) average between *Dispersion of analysts' earnings forecasts* and *Dispersion of analysts' recommendations.*

In Table 6 we regress bubble-intensity measures on *Analyst coverage* and the interaction between *Analyst coverage* and *Dispersion among analysts*. A negative coefficient on the interaction term indicates that *Analyst coverage* is less effective in mitigating bubbles when there is a high degree of disagreement among analysts.

In column (1) of Table 6, we observe that the strong negative association between *Analyst coverage* and *Composite bubble measure* continues to hold in a regression using the subsample of firms with at least two analysts. Column (2) shows that the coefficient on the interaction between *Analyst coverage* and *Dispersion among analysts* is positive and statistically significant (t-statistic = 5.30), consistent with *Analyst coverage* having a weaker effect on bubble magnitudes when analysts' beliefs are less homogenous. The effect is economically significant: The coefficient of 0.027 on the interaction term implies that a one-SD increase in *Dispersion among analysts* (which has zero mean and unity SD) reduces the bubble-mitigating impact of *Analyst coverage* from 0.072 to 0.045 (which is 0.072, the coefficient on *Analyst coverage*, minus the 0.027 interaction term coefficient).

Note that *Analyst coverage* remains strongly statistically significant when the analyst dispersion variables are included in the regression, which (jointly with the positive signal of the interaction term) implies that the partial effect of *Analyst coverage* on bubble intensity is positive when *Dispersion among analysts* is equal to its average value of 0. Similarly, the partial effect of *Dispersion among analysts* on bubble intensity is positive when *Analyst coverage* is equal to its (Table 6) average of 10.1, because $-0.116 + 0.027 \times 10.1 = 0.157$.[22] In fact, because $0.072 \div 0.027 = 2.7$, the partial effect of *Analyst coverage* on bubble intensity is positive as long as *Dispersion among analysts* is not 2.7 SDs or more below its

[20]For each brokerage firm-stock pair, we use the last earnings forecast made during the reference period, scaled by the stock price at the date at which the forecast was made. We then normalize the dispersion variable to zero mean and unit variance. Before the normalization, *Dispersion of analysts' forecasts* has mean equal to 1.19%, which is on the same order of magnitude as the average earnings per price ratio, and it has an SD equal to 0.92%.

[21]Before the normalization, *Dispersion of analysts' recommendations* has a mean of 0.70 and an SD of 0.33.

[22]Note that the sample in Table 6 is restricted to the stocks in which *Analyst coverage* is greater than or equal to 2. This is because it is not possible to compute a dispersion among analysts if there are fewer than two analysts. The sample mean and sample SDs of *Analyst coverage* here are 10.1 and 6.7, respectively, rather than the full-sample averages and SDs of 6.1 and 7.1.

TABLE 6

Regressions Including Interactions with Dispersion among Analysts

Table 6 reports ordinary least squares regressions that explain *Composite bubble measure* and *Turnover* for a subsample of 364 Shanghai A-shares that are followed by at least two analysts. The sample consists of 623 Shanghai A-shares, selected by requiring that shares be traded on at least 90% of the trading days in the reference period. The reference period is from Nov. 29, 2006, to May 29, 2007. The variables are described in Table B1 of Appendix B. We report heteroskedasticity-robust *t*-statistics in parentheses below variable coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variables					
	Composite Bubble Measure			Turnover		
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Analyst coverage	–0.074***	–0.072***	–0.050***	–0.084***	–0.083***	–0.026***
	(–15.79)	(–15.81)	(–8.61)	(–11.83)	(–11.80)	(–2.98)
Dispersion among analysts		–0.116**	–0.087**		0.018	0.018
		(–2.33)	(–2.40)		(0.21)	(0.25)
Analyst coverage × Dispersion among analysts		0.027***	0.016***		0.030***	0.018**
		(5.30)	(3.89)		(3.03)	(2.50)
Log of market capitalization			0.109*			–0.759***
			(1.95)			(–10.69)
Turnover			0.200***			
			(3.60)			
Lagged return volatility			–0.005			0.001
			(–1.63)			(0.05)
Lagged P/E ratio			0.006***			0.004***
			(10.76)			(3.37)
Effective spread			0.015*			–0.092***
			(1.84)			(–9.94)
Depth			–0.048			0.718***
			(–1.26)			(3.92)
Market beta			–0.037			0.784***
			(–0.21)			(2.80)
Liquidity beta			0.211*			0.187
			(1.74)			(1.05)
ΔTurnover			–0.025			
			(–0.30)			
ΔEffective spread			–0.027***			
			(–2.66)			
Industry effects	No	No	Yes	No	No	Yes
Constant	0.247***	0.221***		3.164***	3.145***	
	(3.72)	(3.38)		(31.88)	(32.00)	
No. of obs.	364	364	364	364	364	364
Adj. R^2	0.376	0.405	0.682	0.232	0.280	0.579

