Evidence about Bubble Mechanisms: Precipitating Event, Feedback Trading, and Social Contagion[1]

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Abstract

Shiller's feedback loop theory of bubbles involves three elements: a precipitating event that causes an increase in prices, positive feedback trading, and social contagion that draws in new investors. We use brokerage account records from a large Chinese stock brokerage firm to document that all three components of the Shiller feedback loop are found during the Chinese put warrants bubble. An increase in the stock transaction tax made warrants relatively more attractive for speculative trading and was the precipitating event for the extreme phase of the bubble, causing immediate sharp increases in trading by new and existing investors and a jump in warrant prices. Hazard rate regressions provide evidence of positive feedback trading, and the period of heavy feedback trading coincided with the extreme phase of the bubble following the increase in the transaction tax. Finally, proxies for social contagion explain the entry of new investors.

Key Words: Bubble mechanism, precipitating event, feedback trading, social contagion.

1. Introduction

Shiller's extensive writings about speculative asset price bubbles discuss how three components combine to create and reinforce asset price bubbles (see for example, Shiller 1995, 2008, 2010, 2015).[2] First, a precipitating event causes an increase in prices. This precipitating event need not be related to the assets' fundamental values; for example, Shiller (2015; Chapter 4) suggests that rapid growth in corporate earnings in 1994, 1995, and 1996 contributed to the initiation of the internet bubble of the late 1990s even though the earnings growth had little to do with the internet. Second, he describes a positive feedback loop in which past price increases encourage investors to continue buying, creating further upward pressure on prices (Shiller 2015; Chapter 5). Third, social contagion draws in additional investors. In some places Shiller focuses on the role of the media in spreading stories about the bubbles (for example, Shiller 2015, Chapter 6), while in others he emphasizes the role of direct word of mouth communication, for example writing "the single most important element to be reckoned in understanding this or any other speculative boom is the social contagion of boom thinking, mediated by the common observation of rapidly increasing prices…" (Shiller 2010, p. 41; see also Shiller 2015, Chapter 10).

We use brokerage account records from a large Chinese stock brokerage firm to document that all three components of the Shiller feedback loop are found during the Chinese put warrants bubble. We are able to identify the exogenous event that precipitated the extreme phase of the bubble, and the date on which this event occurred. The brokerage account records allow us to document positive feedback trading throughout the bubble, including its extreme phase. Using the results of hazard rate regressions that predict the reentry into the market of investors who have previously traded put warrants, we estimate the buying due to positive feedback trading during the bubble and find that it was positive and large following the precipitating event, exacerbating the extreme phase of the bubble. We also use the brokerage account records to construct the proxies for social contagion used by Kaustia and Knupfer (2012)

[2] See also Case and Shiller (1988, 1994, 2003), Akerlof and Shiller (2009, Chapter 9), Shiller (1984, 2003, 2007, 2009, 2011, 2014). Shiller (2015, p. 84) summarizes the mechanism "Initial price increases … lead to more price increases as the effects of the initial price increases feedback into yet higher prices through increased investor demand. This second round of price increase feeds back again into a third round, and then into a fourth, and so on. Thus the initial impact of the precipitating factors is amplified into much larger price increases than the factors themselves would have suggested."

and use them to show that social contagion drives the entry of new investors. These results are the first to identify the three components of Shiller's feedback loop in a large dataset of investor trades.

The Chinese put warrants bubble occurred on the Shanghai and Shenzhen stock exchanges during 2005–2008. Between November 2005 and June 2007 18 Chinese companies issued put warrants with maturities of between six months and two years.[3] These warrants gave their holders the right to sell the issuing companies' stocks at predetermined strike prices during specified exercise periods. The 2006–2007 boom in Chinese stock prices caused most of these put warrants to be so far out of the money that they were almost certain to expire worthless. Despite this, the put warrants traded very actively at non-trivial prices, causing many to interpret the warrant trading as a speculative bubble, and Xiong and Yu (2011) build a compelling case that it was a bubble.[4] Among other evidence and arguments, Xiong and Yu (2011) document that many of the put warrants traded at prices far in excess of estimates of their values computed using the Black-Scholes formula, some of the warrants at times traded at prices that exceeded their strike prices, and that toward the end of their lives, some put warrants traded at non-trivial prices even though they were certain to expire out-of-the money even if their underlying stocks traded limit down for every trading day until the warrants' expiration dates.

This speculative bubble is an interesting event to study for at least two reasons. First, we have access to the trading records of a large group of Chinese investors who traded the put warrants during the bubble. We are able to identify the exogenous event that precipitated the extreme phase of the bubble, and the subsequent warrant purchases. The trading records also allows us to study how investors' warrant purchases are related to covariates including the returns on the investors' own previous warrant purchases and the warrant returns of other geographically proximate investors with whom the investors might have had social contact. In contrast, most previous empirical research on bubbles has relied on market data such as prices, returns, and trading volumes or turnover (for example, Hong and Stein 2007, Mei, Scheinkman, and Xiong 2009, and Xiong and Yu 2011), surveys of comparatively small numbers of investors

[3] There were also 54 call warrants. The first call warrant, on BaoGang stock, was issued on August 22, 2005.
[4] In addition to Xiong and Yu (2011), researchers who have interpreted the put warrant trading as a speculative bubble and/or provided evidence that the put warrants were overvalued include Liao, Li, Zhang, and Zhu (2010), Chang, Luo, Shi, and Zhang (2013), Powers and Xiao (2014), and Liu, Zhang and Zhao (2016).

(for example, Case and Shiller 1988, 2003), or limited documentary evidence (for example, Garber 1989, 1990, 2000).[5]

Second, due to Xiong and Yu (2011) one can be confident that the investor trades we study are bubble phenomenon and not a mixture of bubble behavior and rationally motivated trading based on fundamental information. For example, because the prices of Chinese put warrants cannot be rationalized in terms of fundamentals one can be confident that the relations between trades and lagged returns we find are not caused by rational learning or updating of beliefs about fundamental information. In contrast, most other bubbles are controversial, with serious scholars offering arguments that they were not bubbles. For example, Hall (2001) and Li and Xue (2009) argue that the run-up in the prices of technology stocks during 1996–2000 can be explained by technology shocks and Bayesian updating of beliefs about possible future technology shocks. Garber (1989, 1990, 2000) has even offered explanations of the Dutch tulipmania, the Mississippi Bubble, and South Sea Bubble in terms of fundamentals.

Using the stock brokerage account records, we are able to identify that a tripling of the stamp duty imposed on stock trades that was announced at midnight on May 29, 2007 and took effect immediately at the opening of trading on May 30 precipitated the extreme phase of the put warrants bubble, which began on May 30. Because warrants were exempt from the stamp duty it made warrants more attractive than stocks for short-term speculative trading and caused striking increases in the both entry of new investors into the warrant market and the reentry of investors who had previously traded warrants. Market data show a 12-fold increase in warrant turnover on May 30 and an average warrant return of 57.6%, followed by further large positive returns over the next 15 days. The differences between warrant prices and estimates of their fundamental values were much higher on and after May 30, 2007 than before.

Turning to the second element of the Shiller bubble mechanism, we use hazard rate regressions to show that, for the investors who have previously traded put warrants, the probability that they buy again is positively related to their previous put warrant returns. This positive feedback trading occurs throughout the warrants' lives, including the extreme bubble period. The combination of the positive coefficients and the large price increases beginning on May 30, 2007 lead to a burst of positive feedback trading beginning on this date and continuing for more than a month, throughout the extreme phase of the bubble.

[5] Exceptions include Gong, Pan and Shi (2016) who use investor trade data for the BaoGang call warrant.

We provide evidence of social contagion by following Kaustia and Knupfer (2012) and using the brokerage firm data to construct, for each date and investor who has never traded warrant *k*, estimates of the lagged returns that geographically proximate investors have achieved by trading warrant *k*. The lagged returns of geographically proximate investors can provide evidence about social contagion because these are the other investors with whom a given investor is most likely to have social contact. We find that the both the positive parts of lags of the cross-sectional average returns of such same-branch investors and the interaction of the positive parts with the numbers of such same-branch investors predict the numbers of investors who make their first purchases of warrant *k* on each date.

In addition to providing this evidence that the three components of the Shiller bubble mechanism are found in the data, we also reexamine the panel regressions Xiong and Yu (2011) used to support the resale option theory by adding date fixed effects to the panel regressions. The date fixed effects for the dates just after May 30, 2007 are large and positive, providing additional evidence consistent with an important exogenous shock occurring on May 30, 2007. We also include date fixed effects in the hazard rate and social contagion regressions and also find them to be large and positive starting with May 30, 2007.

The Shiller feedback loop is not the only theory of speculative asset price bubbles. Scheinkman and Xiong (2003) have proposed a resale option theory of overvaluation. In addition to documenting the Chinese put warrants bubble, Xiong and Yu (2011) present panel regression evidence that put warrant prices were positively correlated with volatility and turnover, consistent with the resale option theory. This theory or the related model of Hong, Scheinkman and Xiong (2006) has found support in other data (Hong, Scheinkman and Xiong 2006, Hong and Stein 2007, and Mei, Scheinkman, and Xiong 2009). Blanchard and Watson (1983), Allen and Gorton (1993), and Allen and Gale (2000) have proposed other theories of asset price bubbles. The various theories are not mutually exclusive, and our findings that the components of the Shiller feedback loop are found during the Chinese put warrants bubble does not imply that other mechanisms such as the resale option theory did not also contribute to the bubble.

In addition to Xiong and Yu (2011), several other papers explore possible causes of overvaluation of Chinese warrants. Powers and Xiao (2014) find that estimates of the overvaluation of put warrants are correlated with measures of liquidity and volatility, consistent with the resale option theory. They also find that the overvaluation is greater after the May 30, 2007 change in the stamp duty. Liao, Li, Zhang, and Zhu (2010) present evidence that overpricing of call and put warrants traded on the Shanghai Stock Exchange, where issuance of additional warrants was possible, was less severe than in warrants traded on the Shenzhen Stock Exchange, where issuance of additional warrants was not possible. Their finding that warrant prices are decreasing in warrant supply and possible future supply would seem to be consistent with almost any theory of security valuation. Gong, Pan and Shi (2016) provide evidence that the BaoGang call warrant was consistently overvalued, and use account level data to show that on most trading days a majority of purchases were made by investors who had never previously held the warrant and that the ratio of purchases by new investors to total purchases was contemporaneously positively correlated with changes in a measure of overvaluation. They interpret these results to mean that the bubble was created and sustained by new investors, but do not attempt to determine the factors that might cause new investors to buy the warrant. None of these papers provide evidence about any of the three elements of the Shiller feedback loop.

Several papers also explore other aspects of the Chinese warrant market. Liu, Zhang and Zhao (2016) study the spillover effect from the warrant market to the stock market and find that the previous day's unexpected turnover and over-valuation of warrants predict positively the next day's turnover and volatility of the underlying stocks. Liao, Li, Zhang, and Zhu (2010) show that exercise decisions in 0.64% of call and put warrants are irrational in that the investors either exercise are out-of-the-money warrants or fail to exercise in-the-money warrants. Chang, Luo, Shi, and Zhang (2013) show that warrant prices were generally much higher than Black-Scholes values and that changes in warrant price were not highly correlated with changes in the prices of the warrants' underlying common stocks.

The next section of the paper describes the data we use, focusing on the brokerage account records. Section 3 presents evidence that an exogenous shock that precipitated the extreme phase of the bubble occurred on May 30, 2007. Section 4 presents the results about positive feedback trading, while Section 5 presents regression results showing that social contagion contributed to the entry of new investors. Section 6 present the results of adding date fixed effects to the panel regressions that Xiong and Yu (2011) use to provide support for the resale option theory, and Section 7 briefly concludes.

2. Data Description and Summary Statistics

2.1 Background

The put warrants we study were created as part of the Chinese share structure reform initiated in 2005. In this reform, non-tradable shares held by management, the state, or other state-owned enterprises were made tradable. Because this was expected to adversely affect the prices of the tradeable shares held by investors, holders of non-tradable shares were required to compensate holders of tradable shares, usually with cash or additional shares. In a few cases the compensation included warrants, leading to the creation of 36 call warrants and the 18 put warrants that are the focus of this study. In some cases additional warrants were subsequently issued by special purpose vehicles established by financial institutions.

The warrants were listed on either the Shanghai or Shenzhen stock exchanges, and traded like stocks, with one important difference. The difference was that a warrant could be sold on the same day it was purchased. In contrast, a Chinese stock purchased on day t may not be sold until the next trading day $t + 1$, i.e. it must be held for at least one overnight period in a practice referred to as $t + 1$ settlement. This difference from the trading of Chinese stocks enabled intraday speculative trading in the warrants and made it possible for the put warrants to have extremely high trading volumes, and they sometimes did. One might also hypothesize that this contributed to the bubble in the prices of put warrants. An important way in which the warrants were similar to stocks is that, like stocks, short-selling was not permitted. This prevented investors who believed the warrants to be overvalued from entering into short transactions to take advantage of the overvaluation.

2.2 Warrant and Stock information

We focus on the 18 put warrants in which Xiong and Yu (2011) document the existence of a speculative asset price bubble. Like Xiong and Yu (2011), we obtain the warrant daily price and volume, intraday price and volume, numbers of warrants issued, trading period, exercise period, strike price, and exercise ratio, from CSMAR. We obtain daily and intra-day stock price and trading volumes from the same source. We also checked some of the data by obtaining data from a different Chinese financial data vendor, RESSET.

2.3 Brokerage account data

The main data we use are the trading records of a large set of investors who traded the put warrants. We obtain these data from a comprehensive set of brokerage account records from a securities firm in the People's Republic of China. The brokerage account records come from a total of 42 branch offices located in 17 different regions across China where a "region" can be either a province (e.g., Fujian), a municipality (e.g., Shanghai), or autonomous region (e.g., Xinjiang). Some of the brokerage customers traded the put warrants, among other securities, and we analyze the records of the put warrant trades.