average. Also, because $0.116 \div 0.07 = 4.3$, the partial effect of *Dispersion among analysts* on bubble intensity is positive as long as *Analyst coverage* is above 4.3, which is close to the 25th percentile of the distribution of *Analyst coverage* in Table 6.[23]

Column (3) of Table 6 shows that the conclusions from column (2) still hold when all of the control variables are included in the regression. The *t*-statistic for the interaction term between *Analyst coverage* and *Dispersion among analysts* is

[23]Note that it would be misleading to evaluate the marginal effect of *Dispersion among analysts* without considering the interaction term *Analyst coverage* × *Dispersion among analysts*, because not incorporating the interaction term is equivalent to evaluating the partial effect of *Dispersion among analysts* while fixing *Analyst coverage* at 0. This is not informative, because in the sample we use to estimate the regressions in Table 6 (the subsample of stocks with nonmissing *Dispersion among analysts*), *Analyst coverage* is always greater than or equal to 2.

3.89, and the effect remains economically significant, as coefficients imply that a one-SD increase in *Dispersion among analysts* reduces the bubble-mitigating effect of *Analyst coverage* from 0.050 to 0.034.[24]

In the Online Appendix we provide a graphical illustration of the regression results in Table 6. There we sort stocks into six *Dispersion among analysts* bins, and then within each sixtile we further categorize stocks into high and low analyst coverage groups, based on whether the stock's analyst coverage is above or below the overall sample median. Figure OA-2 in the Online Appendix shows that the difference in bubble intensity among low and high *Analyst coverage* bins is always positive but decreases mononotically as the level of disagreement among analysts increases from sixtile 1 to sixtile 6 of *Dispersion among analysts*.

It is important to note that the finding that analyst coverage is less effective in mitigating bubbles when there is more disagreement among analysts is important not only because it sheds light on the mechanism by which analyst coverage mitigates bubbles, but also because it further alleviates concerns about endogeneity. If *Analyst coverage* is correlated with bubble intensity solely because both variables are determined by a third, stock-specific variable orthogonal to all our control variables, then *how* analysts disseminate the information (with more or less disagreement) would be irrelevant. The significance of the interaction term between *Analyst coverage* and analyst disagreement shows this is not the case.

B. Disagreement among Analysts and Turnover Reduction

A second way to investigate whether greater information dissemination mitigates bubbles because it reduces the dispersion of investors' beliefs is by using trading activity (i.e., turnover) as a proxy for the dispersion of investors' beliefs. Trading activity is positively related to belief dispersion not only in Scheinkman and Xiong's (2003) theory of bubbles, but also in several other theories.[25] In columns (4)–(6) of Table 6, we regress *Turnover* on *Analyst coverage* and other explanatory variables.

The results reported in column (4) show that, consistent with greater information dissemination reducing the dispersion of investors' beliefs, *Analyst coverage* is negatively correlated with *Turnover* (t-statistic $= -11.83$). Following the logic of our earlier Table 6 *Composite bubble measure* regressions, we expect the

[24]The Online Appendix contains additional robustness checks. First, we report results of *Composite bubble measure* regressions interacting *Analyst coverage* with the individual components of *Dispersion among analysts* (*Dispersion of analysts' earnings forecasts* and *Dispersion of analysts' recommendations*). Second, we show that *Analyst coverage* and the interaction term between *Analyst coverage* and dispersion remain statistically significant with the expected sign. Finally, we also report results of regressions using the other bubble-intensity measures (*Cumulative return*, *Announcement return*, and *P/E ratio*) rather than *Composite bubble measure*.