In China, individuals are restricted to have only one brokerage account, and are required to present their national identity cards when opening a brokerage account. This on its face would seem to rule out having multiple brokerage accounts. However, it is possible for one individual to control multiple brokerage accounts by gathering identity cards from friends or neighbors and opening brokerage accounts in their names. To address this, we combine the records from brokerage accounts that share the same "funding account," which is an internal securities firm code that links a single individual to one or more brokerage accounts. Therefore, the unit of our analysis is the funding account, and multiple brokerage accounts linking to the same funding account are treated as a single investor.

We identify a total of 5,692,241 put warrant trades from November 23, 2005, the date when the first warrant was listed, to December 31, 2009, the end of the data. There were 81,811 investors who traded put warrants, consisting of 80,089 individual investors and 1,722 institutional investors. Note that these "institutional investors" are not large financial institutions such as mutual funds, as large institutional investors typically have direct access to the exchanges. Many and perhaps most of the institutional investors in the brokerage firm data are likely to be privately held companies.

Many investors held and traded more than one warrant at the same time. Investors traded an average of 4.9 different warrants. Individuals who traded the put warrants executed a total of 69.3 purchase transactions, on average, lower than the institutional investors' average of 79.8.

On component of Shiller's feedback look theory, positive feedback, speaks to purchases and sales of transactions. For example, if an investor experiences a gain from previous trading, the probability that the investor reenters the market is higher. But in actual data, an investor might use multiple buys to build up a position, and then liquidate the position using multiple sell orders. This raises the issue of how to treat sets of transactions in which multiple buys or sells are used to build up or liquidate a position. A similar issue arises in empirical analyses of the disposition effect.

We resolve this issue by introducing a notion of a "transaction cycle." Starting from a holding of zero units of warrant *k*, a transaction cycle begins with a purchase of some non-zero amount of warrant *k*. It then continues through possibly multiple purchases and sales, until the investor's position in warrant *k* returns to zero. This ends a single transaction cycle, which we treat as a single transaction. The length of the transaction cycle is the time elapsed from the first purchase that begins the cycle to the last sale that ends it. In the case that investors open and close positions on warrant *k* more than once within the same day, we treat these transactions as a single cycle. The rationale for this treatment is that we want to study the impact of an exogenous shock on investors' positive feedback trading, which is an important mechanism in Shiller's theory, and we use date fixed effects to capture the shock. Therefore, we do not allow multiple transactions within a single day.

The return to a transaction cycle is the weighted sum of the sale prices, weighted by the quantities sold in the various sells, divided by the weighted sum of the purchase prices, where again the weights are the quantities purchased in the various buys, minus one.

We define a new investor in warrant *k* on date *t* as one who executes his or her first trade in warrant *k* on date *t*. We define a re-entry investor in warrant *k* on date *t* as one who trades in warrant *k* before date *t* and opens a new transaction cycle on date *t*.

Some of our analyses also use the branch office where an investor trades. In China, an investor must place trades through the branch office at which he originally opened the account. Chinese investors usually open accounts close to where they live.

Panel C in Table 1 reports the numbers of investors trading on each of the 18 put warrants and the average length of the transaction cycles. The majority of transaction cycles are completed ones and there are only a small portion of uncompleted cycles, which happen when investors open a position and hold it until the expiration day.

3. The May 30, 2007 Precipitating Event

Of the18 put warrants, 12 expired prior to May 30, 2007 and one was issued in June, 2007, leaving five that were trading on May 30, 2007. Panels A-E of Figure 1 show the daily closing prices (black line, left-hand axis) and turnover (dashed green line, right-hand axis) of these five warrants for a six-month period roughly centered on May 30, 2007, that is the months March through August, 2007. The five panels clearly show that turnover increased remarkably on May 30. For the five warrants, the ratios of the turnover on May 30 to the turnover on May

29 were 19.11, 12.72, 11.70, 3.47, and 14.70. The average of these five ratios is 12.34, that is on average there was a 12-fold increase in turnover on May 30, 2007. The visual impression is of a discontinuous change. Turnover remained high after May 30; while the turnovers of HuaLing, WuLiang, and JongJi declined from their peaks in early June , the turnovers remained above the levels prior to May 30. JiaFei's turnover drops through the middle of June and then picks up again prior to the last trading date of June 22, 2007, at which point the series ends. ZhaoHang's turnover generally declines until the middle of August, at which point it increases again prior to the last trading data of August 24, 2007. For all five warrants turnover was much more variable after May 30 than it was prior to May 30.

Prices of all five warrants were reasonably stable prior to May 30, 2007, rose sharply for a few days starting on May 30, and then were highly volatile after May 30. The prices of HuaLing, WuLiang, and JongJi declined from the middle of June through early July and then rebounded somewhat, always remaining well above their prices prior to May 30.

Panels A-E of Figure 2 use the brokerage account data to show that both new and returning investors increased their trading on May 30, 2007. Specifically, each panel shows the daily closing price (black line, left-hand axis), the number of new investors on each date (dashed red line, right-hand axis), and the sum of the number of new and returning investors on each date (dotted blue line, right-hand axis). A new investor in warrant *k* on date *t* is one who has not previously traded warrant *k*, while a returning investor is one who has previously traded warrant *k*. The difference between the dotted blue line and the dashed red line is the number of returning investors. The five panels show that for all five put warrants the numbers of both new and returning investors jumped sharply on May 30. Similar to the changes in turnover shown in Figure 1, the visual impression is of a discontinuous change.[6]

Table 2 provides additional evidence to verify that the put warrants bubble was considerably more pronounced after May 30, 2007 than before. The three panels report some statistics related to the severity of the bubble for three different combinations of warrants and time periods. The statistics are the average and maximum daily turnover; the average and maximum bubble size, where the bubble size is the difference between the warrant closing price

[6] Sections 4 and 5 below report the results of various regression models that provide evidence of both positive feedback trading and social contagion. The date fixed effects in these regression models are large and significant starting on May 30, 2007. This provides additional evidence of an important event on May 30, even controlling for the impact of other covariates.

and an estimate of the warrant fundamental value computed using the Black-Scholes formula, and the average and maximum volatility computed from intra-day five minute returns. Panel A reports these statistics for the 12 warrants that expired before May 30, 2007, Panel B reports them for the period prior to May 30 for the five warrants that traded both before and after May 30, and Panel C reports them for the period on and after May 30 for the five warrants that traded after May 30 and a sixth warrant (NanHang) that was issued in June 2007.

Comparison of the results in the Panels A and B of Table 2 to those in Panel C make it clear that the bubble was much more pronounced after May 30, 2007 than before. The average bubble sizes in Panel A for the 12 warrants that expired before May 30 range from –0.113 yuan (HuChang) to 0.606 yuan (HaiEr), and the average bubble size in Panel B for the five warrants that traded both before and after May 30, 2007 during the period before May 30 ranged from 0.129 yuan (HuaLing) to 1.188 yuan (JiaFei). In contrast, in Panel C the average bubble size after May 30 ranged from 0.948 yuan (ZhaoHan) to 3.410 yuan (JiaFei). That is, the maximum (across warrants) of the average daily bubble sizes before May 30 in Panels A and B is less than the minimum of the average daily bubbles sizes after May 30 shown in Panel C. The average daily turnover and volatility display the same feature—the maxima of the average daily turnovers and volatilities before May 30 in Panels A and B are less than the minima of the average daily turnovers and volatilities after May 30 in Panel C. After May 30 the bubble is clearly more pronounced than it was before May 30.

Clearly something important happened on May 30, 2007. What was it?

Prior to May 30, 2007, a stock transaction tax of 0.1% of the value of the shares transacted was imposed on each side of a stock transaction, for a total tax of 0.2%. Warrants were exempt from the tax and also exempt from $t + 1$ settlement, making them attractive to investors interested in short-term speculation. The Chinese regulatory authorities had become concerned about the 2006-2007 boom in stock prices, and there were rumors that they would attempt to dampen the boom by increasing the transaction tax. At midnight on May 29 the Ministry of Finance announced a tripling of the transaction tax to 0.3% of the value transacted on each side of a transaction, for a total of 0.6%, effective immediately at the opening of trading on May 30[7].

[7] http://www.mof.gov.cn/zhengwuxinxi/caizhengxinwen/200805/t20080519_26343.html, website of Ministry of Finance.

The transaction tax had an immediate negative impact on the stock market, with the Shanghai and Shenzhen stock indexes falling by 6.15% and 5.78%, respectively, on May 30. Because the transaction tax was not imposed on warrants it increased the relative attractiveness of the warrants for short term speculation and we see the significant increase in trading of put warrants on May 30 as shown in the first half of this section. This was a precipitating event that exacerbated the put warrants bubble.

Looking at the comparative stability of the warrant prices before May 30 in Figures 1 and 2, one wonders if the bubble would have received so much attention absent the increase in its magnitude due to the May 30, 2007 increase in the stock transaction tax.

4 Positive Feedback Trading

The second component of Shiller's feedback loop theory of speculative bubbles is positive feedback trading in which an investor is more likely to trade again if his or her past returns were positive. We explore positive feedback effect by estimating Cox proportional hazard models of the probability of a subsequent purchase of warrant *k* by an existing investor who has previously completed a transaction cycle in warrant *k*, i.e. we model the reentry of investors into warrant *k*. The covariates of main interest are the investor's returns on his or her previous purchases of warrant *k*, and, to allow for a discontinuity at a return of zero, dummy variables that take the value one if the return was positive. We choose a proportional hazards model because its specification considers the time that has elapsed since an investor completed the last transaction cycle. Specifically, consider an investor A who had a large positive return yesterday and investor B who had a large positive return 3 months ago but has not yet traded again. Investor A is more likely to trade on date *t* than investor B, who has probably left the warrant market and is unlikely to trade on date *t*.

The proportional hazards model specifies that $\lambda_{i,k,t}(\tau)$, the hazard function of starting a new transaction cycle for the existing investor *i* in warrant *k* at day *t*, τ trading days after the end of the investor's last transaction cycle, takes the following form:

$$\lambda_{i,k,t}(\tau) = \lambda(\tau) \times e^{x_{i,k,t}\beta}, \qquad (1)$$

where $\lambda(\tau)$ is the baseline hazard rate and $x_{i,k,t}$ is a vector of covariates that proportionally shift the baseline hazard. For investors who have previously completed one transactions cycle $X_{i,k,t}\beta$ is given by

$$X_{i,k,t}\beta = \beta_1 \times Return\_lag1_{i,k,t} + \beta_2 \times \mathrm{I}\big(Return\_lag1_{i,k,t} > 0\big) + \text{Controls} + \alpha_m + \alpha_k + \alpha_t \quad (2)$$

where $Return\_lag1_{i,k,t}$ is the return of last transaction cycle of investor i in warrant k before date t. The dummy variable $\mathrm{I}\big(Return\_lag1_{i,k,t} > 0\big)$ takes the value one if $Return\_lag1_{i,k,t} > 0$, otherwise is otherwise. This variable is included to allow for the possibility of a discontinuity at a return of zero. The variables α_m, α_k and α_t are maturity, warrant, and date fixed effects, respectively.

The control variables include three lags of $\text{WarrantReturn}_{k,t}$, the daily return of warrant k on date t, three lag of $\text{TurnoverRatio}_{k,t}$, the market trading volume in warrant k on date t, divided by number of warrants outstanding, and one lag of $\text{AdjustedFundamental}_{k,t}$, the adjusted fundamental value of warrant k on date t, which is computed as follows:

$$\text{Adjusted fundamental Value} = \left(\frac{Stock\ Price - Strike\ Price}{Stock\ Price}\right)/Maturity$$

We use the adjusted fundamental value rather than the Black-Scholes value here because we hypothesize that investors should be more sensitive to the difference of underlying stock price and strike price when making investment decision in warrant k than the warrant's theoretical price, which is not intuitive.

The positive feedback theory implies that the coefficients β_1 should be greater than zero. Also, if the coefficient on β_2 is non-zero, we expect it to be positive.

The specification for investors who have previously completed two cycles is similar to the one-cycle model, except that we add the variables $Return\_lag2_{i,k,t}$ and $\mathrm{I}(Return\_lag2_{i,k,t})$ to the model to capture the effect of the returns on the second most recent cycle. For investors with three or more previous cycles we also include $Return\_lag3\_more_{i,k,t}$ and $\mathrm{I}(Return\_lag3\_more_{i,k,t} > 0)$, where $Return\_lag3\_more_{i,k,t}$ is the average return of the lag three and earlier transaction cycles of investor i in warrant k before date t.

We estimate the model by the partial likelihood method (Cox 1972). The estimation results are reported in Table 3. For all the three versions of the models, positive returns on previous transaction cycles predict a higher probability that investors open a new transaction cycle. Additionally, the estimated coefficient β_2 indicates that there is a discontinuity at zero. These results indicate the presence of feedback trading.

Figure 3 plots the calendar date fixed effects for a six-month window approximately centered on May 30, 2007. One can see an obvious jump on the May 30, capturing the effect of the shock of the increased transaction tax on existing investors' trading behavior.