[25]See, for example, Shalen (1993), Hong and Stein (2003), and Cao and Ou-Yang (2009). Note, however, in the theory that motivates our work, the *possibility* of future disagreement that determines today's bubble magnitudes, and not only the current disagreement (which is assumed away in the theory). Therefore, realized, contemporaneous turnover may not fully capture the dispersion of beliefs that determines bubble magnitudes. Moreover, trading activity is only a noisy proxy for the current dispersion of beliefs. Work by Lo and Wang (2000) implies that cross-sectional differences in turnover do not entirely reflect cross-sectional differences in the dispersion of investors' beliefs because other factors may also affect turnover. See also Cremers and Mei (2007).

turnover-reducing effect of *Analyst coverage* to be weaker when there is higher dispersion of analysts' beliefs.

Column (5) of Table 6 shows that the coefficient on the interaction term between *Analyst coverage* and *Dispersion among analysts* is positive as expected, and statistically significant at the 1% level (t-statistic = 3.03). The interaction effect is also economically significant. The 0.030 coefficient on the interaction of *Analyst coverage* and *Dispersion among analysts* implies that a one-SD increase of *Analyst coverage* decreases *Turnover* by only 0.30 SD when *Dispersion among analysts* is one SD above its mean of 0. We also observe that *Analyst coverage* is an economically significant determinant of *Turnover* in column (5) on its own. Holding *Dispersion among analysts* constant at its mean value of 0, a one-SD increase in *Analyst coverage* reduces *Turnover* by 0.47 SD. Column (6) shows that these conclusions hold after including a myriad of control variables in the *Turnover* regression. The coefficients on *Analyst coverage* and its interaction with *Dispersion among analysts* remain significant at the 5% level (t-statistics are −2.98 and 2.50, respectively).[26]

The results in Table 6 provide evidence consistent with greater information dissemination reducing bubble intensity by coordinating investors' beliefs, which reduces belief dispersion across investors. This is consistent with the resale option theories of Harrison and Kreps (1978) and Scheinkman and Xiong (2003), and with our simple model of bubble mitigation in Appendix A.

VI. Investigating Other Plausible Mechanisms

The results in Section V suggest that one channel through which analyst coverage mitigates bubbles is by coordinating investors' beliefs, which results in lower belief dispersion. On the basis of these results alone, however, we cannot rule out the possibility that analyst coverage also mitigates bubbles by reducing investors' overoptimism. In this subsection we provide some evidence suggesting that this alternative channel seems unlikely in our setting. In addition, we provide further evidence against explanations in which analyst coverage only appears to mitigate bubbles because it is endogenously correlated with bubble intensities.

A. Analyst Coverage and Overoptimism

We track analyst buy/sell recommendations over time. As previously mentioned, analysts choose one of five recommendation categories: strong buy, buy, hold, sell, and strong sell. We assign scores of +2, +1, 0, −1, and −2 to these categories, respectively. We first compute the mean score across analysts for each stock and each month using only recommendations issued that month, and then we compute the average across stocks each month.

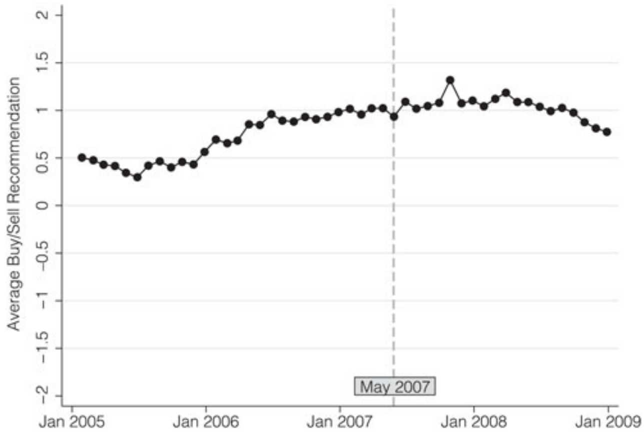
[26]Our Online Appendix contains several robustness checks. We show that the negative association between *Analyst coverage* and *Turnover* also obtains in regressions with the full sample of 623 stocks, rather than just the 364 with at least two analysts. We also report results of *Turnover* regressions interacting *Analyst coverage* with the individual components of *Dispersion among analysts* (*Dispersion of analysts' earnings forecasts* and *Dispersion of analysts' recommendations*).