The May 30, 2007 shock, combined with the positive coefficients on lagged returns, suggest that positive feedback trading might have been important during the extreme phase of the bubble immediately following May 30. To explore this further, we calculate the fitted investor's reentry probability in warrant *k* on date *t* as follows:

$$\hat{P}_{i,k,t} = 1 - \exp\{-\lambda(\tau)\exp\{x_{i,k,t}\hat{\beta}\}\}. \quad (3)$$

We then calculate $\bar{P}_{i,k,t}$ using equation (3) again but setting previous return variables (such as $Return\_lag1_{i,k,t}$ and $\mathrm{I}(Return\_lag1_{i,k,t} > 0)$) to zero. Letting $\overline{Q}_{i,k}$ be the average trade size of investor *i* in warrant *k*, we use $\widehat{(P}_{i,k,t} - \bar{P}_{i,k,t})\bar{Q}_{i,k}$ to measure the effect of positive feedback on the trading behavior of investor *i*. We then calculate the sum $\widehat{(P}_{i,k,t} - \bar{P}_{i,k,t})\bar{Q}_{i,k}$ for each of the five warrants on each day across all the existing one-cycle investors and plot the time series in Panel A of Figure 4. Similarly, Panels B and C plot the corresponding quantities for the two and three-cycle investors. Clearly, we can see that the effect of positive feedback becomes imporant from May 30, 2007. Strikingly, the period when the effect of positive feedback trading was important is exactly the extreme phase of the bubble.

5. Social Contagion

Various writings by Shiller, sometimes with coauthors, have emphasized the role of social contagion in speculative booms and bubbles (Shiller 1984, 1990, 2010, 2015; Akerlof and Shiller 2009; Case and Shiller 1988, 2003). For example, Shiller (2015; Chapter 10) emphasizes the role of social contagion and word of mouth communication, and argues that after millions of years of evolution its importance is "hard-wired into our brains." He argues that people do not give other sources of information the same emotional weight, and cannot remember or use information from these other sources as well. Relatedly, Shiller (2010; p. 41) claims that "…the single most important element to be reckoned in understanding … any … speculative boom is the social contagion of boom thinking."

Recently, Shive (2010) and Kaustia and Knüpfer (2012) have used Finnish data to study the effect of social contagion on purchases of individual stocks and the decision to enter the stock market, respectively. Kaustia and Knüpfer (2012) focus on distinguishing between two plausible channels by which stock market outcomes of peers might influence individuals' entry decisions. In the first channel, individuals might use peer outcomes to update beliefs about long-term fundamentals, such as the equity premium. In the second channel, people cannot directly observe peer outcomes and rely on "word of mouth" verbal accounts and possibly other indirect information. Such verbal accounts are likely be biased toward reporting positive outcomes, as investors are unlikely to benefit from discussing their negative outcomes with their peers. As Kaustia and Knüpfer (2012) discuss, investors might enjoy discussing their positive stock market experiences more than their negative ones. Second, appearing to be a competent investor might carry private benefits. Third, various theories in psychology predict that people have self-serving biases in recalling and interpreting the factors involved in their successes and failures. To the extent such selective reporting is present, peer outcomes will have a stronger influence on the entry of new investors when the outcomes have been better.

Kaustia and Knüpfer (2012) distinguish between the two channels by estimating panel regression models explaining the entry of new stock market investors in which the key variables of interest are transformations of the previous month's average return experienced by investors in the same postal code, as other investors sharing an investor's postal code are those most likely to interact with and influence the entry decision of an investor. Kaustia and Knüpfer find that the lagged average return affects entry decisions when it is positive, but it unrelated to entry decisions when it is negative. This is consistent with selective reporting and peer returns affecting entry via word of mouth communication.

We also look for evidence of social contagion by estimating panel regression models that explain the entry of new investors in the warrant market. Similar to Kaustia and Knupfer (2012), in our regression models the key variables of interest are transformations of the past average returns of other local investors, though in our case the other local investors are those who trade through the same branch office of the brokerage firm. A potential warrant investor is more likely to have social interactions and word-of-mouth communication with other investors who trade using the same branch office, as two investors trading at the same branch office are more likely to live and/or work near each other than are two investors trading through different branch offices. In larger cities in which the brokerage firm has multiple branch offices trading through the same branch office is a proxy for living and/or working in the same or nearby districts. In smaller cities in which the brokerage firm has only one branch office trading through the same branch office is a proxy for living and working in the same city.

An investor who trades warrant k on date t is considered a new investor in warrant k on date t if date t is the first day that he or she trades warrant k. In some analyses we use periods of half day, in which case an investor is a new investor during half-day period t if period t is the first one during which he or she trades warrant k. The unit of observation is branch-warrant-day, or branch-warrant-period when we use half-day periods. The key predictive variables are measures of the past trading performance of other investors who trade at the same branch office. Specifically, we predict whether investor i who trades at branch j will trade warrant k using transformations of the lagged daily or periodic average return of the other investors in the same branch, which we call the branch average return and denote $\text{BranchAverageReturn}_{jkt}$. To compute the average return of branch j investors in warrant k on date t we consider the trades and positions of all branch j investors who either traded or held warrant k on day t. For each such investor i and day t, we first compute X_{ikt}, equal to the sum of: (a) the value of the position in warrant k held by investor i at the close of trading on day $t-1$, where the value is the product of the $t-1$ closing price and the number of warrants held; and (b) the value of all warrants purchased during day t, where the value is the product of the purchase price and the quantity. Second, we compute Y_{ikt}, equal to the sum of: (c) the value of the position in warrant k that investor i held at the close of trading on day t, where the value is the product of the day t closing price and the number of warrants held; and (d) the value of the warrants sold during day t, where the value is the product of the sale price and the number of warrants sold. The day t return for the investor i in warrant k is then defined as $r_{ikt} = Y_{ikt}/X_{ikt} - 1$. The day t return for the branch j investors in warrant k, $\text{BranchAverageReturn}_{jkt-1}$, is then the average return over the branch j investors that either traded or held put warrant k on day t. The $\text{BranchAverageReturn}_{jkt}$ is highly correlated with the market-wide warrant return $\text{WarrantReturn}_{kt}$ but differs from it because there is considerable intraday trading in warrants and warrant holding periods are often less than one day.

In various specifications we include lags of the branch average return $\text{BranchAverageReturn}_{jkt}$, and the transformed average return $\max[\text{BranchAverageReturn}_{jkt}, 0]$. As discussed above the motivation for the transformation is that social contagion effects via "word-of-mouth" are likely to be stronger if other branch j investors have experienced positive returns in warrant k, because investors are more likely to discuss their past investment successes with their friends and colleagues than their past failures. In contrast, the performance of investors who trade at other branches is less likely to affect the entry of investor i into the warrant market.

Another variable that helps capture the potential influence of other investors in the same branch consists of the number of branch j investors that either traded or held warrant k on date t, $\text{BranchInvestors}_{jkt}$. This term captures the fact that it is more likely that a potential new investor is influenced by other investors to enter the warrant market if there are more such other investors at the same branch, because these are the other investors with whom a potential new investor might interact. We also include an interaction term consisting of the product of $\text{BranchAverageReturn}_{jkt}$ and $\text{BranchInvestors}_{jkt}$ and the corresponding interaction term $\max[\text{BranchAverageReturn}_{jkt}, 0] \times \text{BranchInvestors}_{jkt}$ either in place of or in addition to the variables $\text{BranchAverageReturn}_{jkt}$ and $\text{BranchAverageReturn}_{jkt} \times \text{BranchInvestors}_{jkt}$. These interaction term captures the fact that it is more likely that a potential new branch j investor is influenced by the past returns of other branch j investors if there are more branch j investors with whom the potential new investor might interact.

Our regression specifications also include various lags of the number of new investors at branch j in warrant k, $\text{NewBranchInvestors}_{jkt}$. In addition, we include lags of the return and turnover of warrant k, and also the total number of brokerage new investors trading warrant k. The panel regressions are also all estimated with branch-level fixed effects.

Below we find that the lagged branch-level returns and transformations of them are significantly related to the entry of new warrant investors. Our panel regression design and the controls we include rule out alternative mechanisms based on reverse causality and common unobservables that might explain the relations between branch-level warrant returns and entry that we find. First, consider reverse causality—the possibility that initial purchases of warrant k causes existing warrant k investors trading through branch j to experience higher returns via "price pressure" on warrant k. While this mechanism might affect the contemporaneous relation between entry and returns, it does not explain the relation between lagged returns and entry. Thus, this reverse causality mechanism cannot explain our results. Moreover, to the extent that investors anticipate future price pressure due to the entry of new investors, this implies that the entry of new investors should be correlated with lagged warrant returns, not the returns experienced by investors at branch j. Our inclusion of lagged warrant returns in the regressions should capture any such relation.

Common time-invariant unobservables might also generate a positive relation between the branch-level returns and entry into the warrant market. For example, it is conceivable that investors in some branches are more financially sophisticated than those in other branches. This might cause both higher branch-level warrant returns and entry by other investors who trade at the same branch. This possible influence is eliminated by our use of branch-level fixed effects.

Because branch-level returns are correlated with market-wide warrant returns, common time-varying shocks might also produce a positive relation between branch-level returns and entry into the warrant market. For example, high warrant returns are likely to be associated with increased investor attention to warrants, which might cause some investors to enter the warrant market. We control for this possibility and any other market-wide time-varying influences by including lagged warrant returns and the lagged numbers of brokerage-level new investors in the regression specifications.

A remaining issue involves the possibility of branch-level time-varying shocks. Some of the possible channels discussed in Kaustia and Knüpfer (2012) by which branch-level time-varying shocks might explain a correlation between branch-level warrant returns and entry, e.g. changing prospects of the local economy that work through the stock returns of local companies, are not relevant because the put warrant returns are not plausibly related to the fundamentals of the local economies. Another possibility is that the results are driven by time-varying shocks that are unique to a branch or small subset of branches, e.g. local media coverage or some other source of local information or "noise." This channel seems unlikely because the information or noise would have to be something that caused or was correlated with both branch-level returns and entry but not captured by the warrant returns used as controls, and also not a mechanism of social contagion.[8] Despite our skepticism regarding this possible channel, below we carry out additional analyses on a subsample that drops the observations from branches where this possible

[8] One possible story is that regional media coverage of the warrant market might be correlated with warrant returns and also cause entry. But if branch-level warrant returns cause the media coverage which then causes entry, then this can reasonably interpreted as a mechanism of social contagion, intermediated by the media. That is, investor A does not communicate directly with investor B, but rather with a reporter who then communicates with investor B. Even for this mechanism to explain our results, it must be that local media coverage is driven by the branch-level average returns, not the warrant returns. While it is certainly possible for local media to have knowledge of the warrant returns achieved by some local branch investors, it seems unlikely that they would have access to a large enough sample to have knowledge of the branch-level average return. Given that we control for the warrant return, it seems unlikely that this possible channel can explain our results.

channel is least unlikely to be relevant. We also include warrant fixed effect, warrant maturity effect, and date fixed effect.

Table 4 reports the results of panel regressions that use a one-day interval, i.e. the new investor variable $\text{BranchNewInvestors}_{jkt}$ consists of the new investors at branch j in warrant k on day t. The first three columns of Table 4 report the results of specifications of the whole sample. Performance of investors in the same branch is measured by both $\text{BranchAverageReturn}_{jkt}$ and its positive part $\max[\text{BranchAverageReturn}_{jkt}, 0]$. Consistent with social contagion via word-of-mouth effects, the estimated coefficients on the first lags of $\max[\text{BranchAverageReturn}_{jkt}, 0]$ and the interaction term $\max[\text{BranchAverageReturn}_{jkt}, 0] \times \text{BranchInvestors}_{jkt}$ are highly significant in all three regression models. The coefficient on the second lag of the interaction term is significantly negative in the two specifications that include at least two lags, but these coefficients on the second lags are much smaller than the coefficients on the first lags.

The coefficients on the lagged numbers of new investors at branch j are highly significant for all lags that appear in the regression. In contrast, the coefficients on the lags of $\text{BrokerageNewInvestors}_{kt}$ are much smaller, and the coefficient for the second lag is negative in the two specifications in which at least two lags appear. This finding that the lagged numbers of new investors at branch j are much more strongly related to the arrival of new investors at branch j than are the lagged numbers of brokerage new investors is consistent with social contagion, but is also consistent with the presence of branch-level unobservable variables that affect entry. Unsurprisingly, the first lag of the market warrant return ($\text{WarrantReturn}_{kt-1}$) is also strongly related to the entry of new investors.

At first glance, the negative coefficients on the first lag of the branch average return might seem anomalous. However, this variable is highly correlated with the warrant return, which carries a larger positive coefficient. The coefficients on the lags of $\text{WarrantReturn}_{kt}$ and $\text{BranchAverageReturn}_{jkt}$ are of opposite sign for all lags, consistent with the coefficients on the lags of $\text{BranchAverageReturn}_{jkt}$ being affected by the multicollinearity. The negative coefficient on the first lag of $\text{BranchAverageReturn}_{jkt}$ is not evidence against social contagion.

Last three columns in Table 4 report the results from re-estimating the specification but using a subsample that drops those combinations of warrants and brokerage branches for which the branch office is either located in the same city as the headquarters of the company whose stock provides the underlying asset of the warrants or located in the city where the underlying stock is listed. The results for this subsample are very close to those reported in the first three columns of Table 4. These results provide an additional piece of evidence that our results are not driven by branch-level time-varying shocks.

Table 5 reports the results of regressions similar to those in Table 4, but using a half-day rather than one-day interval, where the half-day is either the morning session (9:30 a.m.-11:30 a.m.) or the afternoon session (1:00-3:00 p.m.). In the Table 5 regressions the time index t indexes half-day periods, and the various variables are measured over intervals of one-half day. Specifically, the return variable for the morning session is measured from the close of the previous afternoon session to the close of the morning session, while the return variable for the afternoon session is measured from the close of the morning session to the close of the afternoon session. Due to the use of the half-day period, the specifications include two, four, or six lags of the right-hand side variables rather than one, two, or three.

The results for these regression using a half-day interval are consistent with the results of the regressions using a daily interval, and thus also consistent with social contagion. In the specifications in the first three columns that include lags of both $\text{BranchAverageReturn}_{jkt}$ and $\max[\text{BranchAverageReturn}_{jkt}, 0]$ and their interaction terms among the right-hand side variables, the coefficients on the first two lags of the interaction term $\max[\text{BranchAverageReturn}_{jkt}, 0] \times \text{BranchInvestors}_{jkt}$ are positive and significantly different from zero. This is exactly as predicted by social contagion. The coefficients for the longer lags are negative (and significant), but smaller than those for the first two lags. Turning to the other return variables, in each specification the sum of the coefficients on the different lags of $\max[\text{BranchAverageReturn}_{jkt}, 0]$ is large. Similarly, in each specification the sum of the coefficients on the other interaction term $\text{BranchAverageReturn}_{jkt} \times \text{BranchInvestors}_{jkt}$ is large. While the coefficients on the various lags of $\text{BranchAverageReturn}_{jkt}$ are generally negative and large, as previously pointed out the branch average return is positively correlated with the market return, and whenever the coefficient on a lag of $\text{BranchAverageReturn}_{jkt}$ is negative the corresponding coefficient on the same lag of the market return is positive. Overall, the estimated coefficients on the variables constructed from the branch average returns provide strong support for the social contagion hypothesis. In addition, the coefficients on the various lags of $\text{BranchNewInvestors}_{jkt}$ are highly significant, consistent with social contagion but also consistent with unobservable branch level variables that cause entry.

Last three columns in Table 5 report the results using a subsample that drops those combinations of warrants and brokerage branches for which the branch office is either located in the same city as the headquarters of the company whose stock provides the underlying asset of the warrants or located in the city where the underlying stock is listed. The results for this subsample are very close to those reported in the first three columns of Table 5.

Overall the results in Tables 4 and 5 provide strong evidence for social contagion via word of mouth effects. Notably, the estimated coefficients indicate that the positive part of the branch-level return max[BranchAverageReturn$_{jkt}$, 0] and the interaction term max[BranchAverageReturn$_{jkt}$, 0] × BranchInvestors$_{jkt}$ are strongly related to the entry of new investors. The panel regression specifications and controls we include rule out the possibility that the relations we find are explained by alternative mechanisms.

There might be, however, a lingering concern that our results are driven by time-varying shocks that are unique to a branch or small subset of branches, e.g. local media coverage or some other source of local information or "noise." This channel seems unlikely because the information or noise would have to be something that caused or was correlated with both branch-level returns and entry but not captured by the warrant returns used as controls, and also not social contagion. That said, local information, rumours, or "noise" might conceivably be correlated with both branch-level warrant returns and entry.

The combinations of warrants and branches most likely to be prone to this issue are those for which the branch office is either located in the same city as the headquarters of the company whose stock provides the underlying asset of the warrants or located in the city (either Shanghai or Shenzhen) where the underlying stock is listed, because seems more likely that investors will have access to (possibly incorrect or irrelevant) correlated information if they are in the same city as the headquarters of the company whose stock provides the underlying asset of the warrants or the city where the underlying stock is traded. We address this possibility in one final set of analyses that uses a subsample that excludes the combinations of warrants and branches most likely to be prone to this issue are those for which the branch office is either located in the same city as the headquarters of the company whose stock provides the underlying asset of the warrants or located in the city where the underlying stock is listed. If the results are driven by such a mechanism, the results should using this subsample should be different from those using the entire sample.

Figure 5 plots the date fixed effect dummies in the social contagion regression. We can see that impact of date fixed effect on investor entry become significantly larger from May 30, 2007, when the stamp duty event happened.

6. Panel Regressions

For each of the 18 put warrants, Xiong and Yu (2011) determine a zero-fundamental period in which an estimate of the fundamental value of the warrants computed using the Black-Scholes formula and historical volatility is less than ¥0.005. Using data from the zero-fundamental period, they estimate unbalanced panel regressions in which they regress the daily warrant prices on turnover, an estimate of the daily volatility computed from 5-minute intraday returns, the warrant float, and time-to-maturity fixed effects, and obtain positive coefficients on turnover and volatility and a negative coefficient on float. The resale option theory of Scheinkman and Xiong (2003) predicts positive correlations on turnover and volatility, and Xiong and Yu (2011) interpret the panel regression results as supportive of the resale option theory.

We revisit these panel regressions by adding calendar date fixed effects to the panel regressions in addition to the time-to-maturity fixed effects included by Xiong and Yu (2011). We are interested in seeing whether the date fixed effects are positive and significant after May 30, 2007, controlling for the turnover and volatility variables suggested by the resale option theory and used by Xiong and Yu (2011). Our claim in Section 3 that the May 30, 2007 tripling of the stock transaction tax was an important exogenous event for the warrant market implies that the calendar date fixed effects should be positive starting on that date.

Columns (1)-(4) of Table 6, Panel A replicate the panel regression results reported in the corresponding columns of Xiong and Yu (2011) Table 5. The *t*-statistics are based on standard errors that are clustered by date. The first three columns each report the results of regressions that include the variables one at a time, while column (4) presents the results of a specification that includes all three variables. For completeness, columns (5) and (6) of Panel A report the results of specifications that include two right-hand side variables at a time and are not in Xiong and Yu (2011). The coefficient point estimates and *t*-statistics in columns (1)-(4) of Panel A are very similar, but not quite identical, to those reported in the corresponding columns of Xiong and Yu (2011) Table 5.[9]

Panel B reports the results of the same set of regression models but also adding calendar date fixed effects to the regression specifications. Figure 5 displays the calendar date fixed effects during the months of March through August, 2007, which is a six-month window approximately centered on May 30, 2007. Similar to Figures 3 and 4, this figure also reveals a pronounced change in the calendar date fixed effects around May 30. These results are additional evidence that the May 30, 2007 tripling of the transaction tax had an important impact on the put warrant market.

Interestingly, the results in Panel B for the regression specifications that include calendar date fixed effects are quite different than those in Panel A. In the specifications that include one right-hand side variable at a time the point estimates of the coefficients on turnover and volatility are now negative, though not significantly different from zero. In the specification that includes all three variables turnover is significantly negatively related to price. In this specification volatility is positively related to the put warrant prices, consistent with the resale option theory, though the significance is only barely at the 10% level (t-statistic = 1.65). The coefficient on the warrant float is always negative and highly significant, which is unsurprising since most theories of security valuation would imply that price is decreasing in the security supply.

7. Conclusion

There is compelling evidence that the Chinese put warrants bubble was in fact a bubble. The extreme period of the bubble began on May 30, 2007 with the tripling of the stock transaction tax. The tax did not apply to warrant trades, and increased the relative attractiveness of warrants for short term speculative trading. This increase in the transaction tax served as a precipitating event for the extreme phase of the bubble. It caused a sudden, sharp increase in the numbers of investors buying put warrants, abrupt increases in turnover and volatility, and a sudden rise in the prices of the five put warrants that were trading on that date.

We use hazard rate regressions to document the existence of positive feedback trading throughout the period that the put warrants were available for trading. In these hazard rate

[9] The various challenges we faced in reverse engineering the zero-fundamental periods used by Xiong and Yu (2011) and the other details of how they estimated the regression reported in their Table 5 are detailed in the appendix.

regressions, the probability that an investor reenters the warrant market is positively related to the past returns he has achieved trading warrants. Using the estimates of the hazard rate regressions, we show that the feedback trading involved heavy buying during the extreme period of the bubble. The period of heavy buying due to feedback trading coincided with the extreme period of the bubble.

Turning to new investors, we show that entry of new investors into the warrant market is positively related to the positive parts of the returns of the geographically proximate investors with whom the new investors might plausibly have had social contact. Based on the arguments in Kaustia and Knüpfer (2012), this provides evidence that social contagion contributed to the entry of new investors into the put warrant market.

These results provide evidence that the three elements of the Shiller feedback loop theory—precipitating event, feedback trading, and social contagion—are found in the Chinese put warrants bubble. To our knowledge we are the first to identify the three components of Shiller's feedback loop theory in a large dataset of investor trades. The evidence that the period in which feedback trading was important coincided with the extreme period of the bubble is particularly striking.

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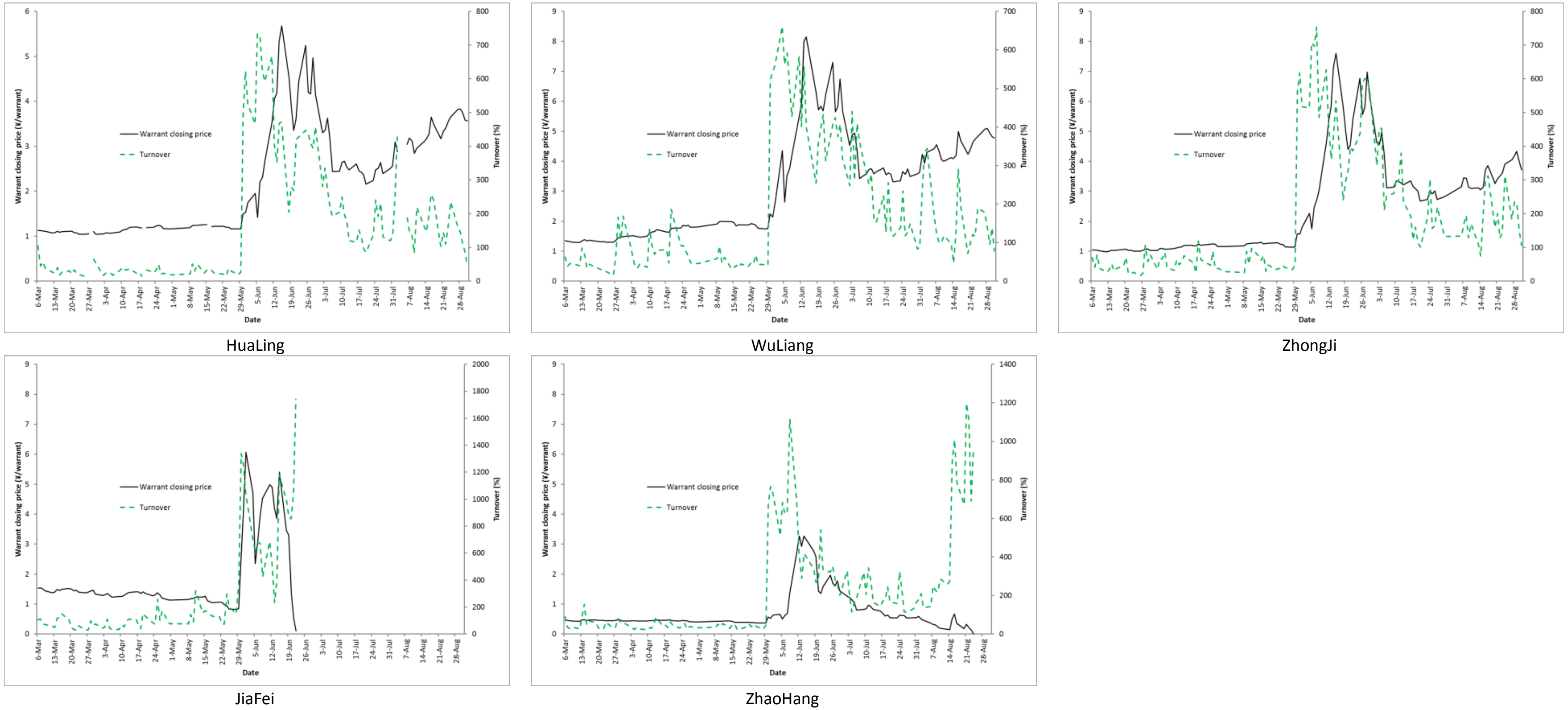


Figure 1. Price and turnover in 5 put warrants. These figures plot the daily closing price and turnover of 5 put warrants that experience the stamp tax event on 30-May 2007, from 6-Mar 2007 to 31-Aug 2007 (3 months before and after the shock). These figures show the exogenous shock on the put warrants.