Figure 3 plots the time series of the cross-sectional average buy/sell recommendation. Note that the average is close to +1 from mid-2006 to early 2008, including during our entire reference period from Nov. 29, 2006, to May 30, 2007. If anything, the average recommendation becomes slightly more optimistic over that time. The lack of time-series variation in the average analyst recommendation indicates that analysts do not become less optimistic as the bubble develops. In turn, this suggests that it is unlikely that analyst coverage mitigates bubbles in our setting by leaning against high valuations, thereby reducing investor overoptimism.

FIGURE 3

Average Buy/Sell Recommendation

Figure 3 illustrates the average analyst buy/sell recommendation over time. Recommendations are assigned scores 0 (hold), +1 (buy), −1 (sell), +2 (strong buy), and −2 (strong sell). We first compute the mean score across analysts for each stock and each month using only recommendations issued that month, and then we compute the average across stocks each month. The sample consists of 623 Shanghai A-shares.



B. Endogeneity of Analyst Coverage

Earlier in the paper we present multiple pieces of evidence that address the concern analyst coverage may not mitigate bubbles because it is merely endogenously correlated with bubble intensities. Nonetheless, in this section we briefly flesh out three specific endogeneity-based explanations and examine further evidence relating to them.

Lazy Analysts. It is possible that, to the extent that analyst expertise is a scarce resource in China, analysts choose to cover stocks for which forecasting earnings and issuing recommendations is easier. There could be less room for disagreement about these stocks, and hence they would develop smaller bubbles according to the logic of resale option theories of bubbles. However, we do not find that analyst coverage is greater for stocks that are easier to value as measured by the disagreement among analysts, which is a measure of "hard-to-valueness" (e.g., Zhang (2006)). The correlation between *Analyst coverage* and dispersion of earnings forecasts is both economically and statistically insignificant (correlation = −0.03, *p*-value = 0.57). Moreover, the correlation between *Analyst coverage* and dispersion of buy/sell/recommendations is nearly statistically significant at the 10% level, but in the opposite direction than this explanation predicts (correlation = 0.085, p-value = 0.11).[27]

Moreover, in untabulated regressions we add disagreement among analysts and measures of firm age as explanatory variables in the regressions in Table 3 and find that the coefficient on *Analyst coverage* remains highly economically and statistically significant. Note also that the regressions in Table 3 already have industry fixed effects included, which controls for the possibility that some industries are more bubble-prone (or harder to value) than others.

Overall, the evidence does not support an alternative explanation in which the negative correlation between *Analyst coverage* and bubble intensity is explained by analysts choosing to cover stocks of firms that are older, are in more stable or easier to value industries, or have less disagreement among analysts, all of which may relate to the ease of forecasting earnings and issuing recommendations.

Institutional Sell-Off. It is possible that stocks with greater institutional ownership before the bubble, which may attract more analyst coverage, also develop smaller bubbles because institutions influence prices downward by selling their shares. If this were true, one would expect bubble intensities to be positively correlated with changes in the number of stocks held by mutual funds. However, the correlation between our *Composite bubble measure* and the change in the number of shares held by mutual funds from June 2005 to June 2007 (scaled by number of tradable shares in June 2007) is economically and statistically insignificant (correlation = −0.046, p-value = 0.25). We find similarly negative, economically small, and statistically insignificant correlations when we measure the change in shares from June 2006 to June 2007, or from Dec. 2006 to June 2007. Note that even if these correlations were significant, their signs are opposite from those expected. Moreover, in untabulated results the coefficient on *Analyst coverage* remains highly economically and statistically significant when we add the change in the number of shares owned by mutual funds as an explanatory variable in the regressions in Table 3. Therefore, evidence does not support the idea that stocks with larger pre-bubble institutional ownership develop smaller bubbles due to institutional selling pressure.

Pump and Dump. It is possible that, when there are very few analysts, the mean forecast is dominated by one or two very optimistic forecasts. These forecasts could be strategically placed by analysts seeking to profit from a pump-and-dump strategy. Unethical analysts would choose to cover stocks that are covered by none or a just a few other analysts, and buy shares of these stocks. Then they would issue knowingly overoptimistic recommendations in order to inflate stock prices. At that point, they would sell shares and realize profits. We investigate this possibility in two different ways.