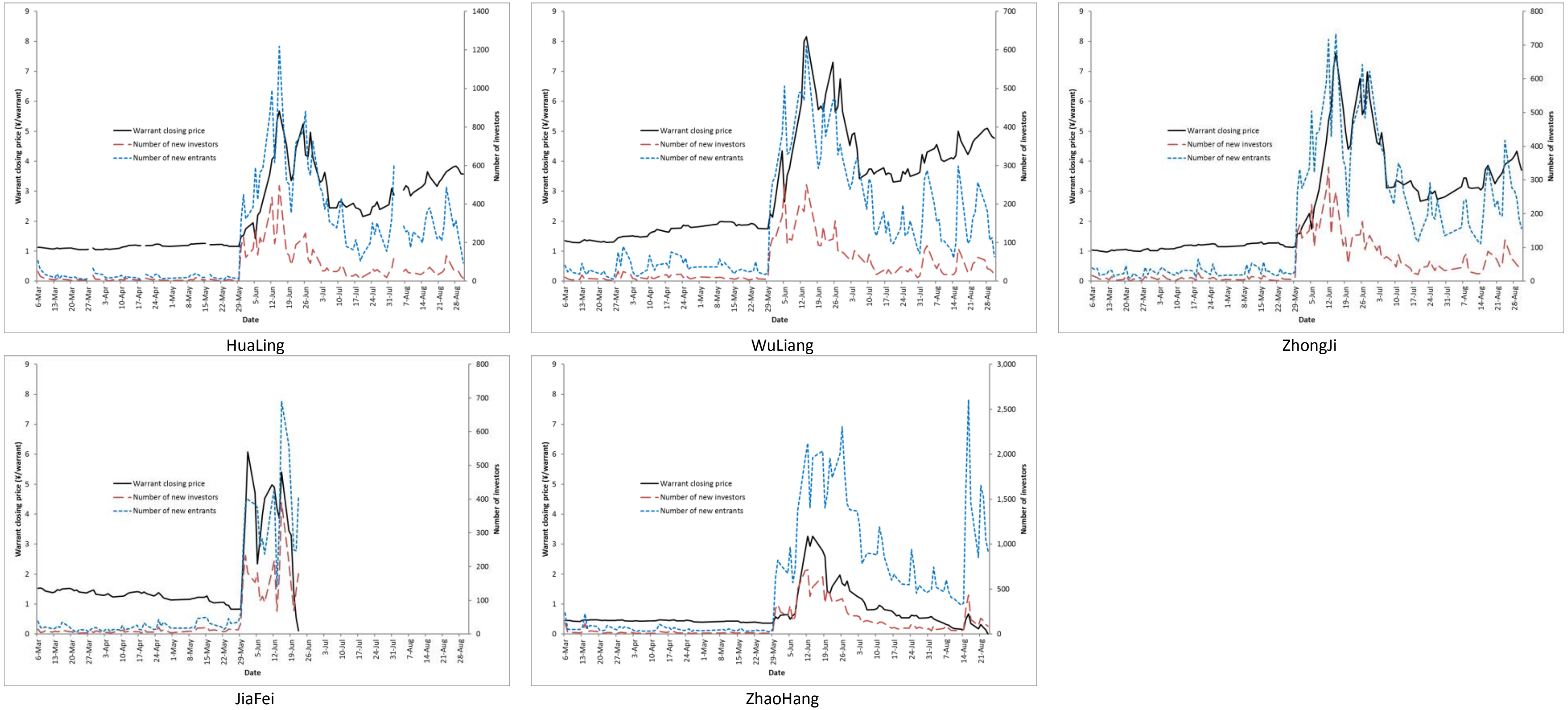
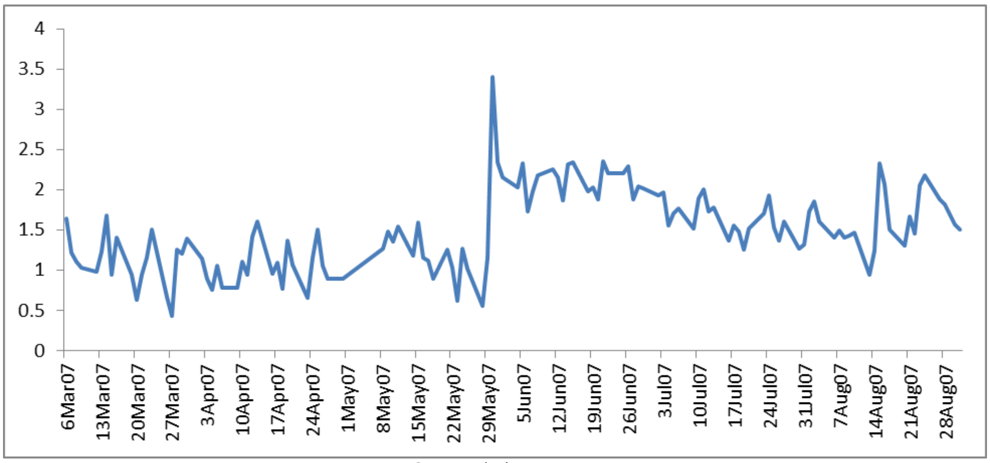
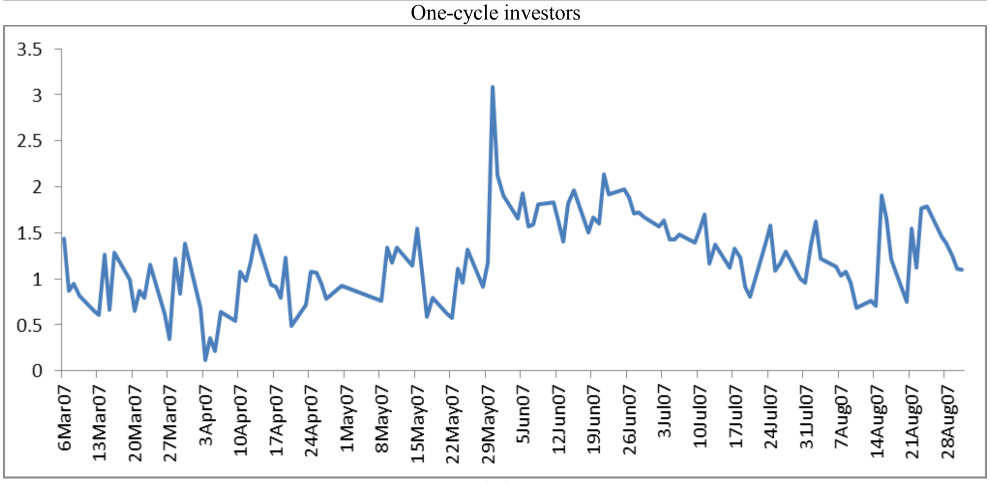


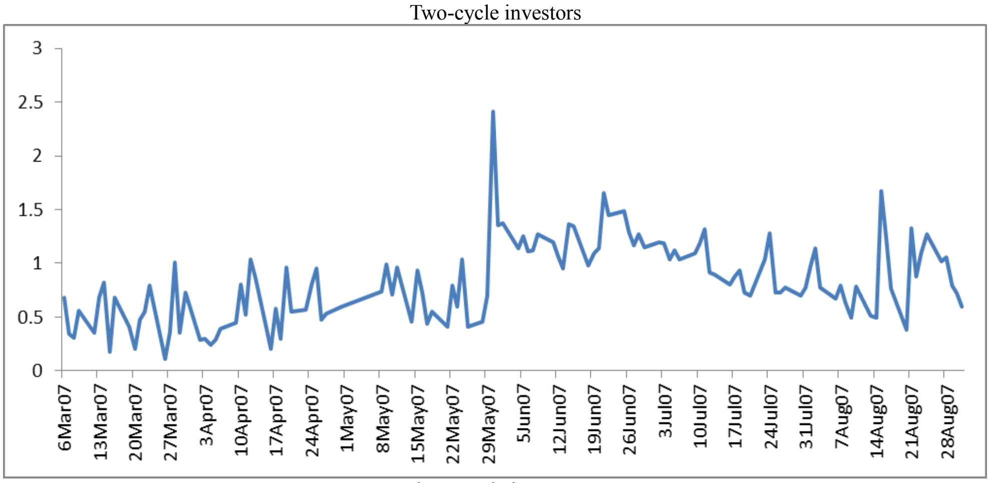
Figure 2. Price and investors entry in 5 put warrants. These figures plot the daily closing price, number of new investors and number of new entrants in 5 put warrants that experience the stamp tax event on 30-May 2007, from 6-Mar 2007 to 31-Aug 2007 (3 months before and after the shock). New investor and new entrant are defined as described in the text. These figures show the exogenous shock on the put warrants.



One-cycle investors



Two-cycle investors



Three-cycle investors

Figure 3. Date fixed effects in positive feedback regressions by investor type. This figure plots the coefficients on date dummies in the positive feedback regressions by investor types with date fixed effects (Panel B in Table III) from 6-Mar 2007 to 31-Aug 2007 (3 months before and after the shock). The figure shows exogenous shock's effect on investor reentries. Three figures correspond to three regressions, and show exogenous shock's effect on one-cycle, two-cycle and three-cycle investors respectively.

Panel A. One-cycle investors

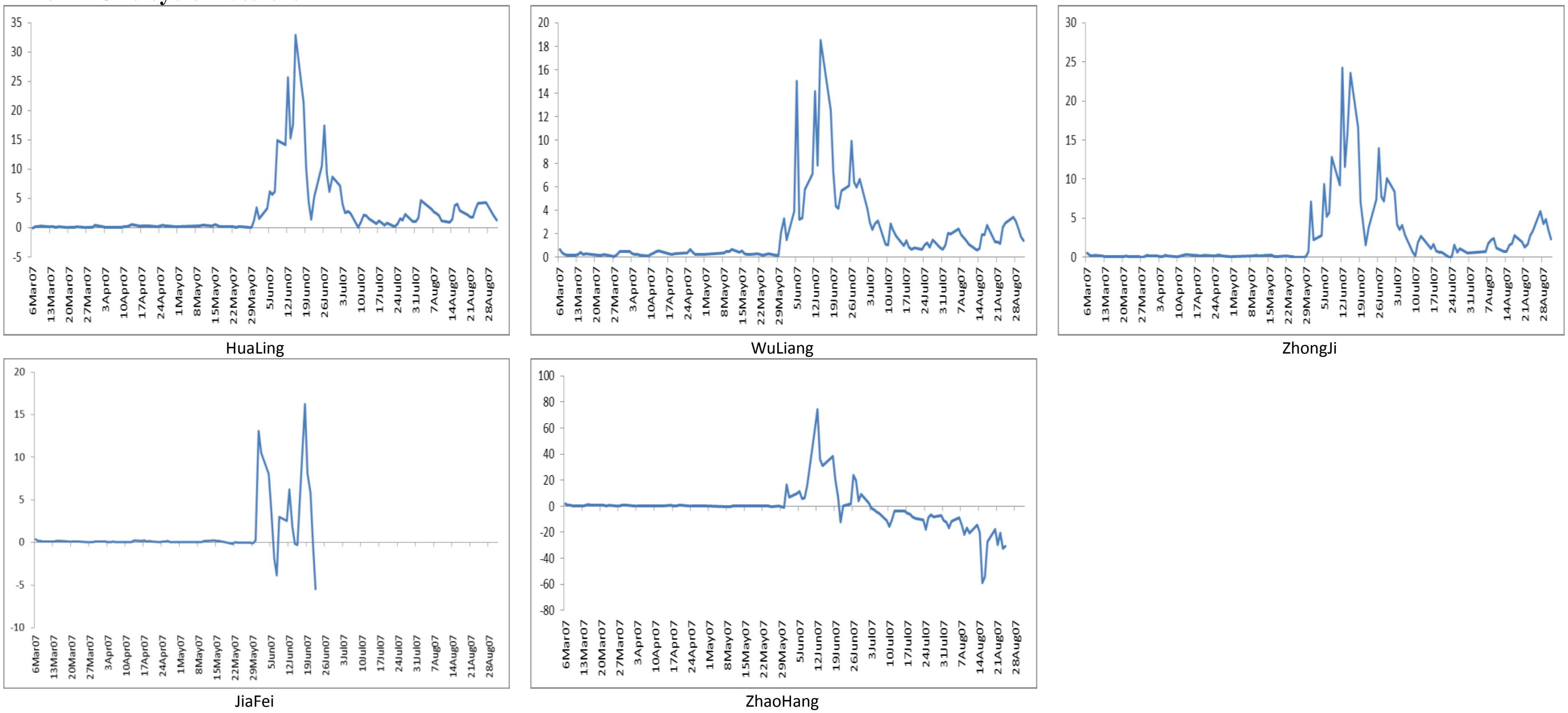
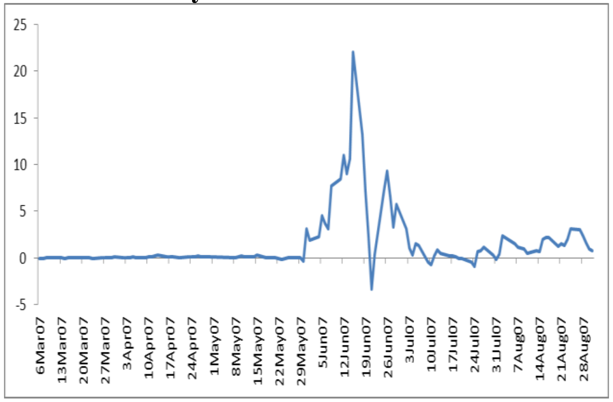
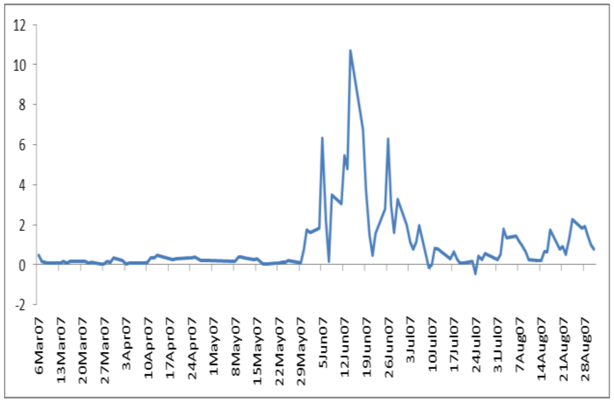


Figure 4. Positive feedback effect accompanied with exogenous shock. This figure plots the reduction of predicted reentry number of existing investors by three investor types when the coefficient on the previous return variables ($Return_{ikn-1,t}$, $Return_{ikn-2,t}$, $Return_{ik\leqslant n-3,t}$, $I(Return_{ikn-1,t}>0)$, $I(Return_{ikn-1,t}>0)$ and $I(Return_{ik\leqslant n-3,t})>0$) are set to be zero in hazard rate model of Panel B in Table 3. Panel A, B and C shows positive feedback effect accompanied with exogenous shock on one-cycle, two-cycle and three-cycle investors respectively.