First, we create a variable *Analyst recommendation,* equal to the mean analyst recommendation in the reference period (as before, we scale analyst

[27]The firm's age provides an alternative way to measure a stock's hard-to-valueness. We find the correlation between *Analyst coverage* and the firm's age based on date of incorporation is −0.14 (p-value < 0.01), and that between *Analyst coverage* and the firm's age based on date of stock-exchange listing is −0.19 (p-value < 0.01). Both of these negative correlations refute the notion that analyst coverage in China is greater for firms that are easier to value.

recommendations from −2 to +2). The pump-and-dump hypothesis suggests that analysts inflate the bubble, which implies a positive correlation between bubble magnitudes and *Analyst recommendation*. To investigate, we add *Analyst recommendation* as an explanatory variable in the Table 3 regression models and report the results in Panel C of Table B2 in Appendix B. In contrast to the pump-and-dump hypothesis, we find that the coefficient on *Analyst recommendation* is either insignificant (columns (1), (2), and (4)) or has the opposite of what this hypothesis predicts (columns (3), (5), (6), (7), and (8)).

Second, to the extent that a subset of analysts actually do follow the pump-and-dump strategy, we would expect them to employ the strategy in stocks with fewer analysts, where their inflated recommendations would be more influential. This implies that we should not observe an association between *Analyst coverage* and bubble intensity in stocks that are covered by a large number of analysts. To investigate, in untabulated results we estimate the column (8) regressions of Table 3, but we restrict the sample to stocks with above-median *Analyst coverage*, or to stocks in the fourth quartile of *Analyst coverage*. In both cases we find that the coefficient on *Analyst coverage* is still economically and statistically significant at the 1% level. Therefore, our results are not consistent with the pump-and-dump hypothesis.

VII. Conclusion

This paper studies the role of analyst coverage in the formation of asset price bubbles. We focus on the 2007 Chinese stock market, which offers an ideal setting. As of 2007, the Chinese market not only had institutional characteristics that are conducive to asset pricing bubbles, but it also displayed classic features of a bubble and was said to be in a bubble by several prominent observers at the time. This setting allows us to construct several firm-specific measures of bubble intensity, including measures that are not available in other settings such as the U.S. Internet bubble of the late 1990s. Collectively, these measures alleviate concerns that results are driven by measurement error due to unobservable cross-sectional variation in fundamental values.

Regardless of the bubble-intensity measure we use, we find smaller bubbles in stocks with greater analyst coverage. We present compelling evidence that this finding is *not* driven by a positive correlation between analyst coverage and firm size. Moreover, our results are robust to including a battery of additional control variables, as well as addressing concerns about analyst coverage being an endogenous regressor.

We further show that analyst coverage is less effective in mitigating bubbles when there is more disagreement among analysts. This result is important for two reasons. First, it further alleviates concerns about an endogeneity explanation for our key finding. If analyst coverage were correlated with bubble intensities because both variables are determined by a third variable orthogonal to all of our control variables, one would not expect how analysts disseminate information (with more or less disagreement) to be relevant. Second, this result sheds light on *why* analyst coverage may mitigate bubbles. Specifically, it suggests an information mechanism consistent with resale option theories of bubbles

(Harrison and Kreps (1978), Scheinkman and Xiong (2003)). That is, analyst coverage may mitigate bubbles by coordinating and thus reducing the dispersion in investors' beliefs, which in turn reduces the resale option component of asset prices. In Appendix A we present a simple model illustrating this bubble-mitigation mechanism. Consistent with the mechanism, we document that stocks with greater analyst coverage display lower turnover and that, analogous to what we find for bubble intensities, the abating effect of analyst coverage on turnover is weaker when there is more disagreement among analysts.

To the extent that information about asset fundamentals is a public good and thus tends to be underprovided in a laissez faire setting, our results suggest that policy makers concerned with mitigating asset price bubbles should encourage public information dissemination. As argued by Daniel, Hirshleifer, and Teoh (2002), regulating disclosure by firms and by information intermediaries may make asset prices more efficient providers of signals for resource allocation in an economy. In this regard, we note that some exchanges recognize the importance of security analysts as disseminators of information, and that the natural provision of analyst coverage by the marketplace may be suboptimal. These exchanges (e.g., Singapore, Malaysia, and London Stock Exchange's AIM) actively sponsor the provision of analyst coverage by subsidizing it, either directly or indirectly, and by organizing the matching of firms to analysts.