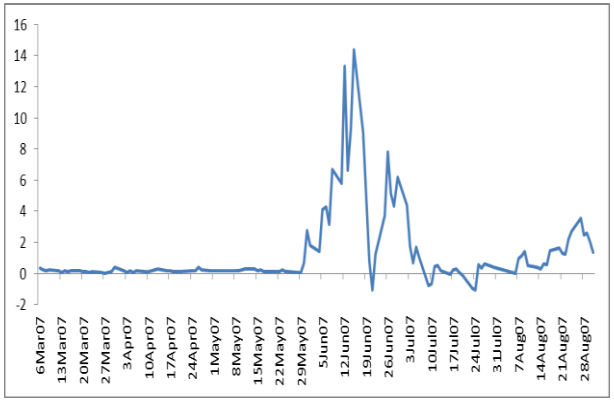
Panel B. Two-cycle investors



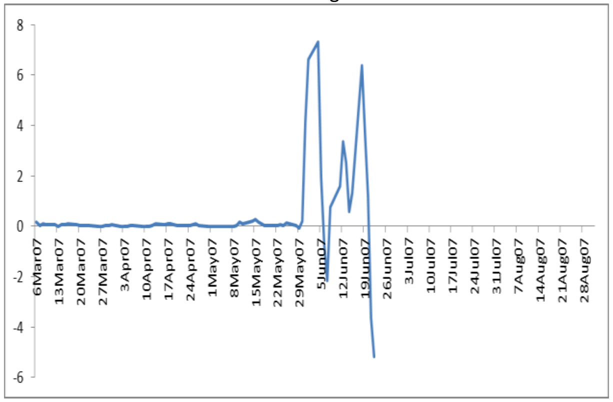
HuaLing



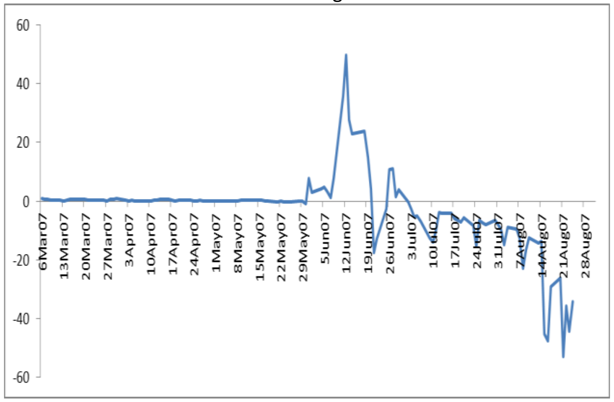
WuLiang



ZhongJi

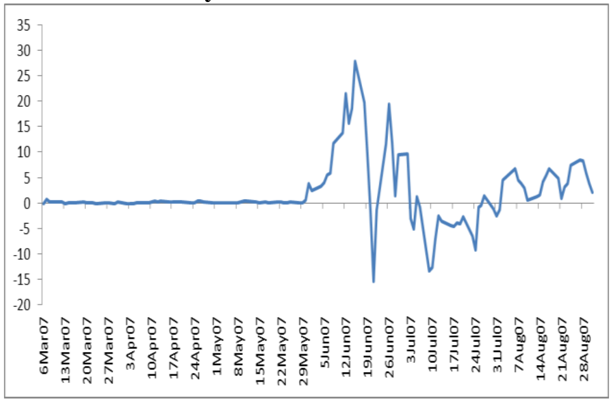


JiaFei

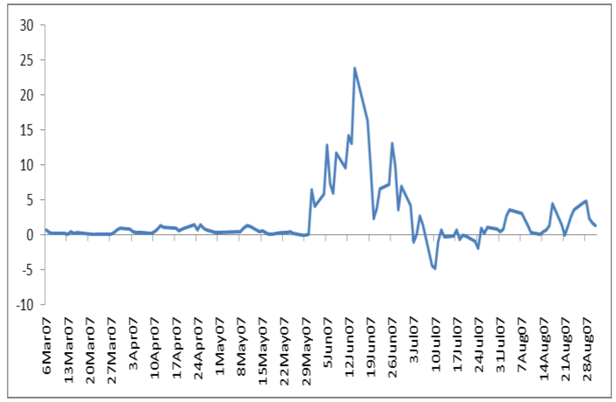


ZhaoHang

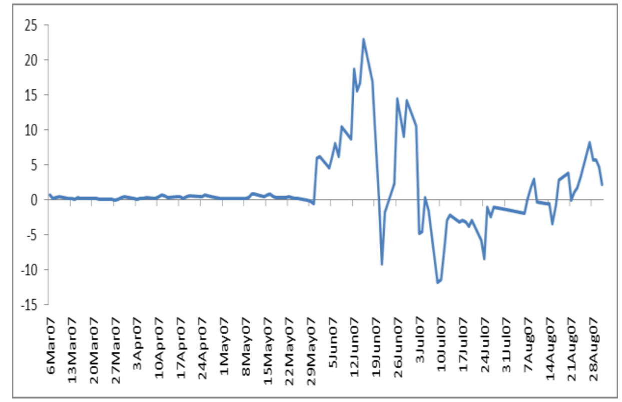
Panel C. Three-cycle investors



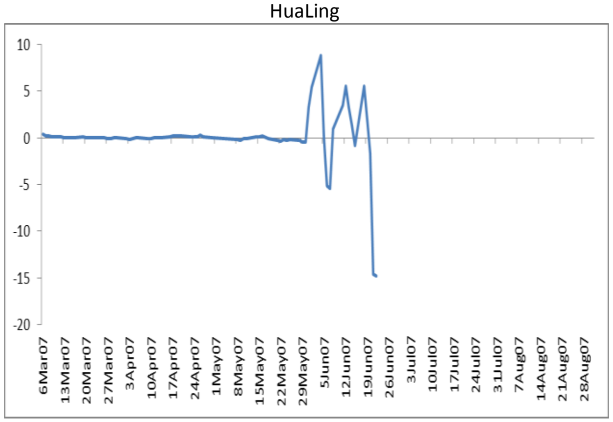
HuaLing



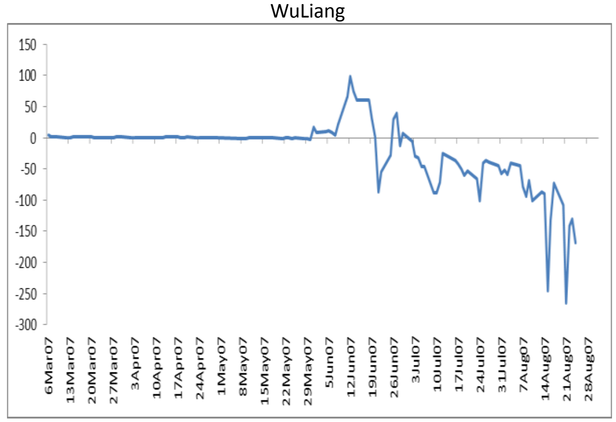
WuLiang



ZhongJi

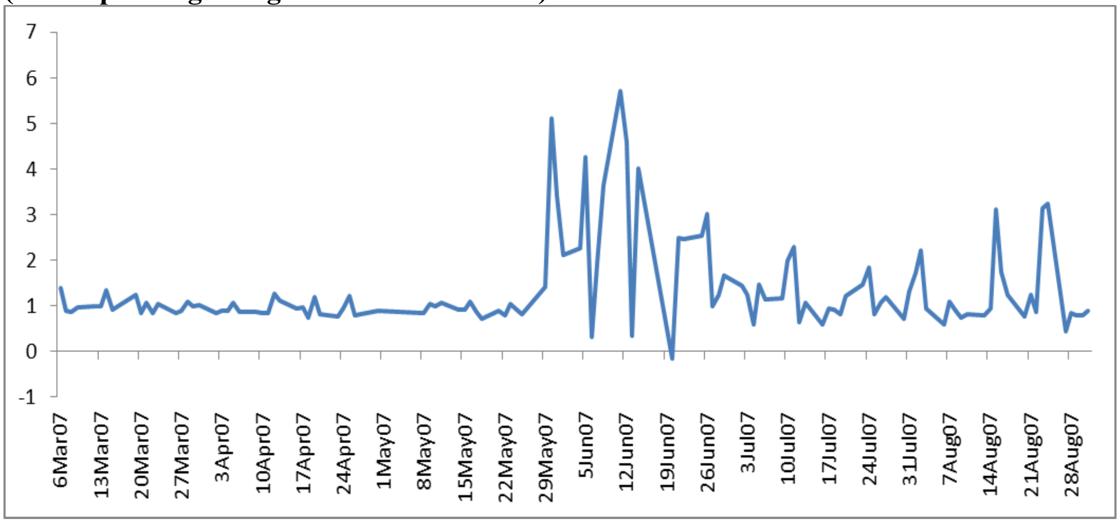


JiaFei



ZhaoHang

Panel A. Date fixed effects in the social contagion regression for one day period (Corresponding to regression 3 in Table IV)



Panel B. Date fixed effects in the social contagion regression for one-half day period (Corresponding to regression 3 in Table V)

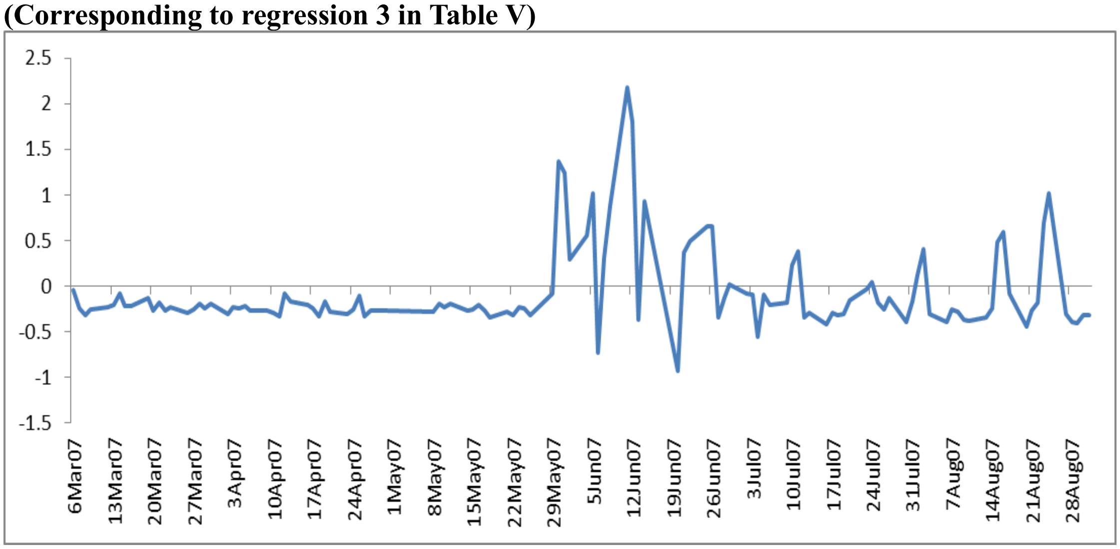


Figure 5. Date fixed effects in the social contagion regressions. This figure plots the coefficients on date dummies in the social contagion regressions from 6-Mar 2007 to 31-Aug 2007 (3 months before and after the shock). Panel A shows the date fixed effects in the regression for a time period of one day (Table IV, regression 3). Panel B shows the date fixed effects in the regression for a time period of one-half day (Table V, panel B, regression 3).

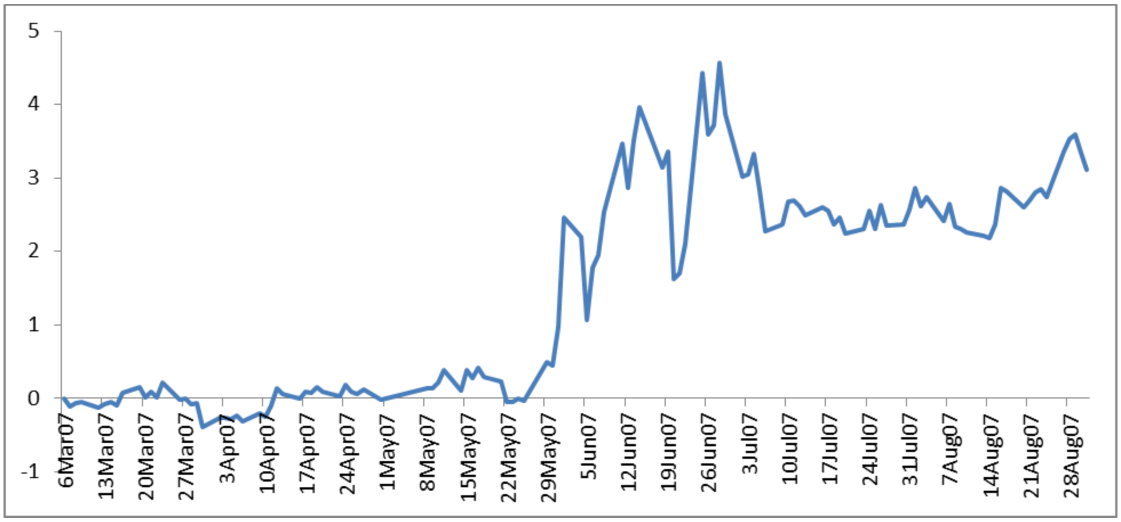


Figure 6. Date fixed effects in the panel regressions of warrant prices with date and maturity fixed effects. This figure plots the coefficients on date dummies in the regression of warrant prices against Turnover, Vol and Float with date and maturity fixed effects (corresponding to regression 10 in Table VI, Panel B) from 6-Mar 2007 to 31-Aug 2007 (3 months before and after the shock).

Table I
Summary Information and Statistics on 18 Put Warrants

This table shows summary information and statistics for each of 18 put warrants. Panel A shows the summary market information (warrant name, trading period, total trading days, the closing price of underlying stock on the first and last trading day, the strike price and exercise ratio at the first and last trading day, and total shares outstanding at the start and the end of warrant trading. Panel B reports, for each warrant, its time-series average/maximum of its daily stock closing price, warrant closing price, daily warrant price, daily turnover rate (in percentage) and daily trading volume (in million yuan). Panel C presents summary statistics on brokerage investor trading for each warrant, including total number of investors, completed and uncompleted transaction cycles ,and the average length of transaction cycle (in calendar days).

Panel A: Summary market information

	Trading period			Warrant information at trading start				Warrant information at trading end			
Name	Begin	End	Trading Days	Shares	Stock price	Strike price	Exercise Ratio	Shares	Stock price	Strike price	Exercise Ratio
WanKe	2005/12/5	2006/8/28	174	2140	3.78	3.73	1	2140	6.79	3.64	1
ShenNeng	2006/4/27	2006/10/19	102	438	6.31	7.12	1	438	7.25	6.69	1
WuGang	2005/11/23	2006/11/15	235	474	2.77	3.13	1	474	3.35	2.83	1
JiChang	2005/12/23	2006/12/15	234	240	6.77	7	1	267	7.94	6.9	1
YuanShui	2006/4/19	2007/2/5	194	280	4.27	5	1	359	6.54	4.9	1
HuChang	2006/3/7	2007/2/27	235	568	11.85	13.6	1	584	25.52	13.36	1
BaoGang	2006/3/31	2007/3/23	233	715	2.1	2.45	1	834	5.7	2.37	1
WanHua	2006/4/27	2007/4/19	236	85	16.42	13	1	189	38.75	9.22	1.41
GangFan	2005/12/5	2007/4/24	331	233	3.3	4.85	1	233	10.72	3.16	1.53
HaiEr	2006/5/22	2007/5/9	231	607	4.74	4.39	1	757	15.79	4.29	1
YaGe	2006/5/22	2007/5/14	237	635	6.8	4.25	1	734	26.44	4.09	1
MaoTai	2006/5/30	2007/5/22	234	432	48.39	30.3	0.25	766	94.84	30.3	0.25
JiaFei	2006/6/30	2007/6/22	232	120	20.3	15.1	1	120	45.21	15.1	1
ZhaoHang	2006/3/2	2007/8/24	359	2241	6.37	5.65	1	5482	39.04	5.45	1
ZhongJi	2006/5/25	2007/11/16	352	424	13.98	10	1	424	24.11	7.3	1.37

HuaLing	2006/3/2	2008/2/22	442	633	3.64	4.9	1	633	12.45	4.72	1
WuLiang	2006/4/3	2008/3/26	468	313	7.11	7.96	1	313	25.92	5.63	1.4
NanHang	2007/6/21	2008/6/13	239	1400	8.99	7.43	0.5	1637	8.48	7.43	0.5

Panel B. Summary statistics on standard market variables

	Stock price		Warrant Price		Daily turnover (percent)		Yuan volume(million)	
Name	Average	Maximum	Average	Maximum	Average	Maximum	Average	Maximum
WanKe	5.58	6.98	0.433	0.893	66	547	504	3832
ShenNeng	7.23	8.32	0.810	1.78	135	616	396	1669
WuGang	2.77	3.63	0.691	1.86	88	1695	371	3455
JiChang	6.65	8	1.176	2.05	104	725	339	1583
YuanShui	5.31	7	0.994	2.084	110	1471	362	2589
HuChang	15.68	29.94	1.164	1.906	84	991	453	2602
BaoGang	2.80	5.7	0.563	0.939	115	1406	485	2969
WanHua	21.39	38.83	1.482	4.202	101	1438	221	1700
GangFan	4.28	10.72	1.229	2.252	79	1316	215	1307
HaiEr	7.41	16.26	0.725	1.611	65	1072	306	2165
YaGe	9.13	28.92	0.685	1.76	79	972	354	4123
MaoTai	69.09	113.2	1.030	3.465	65	815	382	4683
JiaFei	25.51	47.2	1.650	6.07	122	1741	353	7990
ZhaoHang	14.53	39.04	0.515	3.269	106	1198	3179	45683
ZhongJi	21.53	36.18	1.724	7.12	131	1662	1352	17053
HuaLing	7.24	14.3	1.647	5.33	105	1306	1349	14364
WuLiang	26.02	51.04	2.119	8.15	137	1841	1049	12047
NanHang	18.25	28.73	0.994	2.359	139	1261	10041	45419

Panel C. Summary statistics on brokerage investors trading

		Completed cycle		Uncompleted cycle	
Name	Investor number	Number	Average length	Number	Average length
WanKe	6270	21038	6.71	540	52.76
ShenNeng	2727	7860	3.07	101	26.04
WuGang	5259	14959	6.65	695	64.76
JiChang	3966	12162	3.65	448	50.72
YuanShui	3796	11454	3.51	297	73.89
HuChang	4081	12708	3.92	290	66.09
BaoGang	5135	16997	4.08	383	84.94
WanHua	2627	7816	3.94	157	80.39
GangFan	4206	12720	3.94	153	67.03
HaiEr	4612	11338	6.28	331	78.98
YaGe	4668	13016	6.23	357	87.91
MaoTai	5399	14756	8.96	476	87.32
JiaFei	4893	11964	1.70	134	25.88
ZhaoHang	20377	95401	4.30	1168	122.34
ZhongJi	11447	42520	3.12	349	35.25
HuaLing	13543	54199	3.70	402	73.79
WuLiang	11364	44722	3.45	318	82.96
NanHang	24975	150195	7.91	922	85.31

Table II
Summary Statistics on 18 Put Warrants by Periods

The table reports the summary statistics on 18 put warrants by periods. Panel A,B,C show for each warrant of different periods, its time-series average and maximum of daily turnover rate (in percentage), daily bubble size (warrant price minus Black-Scholes value) and intraday 5-minutes warrant return volatility (in percentage).

Panel A. Summary statistics on 12 warrants that expire before 30-May 2007
(For the whole period of the warrants)

	Daily turnover (percent)		Bubble Size		Volatility (percent)	
Name	Average	Maximum	Average	Maximum	Average	Maximum
WanKe	66	547	0.309	0.659	116	2327
ShenNen	135	616	0.424	1.192	140	1447
WuGang	88	1695	0.233	1.235	104	2287
JiChang	104	725	0.489	1.146	91	441
YuanShu	110	1471	0.604	1.658	111	1426
HuChang	84	991	-0.113	1.158	92	1249
BaoGang	115	1406	0.107	0.627	99	1018
WanHua	101	1438	1.108	3.952	109	1717
GangFan	79	1316	0.261	1.439	86	1456
HaiEr	65	1072	0.606	1.327	90	1569
YaGe	79	972	0.498	1.492	91	1375
MaoTai	65	815	0.351	1.943	90	1617

Panel B. Summary statistics on 5 warrants that expire after 30-May 2007
(For the period before 30-May 2007)

	Daily turnover (percent)		Bubble Size		Volatility (percent)	
Name	Average	Maximum	Average	Maximum	Average	Maximum
JiaFei	74	415	1.188	2.344	68	359
ZhaoHan	44	279	0.207	0.510	64	703
ZhongJi	40	243	0.748	1.997	65	245
HuaLing	34	143	0.129	1.255	49	387
WuLiang	62	302	0.978	2.525	84	368

Panel C. Summary statistics on 6 warrants that expire after 30-May 2007
(For the period after 30-May 2007)

	Daily turnover (percent)		Bubble Size		Volatility (percent)	
Name	Average	Maximum	Average	Maximum	Average	Maximum
JiaFei	814	1741	3.410	6.070	729	1623
ZhaoHan	404	1198	0.948	3.269	331	1716
ZhongJi	331	1662	3.075	7.120	213	1166
HuaLing	221	1306	2.345	5.316	148	1261
WuLiang	238	1841	3.099	8.149	141	1467
NanHang	139	1261	0.948	2.184	131	1963

Table III

Positive Feedback Regressions by Investor Type

This table presents proportional hazard regressions of indicator variable for reentries of existing investor against the investor's previous transaction cycle returns by three investor types. The investor type is defined according the numbers of investors' previous transaction cycles. The left-side variable in hazard rate model is the event variable for reentry. The event' variable takes a value of 1 if the investor in warrant k starts a new transaction cycle in warrant k on date t, otherwise takes a value of 0. The explanatory variables include previous return variables and standard market variables. $Return\_lag1_{i,k,t}$ and $Return\_lag2_{i,k,t}$ are the returns of lag 1 and 2 transaction cycles of investor i in warrant k before date t respectively. $Return_lag3_more_{i,k,t}$is the average return of the lag three and earlier transaction cycles of investor i in warrant k before date t. $Maturity_{k,t}$ is the number of calendar days left in warrant k on date t before the end of trading. $WarrantReturn_{k,t}$ is the daily return of warrant k on date t, and $TurnoverRatio_{k,t}$ is the market trading volume in warrant k on date t, divided by number of warrants outstanding on date t. $AdjustedFundamental_{k,t}$ is the adjusted fundamental value of warrant k on date t, and is computed as described in the text. Panel A and B show regressions including different fixed effects.

Tables will be updated soon.

Table IV
Social contagion Regressions for One-Day Interval

This table reports the panel regressions for testing social contagion effect on the entry of new investors using one-day interval. The dependent variable is the number of branch j investors who trade warrant k for the first time on date t, denoted as $BranchNewInvestors_{jk,t}$. A branch j investor who trades warrant k on day t is considered to be a new investor in warrant k on date t if date t is the first date on which the investor trades warrant k. Explanatory variable $BranchAverageReturn_{jk,t}$ is the average date t return on the positions in warrant k of branch j investors who either held or purchased warrant k on date t. $BranchInvestors_{jk,t}$ is the number of branch j investors who either held or purchased warrant k on date t, $BrokerageInvestors_{k,t}$ is the number of brokerage firm investors who either hold or buy warrant k on date t, $WarrantReturn_{k,t}$ is the (close-to-close) return of warrant k on date t, and $TurnoverRatio_{k,t}$ is the market trading volume in warrant k on date t, divided by number of warrants outstanding. Regression (1) to (3) use the whole sample, and 4) to 6), as a robust check, use a subsample that excludes observations for which the branch office is either located in the same city as the headquarters of the company whose stock provides the underlying asset of the warrants or located in the city (either Shanghai or Shenzhen) where the underlying stock is listed. All the regressions include warrant, date and maturity fixed effects, and the t-statistics (in the parentheses) are based on standard errors computed by clustering by branch and warrant (the cross-section).

Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
$BranchNewInvestors_{jkt-1}$	0.538	0.419	0.438	0.540	0.422	0.442
	(8.01)	(9.01)	(5.84)	(7.89)	(8.93)	(5.81)
$BranchNewInvestors_{jkt-2}$		0.248	0.183		0.248	0.182
		(13.98)	(14.30)		(13.89)	(13.77)
$BranchNewInvestors_{jkt-3}$			0.118			0.118
			(5.13)			(5.04)
$BranchAverageReturn_{jkt-1}$	-2.804	-1.909	-2.027	-2.877	-1.925	-2.037
	(-5.22)	(-4.48)	(-4.94)	(-5.05)	(-4.15)	(-4.56)
$BranchAverageReturn_{jkt-2}$		-0.0464	-0.251		0.0164	-0.191
		(-0.14)	(-0.75)		(0.05)	(-0.53)
$BranchAverageReturn_{jkt-3}$			0.426			0.430
			(1.85)			(1.78)
$Max(BranchAverageReturn_{jkt-1},0)$	2.737	1.473	1.481	2.812	1.525	1.542
	(4.71)	(2.27)	(2.22)	(4.59)	(2.17)	(2.13)
$Max(BranchAverageReturn_{jkt-2},0)$		0.0895	-0.0805		0.0251	-0.213
		(0.27)	(-0.26)		(0.07)	(-0.67)
$Max(BranchAverageReturn_{jkt-3},0)$			-0.371			-0.374
			(-1.59)			(-1.52)
$BranchInvestors_{jkt-1}$	-0.00143	-0.00204	0.00318	-0.00158	-0.00310	0.00204
	(-0.30)	(-0.45)	(0.40)	(-0.33)	(-0.64)	(0.25)
$BranchInvestors_{jkt-2}$		0.00438	-0.0187		0.00543	-0.0181
		(0.88)	(-3.49)		(1.03)	(-3.32)

$BranchInvestors_{jkt-3}$			0.0159			0.0164
			(2.17)			(2.14)
$BranchAverageReturn_{jkt-1}$	-0.0405	-0.0289	-0.0225	-0.0407	-0.0288	-0.0223
$\times BranchInvestors_{jkt-1}$	(-8.57)	(-8.08)	(-5.14)	(-8.42)	(-8.08)	(-4.91)
$BranchAverageReturn_{jkt-2}$		0.0306	0.0282		0.0312	0.0285
$\times BranchInvestors_{jkt-2}$		(3.01)	(3.52)		(3.06)	(3.53)
$BranchAverageReturn_{jkt-3}$			0.0106			0.0109
$\times BranchInvestors_{jkt-3}$			(1.64)			(1.66)
$Max(BranchAverageReturn_{jkt-1},0)$	0.118	0.108	0.0977	0.118	0.108	0.0971
$\times BranchInvestors_{jkt-1}$	(6.73)	(5.90)	(5.77)	(6.67)	(5.85)	(5.72)
$Max(BranchAverageReturn_{jkt-2},0)$		-0.0497	-0.0415		-0.0506	-0.0422
$\times BranchInvestors_{jkt-2}$		(-3.33)	(-3.34)		(-3.39)	(-3.43)
$Max(BranchAverageReturn_{jkt-3},0)$			-0.0167			-0.0168
$\times BranchInvestors_{jkt-3}$			(-3.24)			(-3.20)
$BrokerageNewInvestors_{kt-1}$	-0.00211	0.000406	0.00205	-0.00227	0.000494	0.00248
	(-1.80)	(0.47)	(2.36)	(-1.82)	(0.54)	(2.75)
$BrokerageNewInvestors_{kt-2}$		-0.00119	-0.00169		-0.00138	-0.00196
		(-3.05)	(-3.13)		(-3.40)	(-3.40)
$BrokerageNewInvestors_{kt-3}$			-0.00150			-0.00171
			(-3.77)			(-4.06)
$WarrantReturn_{kt-1}$	1.757	1.143	1.108	1.835	1.148	1.109
	(4.67)	(3.64)	(3.88)	(4.66)	(3.39)	(3.58)
$WarrantReturn_{kt-2}$		-0.926	-0.815		-0.959	-0.837
		(-5.50)	(-3.43)		(-5.32)	(-3.21)
$WarrantReturn_{kt-3}$			-0.194			-0.186
			(-1.57)			(-1.45)
$TurnoverRatio_{kt-1}$	-0.000965	-0.0000937	-0.000322	-0.000963	-0.0000589	-0.000340
	(-6.44)	(-0.57)	(-1.44)	(-6.16)	(-0.34)	(-1.40)
$TurnoverRatio_{kt-2}$		-0.000270	0.000286		-0.000253	0.000307
		(-1.80)	(1.45)		(-1.58)	(1.44)
$TurnoverRatio_{kt-3}$			-0.000372			-0.000352
			(-3.05)			(-2.73)
Constant	13.22	-4.488	-0.266	14.05	-4.920	-0.446
	(4.60)	(-3.02)	(-0.18)	(4.71)	(-3.21)	(-0.29)
Maturity Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Warrant Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observation	179384	174396	169988	171050	166397	162247
R-square	0.473	0.581	0.58	0.474	0.582	0.58