Appendix A. A Simple Model of Bubbles and Analyst Coverage

There is one risky asset, two groups of risk-neutral investors (A and B), and three dates. Investors trade at date 0 and date 1, and at date 2 the risky asset pays terminal dividend $d = 1$ or $d = 0$. The two groups of investors have common priors at date 0: the probability that $d = 1$ is equal to p. Therefore, if there was no trading at date 1, the equilibrium price of the risky asset at date 0 would be equal to p.

We assume, however, that at date 1 both groups of investors each observe two independent signals a and b about the asset's payoff. The signals are equally informative:

$$\begin{aligned}
\Pr[a=1|d=1] &= \Pr[b=1|d=1] = q > \frac{1}{2}, \\
\Pr[a=0|d=0] &= \Pr[b=0|d=0] = q > \frac{1}{2}.
\end{aligned}$$

Investors are assumed to be overconfident *a la* Scheinkman and Xiong (2003): Group A investors only consider signal a (disregarding b), and similarly, group B investors only consider signal b. After observing the signals, investors trade at date 1 in a market that, as in Scheinkman and Xiong, is subject to short-sale constraints. Therefore, if investors disagree (i.e., if signal a is different from signal b), the date 1 price only reflects the beliefs of the most optimistic investor group.

We compute equilibrium prices at date 1 under the four scenarios: $(a,b) = (0,0)$, $(a,b) = (1,1)$, $(a,b) = (0,1)$, and $(a,b) = (1,0)$. Given date 1 prices, it is straightforward to derive the equilibrium price at date 0, which results in Proposition 1.

Proposition 1. There Is a Bubble in the Asset Price.

The asset price at date 0 is

$$P_0 = p\left(1 + \frac{(2q-1)q(1-q)(1-p)}{(2q-1)^2 p(1-p) + q(1-q)}\right) > p. \tag{A-1}$$

Proof. See Online Appendix. □

Proposition 1 shows that the equilibrium price at date 0 is larger than the price that would obtain if investors had to buy and hold the asset until its termination date 2. Thus, as in Harrison and Kreps (1978) and Scheinkman and Xiong (2003), there is an asset price bubble. The option to sell the asset at date 1 to more optimistic investors creates a wedge between the asset's market price at date 0 (P_0) and its "fundamental value" (p).

Now suppose there are stock analysts producing research about the risky asset. At date 1, these analysts collectively produce a signal c about the asset. Both groups of investors (A and B) observe the signal and believe it carries information according to the following distribution:

$$\begin{aligned} \Pr[c=1|d=1] &= r \geq \frac{1}{2}, \\ \Pr[c=0|d=0] &= r \geq \frac{1}{2}. \end{aligned}$$

Note that the signal is stronger for larger r, and that investors deem the analyst signal uninformative when $r = ½$. In our empirical analysis, *Analyst coverage* (the number of analysts issuing research reports) proxies for r.

After receiving signals a, b, and c, investors trade at date 1. As before, investors are overconfident (group A investors disregard signal b, and group B investors disregard signal a), but both incorporate c, believing it conveys useful information. There are short-sale constraints, such that, if investors disagree, the asset price only reflects the beliefs of the most optimistic investor group. We compute date 1 prices under each of the eight scenarios (different combinations of a, b, and c). Given date 1 prices, we calculate the equilibrium price at date 0, now with analyst coverage.

Proposition 2. A Stronger Public Information Signal Results in a Smaller Bubble.

The price at date 0 with analyst coverage is $P_0^{\text{analyst}} = p(1+f(r))$, where

$$\begin{aligned} f(r) &= (2q-1)\,q\,(1-q)\,(1-p)\,r\,(1-r) \\ &\times \frac{pq\,(1-q)\,(1-p) \;+\; r\,(1-r)\;\{p\,(1-p)+q\,(1-q)-8pq\,(1-q)\,(1-p)\}}{\{pq+(1-p-q)\,r\}\;\{qr+(1-q-r)\,p\}\;\{pr+(1-p-r)\,q\}\;\;\{(1-q)\,(1-r)-(1-q-r)\,p\}}. \end{aligned}$$

The function $f(r)$ is strictly decreasing in r for $½ \leq r \leq 1$. Moreover, when $r = ½$, then

$$f\left(\frac{1}{2}\right) = \frac{(2q-1)\,q\,(1-q)\,(1-p)}{(2q-1)^2\,p\,(1-p)+q\,(1-q)}, \tag{A-2}$$

that is, P_0^{analyst} is at its maximum and equal to P_0 in Proposition 1 when the public information signal is not informative.