Table V
Social contagion Regressions for One-half Day Interval

This table reports the panel regressions for testing social contagion effect on the entry of new investors. The dependent variable is the number of branch j investors who trade warrant k for the first time during each half-day period t, denoted $BranchNewInvestors_{jk,t}$. Each half-day period, indexed by t, consists of either the morning or afternoon session. A branch j investor who trades warrant k during period t is considered to be a new investor in warrant k during period t if period t is the first half-day period on which the investor trades warrant k. The explanatory variable $BranchAverageReturn_{jk,t}$ is the average period t return on the positions in warrant k to branch j investors who either held or purchased warrant k during period t. $BranchInvestors_{jk,t}$ is the number of branch j investors who either held or purchased warrant k during period t, $BrokerageInvestors_{k,t}$ is the number of brokerage firm investors who either held or purchased warrant k during period t, and $TurnoverRatio_{k,t}$ is the market trading volume in warrant k on date t, divided by number of warrants outstanding. The $WarrantReturn_{k,t}$ is the return of warrant k during period t, where the return during the morning session is the return from the previous day's closing price to the end of the morning session and the return during the afternoon session is the return from the last price of the morning session to the day's closing price. Regression (1) to (3) use the whole sample, and 4) to 6), as a robust check, use a subsample that excludes observations for which the branch office is either located in the same city as the headquarters of the company whose stock provides the underlying asset of the warrants or located in the city (either Shanghai or Shenzhen) where the underlying stock is listed. All the regressions include warrant, date and maturity fixed effects, and the t-statistics (in the parentheses) are based on standard errors computed by clustering by branch and warrant (the cross-section).

Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
$BranchNewInvestors_{jkt-1}$	0.355	0.270	0.256	0.357	0.272	0.258
	(9.18)	(8.30)	(6.59)	(9.14)	(8.23)	(6.53)
$BranchNewInvestors_{jkt-2}$	0.249	0.185	0.206	0.250	0.186	0.209
	(8.09)	(12.13)	(6.09)	(7.98)	(12.06)	(6.12)
$BranchNewInvestors_{jkt-3}$		0.129	0.0939		0.129	0.0925
		(16.13)	(7.71)		(16.39)	(7.50)
$BranchNewInvestors_{jkt-4}$		0.137	0.112		0.138	0.113
		(11.94)	(10.44)		(11.90)	(10.29)
$BranchNewInvestors_{jkt-5}$			0.0395			0.0392
			(1.83)			(1.78)
$BranchNewInvestors_{jkt-6}$			0.0787			0.0780
			(7.82)			(7.65)
$BranchAverageReturn_{jkt-1}$	-0.321	-0.475	-0.568	-0.287	-0.442	-0.528
	(-2.07)	(-3.39)	(-3.56)	(-1.82)	(-2.97)	(-3.14)
$BranchAverageReturn_{jkt-2}$	-1.111	-0.788	-1.022	-1.123	-0.782	-1.030
	(-4.25)	(-4.68)	(-5.26)	(-4.15)	(-4.44)	(-5.05)
$BranchAverageReturn_{jkt-3}$		0.464	0.275		0.425	0.225
		(2.23)	(1.85)		(2.01)	(1.47)
$BranchAverageReturn_{jkt-4}$		-0.799	-0.864		-0.811	-0.874

		(-3.04)	(-3.81)		(-2.95)	(-3.65)
$BranchAverageReturn_{jkt-5}$			0.599			0.632
			(3.73)			(3.77)
$BranchAverageReturn_{jkt-6}$			0.540			0.582
			(3.91)			(4.02)
$Max(BranchAverageReturn_{jkt-1},0)$	0.301	0.220	0.292	0.306	0.233	0.303
	(0.82)	(0.81)	(1.03)	(0.81)	(0.80)	(1.00)
$Max(BranchAverageReturn_{jkt-2},0)$	1.418	0.102	0.321	1.465	0.0979	0.334
	(2.09)	(0.25)	(0.72)	(2.06)	(0.23)	(0.72)
$Max(BranchAverageReturn_{jkt-3},0)$		-0.396	-0.356		-0.362	-0.315
		(-2.58)	(-2.06)		(-2.27)	(-1.70)
$Max(BranchAverageReturn_{jkt-4},0)$		0.777	0.657		0.772	0.651
		(3.54)	(4.01)		(3.40)	(3.82)
$Max(BranchAverageReturn_{jkt-5},0)$			-0.468			-0.492
			(-2.53)			(-2.60)
$Max(BranchAverageReturn_{jkt-6},0)$			-0.441			-0.467
			(-3.15)			(-3.20)
$BranchInvestors_{jkt-1}$	-0.0109	0.00157	0.00325	-0.0111	0.00135	0.00304
	(-1.81)	(0.22)	(0.77)	(-1.78)	(0.19)	(0.70)
$BranchInvestors_{jkt-2}$	0.00942	-0.000184	-0.00725	0.00950	-0.000459	-0.00771
	(2.07)	(-0.03)	(-0.94)	(2.02)	(-0.06)	(-0.98)
$BranchInvestors_{jkt-3}$		-0.0214	-0.0128		-0.0212	-0.0124
		(-6.29)	(-3.05)		(-6.02)	(-2.88)
$BranchInvestors_{jkt-4}$		0.0204	0.0100		0.0206	0.0100
		(5.37)	(2.00)		(5.30)	(1.94)
$BranchInvestors_{jkt-5}$			-0.00896			-0.00907
			(-3.06)			(-2.97)
$BranchInvestors_{jkt-6}$			0.0157			0.0160
			(4.47)			(4.48)
$BranchAverageReturn_{jkt-1}$	-0.0146	-0.00840	-0.00739	-0.0143	-0.00792	-0.00717
$\times BranchInvestors_{jkt-1}$	(-5.29)	(-2.00)	(-1.32)	(-5.20)	(-1.82)	(-1.25)
$BranchAverageReturn_{jkt-2}$	-0.0214	-0.0150	-0.0165	-0.0216	-0.0153	-0.0167
$\times BranchInvestors_{jkt-2}$	(-3.04)	(-3.36)	(-4.96)	(-3.01)	(-3.34)	(-4.89)
$BranchAverageReturn_{jkt-3}$		0.00154	0.00682		0.00182	0.00701
$\times BranchInvestors_{jkt-3}$		(0.18)	(1.73)		(0.21)	(1.77)
$BranchAverageReturn_{jkt-4}$		0.0238	0.0180		0.0241	0.0181
$\times BranchInvestors_{jkt-4}$		(3.36)	(4.54)		(3.35)	(4.45)
$BranchAverageReturn_{jkt-5}$			0.0136			0.0136
$\times BranchInvestors_{jkt-5}$			(1.83)			(1.81)
$BranchAverageReturn_{jkt-6}$			0.00600			0.00603
$\times BranchInvestors_{jkt-6}$			(2.81)			(2.79)

Max(BranchAverageReturn$_{jkt-1}$,0)	0.0549	0.0504	0.0508	0.0539	0.0492	0.0499
×BranchInvestors$_{jkt-1}$	(3.97)	(6.17)	(6.58)	(3.97)	(6.41)	(6.67)
Max(BranchAverageReturn$_{jkt-2}$,0)	0.0667	0.0677	0.0693	0.0673	0.0683	0.0696
×BranchInvestors$_{jkt-2}$	(2.74)	(2.83)	(2.97)	(2.71)	(2.79)	(2.93)
Max(BranchAverageReturn$_{jkt-3}$,0)		-0.0193	-0.0236		-0.0199	-0.0242
×BranchInvestors$_{jkt-3}$		(-4.05)	(-3.97)		(-4.27)	(-4.08)
Max(BranchAverageReturn$_{jkt-4}$,0)		-0.0309	-0.0176		-0.0313	-0.0179
×BranchInvestors$_{jkt-4}$		(-5.25)	(-3.91)		(-5.33)	(-3.98)
Max(BranchAverageReturn$_{jkt-5}$,0)			-0.0261			-0.0260
×BranchInvestors$_{jkt-5}$			(-2.29)			(-2.24)
Max(BranchAverageReturn$_{jkt-6}$,0)			-0.0147			-0.0148
×BranchInvestors$_{jkt-6}$			(-7.33)			(-7.39)
BrokerageNewInvestors$_{kt-1}$	-0.00602	-0.00490	-0.00389	-0.00628	-0.00503	-0.00393
	(-5.05)	(-5.64)	(-4.39)	(-5.03)	(-5.55)	(-4.25)
BrokerageNewInvestors$_{kt-2}$	0.000199	0.00131	0.000774	0.000210	0.00142	0.000830
	(0.37)	(3.88)	(1.77)	(0.37)	(4.01)	(1.83)
BrokerageNewInvestors$_{kt-3}$		0.000172	-0.000318		0.0000601	-0.000369
		(0.52)	(-1.01)		(0.17)	(-1.10)
BrokerageNewInvestors$_{kt-4}$		0.00129	0.00244		0.00131	0.00259
		(4.82)	(7.35)		(4.64)	(7.37)
BrokerageNewInvestors$_{kt-5}$			-0.00205			-0.00221
			(-6.25)			(-6.56)
BrokerageNewInvestors$_{kt-6}$			0.000702			0.000644
			(2.57)			(2.23)
WarrantReturn$_{kt-1}$	0.240	0.308	0.327	0.215	0.270	0.287
	(1.82)	(2.37)	(2.18)	(1.55)	(1.95)	(1.77)
WarrantReturn$_{kt-2}$	0.448	0.505	0.517	0.436	0.483	0.499
	(3.14)	(4.20)	(4.26)	(2.84)	(3.84)	(3.92)
WarrantReturn$_{kt-3}$		-0.281	-0.189		-0.246	-0.149
		(-2.90)	(-1.64)		(-2.49)	(-1.23)
WarrantReturn$_{kt-4}$		0.177	0.317		0.200	0.325
		(1.35)	(2.02)		(1.46)	(1.98)
WarrantReturn$_{kt-5}$			-0.560			-0.595
			(-5.19)			(-5.28)
WarrantReturn$_{kt-6}$			-0.365			-0.388
			(-3.85)			(-3.96)
TurnoverRatio$_{kt-1}$	0.0000956	0.000695	0.000619	0.0000993	0.000702	0.000616
	(1.44)	(9.77)	(7.98)	(1.43)	(9.50)	(7.61)
TurnoverRatio$_{kt-3}$		-0.000800	-0.000711		-0.000802	-0.000728
		(-12.24)	(-8.88)		(-11.96)	(-8.76)
TurnoverRatio$_{kt-5}$			0.000134			0.000165

			(1.72)			(2.01)
Constant	1.406	-0.646	0.371	1.451	-0.727	0.338
	(1.36)	(-1.00)	(0.62)	(1.37)	(-1.09)	(0.54)
Maturity Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Warrant Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observation	353848	344448	336298	337680	328815	321077
R-square	0.409	0.491	0.488	0.410	0.493	0.489

Table VI
Panel regressions of the warrant prices

This table includes the regression results of daily warrant closing price on Turnover (daily warrant turnover), Vol (daily 5-minutes warrant return volatility), and Float (daily total number of shares outstanding, in billions). The regressions use zero-fundamental sample which is defined as in Xiong and Yu (2011). The warrant k on date t is considered to have zero fundamental value if its Black-Sholes value is less than 0.0005 (or for cash settled NanHang if the settlement price will for sure exceed the strike). The zero-fundamental sample contains 863 observations with 42 missing value of Vol. Each panel show regressions including different fixed effects. The t-statistics (in the parenthese) are adjusted for heteroscedasticity and correlation within a trading day.

Panel A: Maturity fixed effects only

Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Turnover	0.212			0.146	0.225	
	(8.31)			(4.91)	(8.43)	
VOL		21.93		15.06		26.93
		(5.19)		(2.78)		(5.66)
Float			-0.301	-0.281	-0.316	-0.291
			(-11.38)	(-10.17)	(-11.40)	(-10.95)
Constant	-2.513	-3.185	0.323	-3.671	-2.385	-3.648
	(-6.40)	(-4.59)	(3.26)	(-4.71)	(-5.35)	(-4.72)
Maturity Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effect	No	No	No	No	No	No
Observation	863	821	863	821	863	821
Adj R-Square	0.181	0.177	0.209	0.322	0.301	0.295

Panel B: Date and maturity fixed effects

Explanatory Variable	(7)	(8)	(9)	(10)	(11)	(12)
Turnover	-0.0168			-0.0928	-0.0336	
	(-0.23)			(-1.96)	(-0.91)	
VOL		-8.452		14.71		6.957
		(-0.58)		(1.65)		(0.93)
Float			-0.512	-0.513	-0.513	-0.505
			(-24.78)	(-21.71)	(-24.95)	(-21.60)
Constant	-0.731	0.347	0.0879	-1.082	0.457	-0.961
	(-0.75)	(0.16)	(0.22)	(-0.90)	(0.89)	(-0.81)
Maturity Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observation	863	821	863	821	863	821
Adj R-Square	0.531	0.462	0.891	0.885	0.891	0.880