Proof. See Online Appendix. □

Proposition 2 shows the bubble-mitigating effect of analyst coverage. The analysts' signal c mitigates the bubble. This obtains because the public signal coordinates investors' beliefs at date 1, reducing their dispersion. The stronger the signal (i.e., larger r), the greater the reduction of belief dispersion, and the smaller is the bubble. The size of the bubble is maximized when the signal c is perceived to be least informative (i.e., when $r = ½$). At that value, the signal c is not believed to carry useful information, and the bubble size is equal to bubble size when there is no analyst coverage. Note that $f(r) = 0$ when $r = 1$, that is, there is no bubble if investors believe that the analyst signal c reveals the future payoff with certainty. In that extreme case, analyst coverage fully dissipates the dispersion of beliefs across investors.

Appendix B. Additional Tables

Table B1 describes the main variables used in the paper. Table B2 contains robustness checks discussed in Section IV.A.

TABLE B1

Description of Variables

Table B1 describes the main variables used in the paper. The sample consists of 623 Shanghai A-shares, selected by requiring that shares be traded on at least 90% of the trading days in the reference period. The reference period is from Nov. 29, 2006, to May 29, 2007. All data are from RESSET.

Variable	Description
Cumulative return	Cumulative return during the reference period.
P/E ratio	Price-earnings ratio using quarterly earnings over the most recent 12 months relative to each day's calculation, using only public information. *P/E ratio* is capped at 250, and a P/E ratio equal to 250 is assigned when stocks have negative earnings. Average during the reference period is calculated from daily data.
Announcement return	Five-day cumulative return beginning on the day the security tax change was both announced and enacted (May 30, 2007).
Composite bubble measure	First principal component of *Cumulative return*, *P/E ratio*, and *Announcement return,* normalized to have a mean of 0 and a variance equal to 1. It has the same orientation of *Cumulative return* and *P/E ratio* (i.e., higher *Composite bubble measure* is associated with larger bubbles).
China-HK premium	Ratio of the price in China divided by the exchange-rate-adjusted price in Hong-Kong, minus 1, for a subsample of 23 dual-listed stocks. Average during the reference period is calculated from daily data.
Analyst coverage	Number of brokerage firms issuing EPS forecasts during the reference period.
Dispersion among analysts	First principal component of dispersion of analyst earnings forecasts and dispersion of analyst buy/sell recommendations, normalized to have a mean of 0 and a variance equal to 1. Dispersion of earnings forecasts is the SD of 2007 EPS forecasts. For each brokerage firm-stock pair, we use the last earnings forecast made during the reference period, scaled by the stock price at the date at which the forecast was made. To calculate dispersion of recommendations, we first map the five possible buy/sell recommendations (strong buy, buy, hold, sell, and strong sell) into one of five integer values ranging from −2 (strong sell) to +2 (strong buy). Then we compute the SD across analysts' recommendations for the stock using the last recommendation made by each analyst during the reference period. Both dispersion variables are defined for the subsample of stocks covered by at least two analysts, and are normalized to have a mean of 0 and a variance of 1.
Market capitalization	Stock price times the number of tradable shares. Average during the reference period is calculated from daily data.
Turnover	Number of shares traded divided by the total number of tradable shares. Average during the reference period is calculated from daily data (annualized).
Lagged P/E ratio	Defined as *P/E ratio,* but for the 6-month period immediately before the reference period.
Lagged return volatility	Annualized SD of average squared daily returns in the 6-month period immediately before the reference period.
Effective spread	Twice the difference between the transaction price and midpoint, divided by the midpoint. First we calculate the daily average, than average daily averages across the reference period. In basis points.
Depth	One-half times the sum of the monetary quantities associated with the best bid and best ask offers. First we calculate the daily average, than average daily averages across the reference period.
Market beta	Coefficient on the value-weighted market return in a regression of daily stock returns onto value-weighted market returns and an aggregate liquidity factor. The regression uses daily data during the reference period.
Liquidity beta	Coefficient on the aggregate liquidity factor in a regression of daily stock returns onto value-weighted market returns and the aggregate liquidity factor. The regression uses daily data during the reference period. The aggregate liquidity factor is defined as the (daily) innovation on the average effective spread across all sample stocks.
ΔTurnover	Average daily turnover in the 6-month period immediately after the reference period minus the average daily turnover in the reference period (annualized).
ΔEffective spread	Average in the 6-month period immediately after the reference period minus the averages in the reference period.
Industry effects	Dummy variables based on 13 industries defined by the China Securities Regulatory Commission (CSRC).

TABLE B2

Using Different Time Windows and Adding Analyst Recommendations

Panel A of Table B2 reports regressions in which variables are defined over 3-, 9-, and 12-month windows ending in May 29, 2007, as opposed to the 6-month window of our baseline results in Table 6. Panel B reports regressions of *Announcement return* calculated over windows consisting of 1, 2, 3, 4, and 10 trading days, as well as 1, 2, and 3 calendar months following the May 30, 2007, tax increase announcement, as opposed to the 5-trading day window of our baseline results in Table 3. We use Tobit regressions for short windows (4 days or less), and OLS regressions for longer windows. Panel C reports regressions in which *Analyst recommendation* is added to Table 3 regressions. *Analyst recommendation* is the average buy/sell analyst recommendation in the reference period (0 is hold, +1 buy, +2 strong buy, −1 sell, −2 strong sell). The regressions include, but we do not report below, all of the other explanatory variables included in Table 3. The variables are described in Table B1 of Appendix B. We report heteroskedasticity-robust *t*-statistics in parentheses below variable coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Redefine Window Lengths for Cumulative Return, P/E Ratio, Composite Bubble Measure, and Explanatory Variables

	Dependent Variable								
	3 Months			9 Months			12 Months		
	Cum. Return	P/E Ratio	Comp. Bubble Meas.	Cum. Return	P/E Ratio	Comp. Bubble Meas.	Cum. Return	P/E Ratio	Comp. Bubble Meas.
Analyst coverage	–3.124***	–2.043***	–0.076***	–2.377***	–0.974***	–0.047***	–1.179	–1.642***	–0.043***
	(–6.65)	(–4.92)	(–11.33)	(–3.34)	(–3.23)	(–10.11)	(–1.15)	(–4.34)	(–8.81)
Other expl. var. in Tab. 3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	623	623	623	617	617	617	612	612	612
Adj. R^2	0.473	0.821	0.736	0.392	0.765	0.720	0.371	0.633	0.697

Panel B. Define Announcement Return Using Different Windows

	Dependent Variable: Announcement Return							
	Announcement Return Window							
	1 Day	2 Days	3 Days	4 Days	10 Days	1 Month	2 Months	3 Months
Analyst coverage	0.421***	0.515***	0.717***	0.740***	0.944***	1.143***	1.007***	1.315***
	(4.46)	(6.96)	(8.10)	(8.82)	(7.71)	(8.35)	(6.43)	(5.90)
Other expl. var. in Tab. 3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	623	623	623	623	623	623	623	623
Lower limit (censoring)	–10.0%	–19.0%	–27.1%	–34.4%	—	—	—	—
Censored observations	449	132	122	109	—	—	—	—
Adj. R^2	—	—	—	—	0.45	0.46	0.38	0.36

Panel C. Add Analyst Recommendation

	Dependent Variable							
	Cumulative Return		P/E Ratio		Announcement Return		Composite Bubble Measure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Analyst coverage	–4.911***	–4.760***	–3.217***	–0.489**	0.846***	0.573***	–0.077***	–0.049***
	(–10.85)	(–6.84)	(–8.99)	(–2.01)	(14.57)	(6.76)	(–18.08)	(–9.17)
Analyst recommendation	–1.691	1.506	–19.323***	–4.863	3.182***	2.677***	–0.257***	–0.139***
	(–0.25)	(0.27)	(–3.09)	(–1.47)	(5.36)	(4.35)	(–4.23)	(–2.97)
Other expl. var. in Tab. 3	No	Yes	No	Yes	No	Yes	No	Yes
No. of obs.	450	450	450	450	450	450	450	450
Adj. R^2	0.166	0.465	0.187	0.846	0.432	0.526	0.467	0.714

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