The Chinese Warrants Bubble: Evidence from Brokerage Account Records*

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Abstract

We use brokerage account records to study trading during the Chinese put warrants bubble and find evidence consistent with extrapolative theories of speculative asset price bubbles. We identify the event that started the bubble and show that investors engaged in a form of feedback trading based on their own past returns. The interaction of feedback trading with the precipitating event caused additional buying and price increases in a feedback loop, and estimates of the trading volume due to this mechanism explain prices and returns during the bubble.

JEL codes: G12, G13, G14, O16, P34

Key words: Speculative bubble, feedback trading, extrapolation, resale option

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We use brokerage account records to study trading during the Chinese put warrants bubble and find evidence consistent with extrapolative theories of speculative asset price bubbles. We identify the event that started the bubble and show that investors engaged in a form of feedback trading based on their own past returns. The interaction of feedback trading with the precipitating event caused additional buying and price increases in a feedback loop, and estimates of the trading volume due to this mechanism explain prices and returns during the bubble.

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1. Introduction

We use brokerage account records of Chinese investors who traded during the Chinese put warrants bubble documented in Xiong and Yu (2011) to study the investors' trading and explore the extent to which it is consistent with leading theories of speculative asset price bubbles. The brokerage account records allow us to identify the precipitating event that caused the initial large put warrant returns that started the bubble. We find that investors engaged in a form of positive feedback trading in which their trading is explained by past returns, consistent with extrapolative theories of speculative asset price bubbles such as Barberis et al (2018). The combination of the precipitating event that caused an initial increase in prices and the feedback trading based on past returns led to additional buying and additional price increases in a feedback loop. Finally, we use the panel regression approach in Xiong and Yu (2011) to show that estimates of the trading volume due to feedback trading explain the size of the bubble. Once we include the estimates of trading volume due to feedback trading in the panel regressions the volatility and turnover variables suggested by the Scheinkman and Xiong (2003) resale option theory are no longer significantly positively related to warrant prices.

The precipitating event was a tripling of the transaction tax imposed on stock trades that was announced at midnight on May 30, 2007 and took effect immediately at the opening of trading on May 30. This tax change was a regulatory reaction to the apparent overvaluation of Chinese stocks, and led to immediate one-day declines of 6.15% and 5.78% in the Shanghai and Shenzhen stock indexes. The decrease in stock prices likely attracted attention to the put warrants because their payoffs are decreasing in stock prices and there was no other financial instrument that allowed investors to obtain such exposure due to the restrictions on short-sales. The stock price declines also increased the Black-Scholes model values of the put warrants, though this effect was small because the put warrants were still far out-of-the-money and thus had very low Black-Scholes values even after the decline in stock prices. The increase in the transaction tax on stock trades also increased the relative desirability of the warrants for short-term trading because warrants were exempt from the tax. Market data show a more than 12-fold increase in warrant turnover and a cross-sectional average one-day warrant return of 57.6% on May 30, followed by further large positive returns over the next 15 days.

We use hazard rate regressions to show that the probability that an investor who has previously traded a put warrant re-enters the market and buys again is positively related to his or her own previous put warrant returns. The evidence of feedback trading based on investors' own past returns is very strong and this trading occurs throughout the warrants' lives. The combination of the positive coefficients on investors' past returns and the large price increases on May 30 caused additional buying, which in turn caused further positive returns, causing yet more buying and then yet higher prices, in a feedback loop similar to the mechanisms in extrapolative theories of asset price bubbles.

We provide evidence that this feedback trading explains the bubble by reexamining the Xiong and Yu (2011) panel regressions showing that put warrant prices are related to volatility and turnover, consistent with the resale option theory of Scheinkman and Xiong (2003). Xiong and Yu (2011) consider a "zero fundamental period" in which the fundamental values of the put warrants were close to zero in order to ensure that their results are not confounded by variation in the warrants' fundamental values. Using data from the zero fundamental period they regress warrant prices on turnover and estimates of the warrants' return volatilities and obtain significantly positive coefficients on turnover and volatility they interpret as supportive of the resale option theory. We use the hazard rate regressions to develop estimates of the trading volumes due to feedback trading during each day of the Xiong and Yu (2011) zero fundamental period. We then include these estimates and a dummy variable for the period after the May 30 tax change as additional covariates in the panel regressions and find that the estimates of buying due to feedback trading explain put warrant prices. Once we include the additional covariates turnover and volatility are no longer significantly positively related to put warrant prices. We also use similar panel regressions to show that the first differences of our estimates of feedback trading volume explain returns during the bubble. These results are inconsistent with the hypothesis that the Scheinkman and Xiong (2003) resale option theory explains the Chinese put warrants bubble.

Finally, we also identify other shocks related to the onset of the financial crisis during 2007 that appear to have contributed to the bubble's extended life.

The finding that investors' own past put warrant returns explain their probabilities of re-entering the put warrant market and buying again is unsurprising in light of the developing experiential literature showing that investors' own experiences are important for a range of financial decisions (Kaustia and Knüpfer 2008, Chiang, Hirshleifer, Qian, and Sherman 2011, Malmendier, Tate, and Yan 2011, Malmendier and Nagel 2011, 2015). This result is also consistent with the finding in Strahilevitz, Odean, and Barber (2011) that an investor's probability of repurchasing a stock he or she previously held depends on whether the previous transaction resulted in a gain or a loss. In the context of asset price bubbles, the idea that extrapolation or feedback from investors' own past returns contributes to bubbles dates at least to Bagehot (1873, p. 60). The existence of a positive correlation between trading volume and some measure of past returns is also a central feature of recent extrapolative models such as Barberis et al (2018) and Liao and Peng (2019).[1]

If feedback trading based on investors' own returns on completed transaction cycles is important it must be that investors repeatedly close out warrant trades and then later reenter the market by buying again, and we observe such trading. The model described by Liao and Peng (2019) generates this in-and-out behaviour by combining extrapolative beliefs with Barberis and Xiong (2012) realization utility, i.e. a preference for realizing gains rather than losses. Realization utility causes investors who hold securities with positive returns to sell while extrapolative beliefs cause investors to buy, generating in-and-out trading behavior and high trading volumes. This trading can also be consistent with the wavering mechanism in Barberis et al (2018) if the changes in beliefs about security values due to wavering are large and short sales are constrained. In this case investors who place high weight on the value signal during a bubble will expect declines in security prices and exit the market, and then later reenter when wavering causes them to place a high weight on the extrapolative signal.

Our results also suggest that the change in the transaction tax played a crucial role in the bubble, because the large returns caused by this event started the feedback trading. Feedback trading existed during the entire period of put warrant trading, both before and after May 30, 2007, but did not create a bubble until it interacted with the large returns on May 30. Similar events play a role in the model of Barberis et al (2018) in which bubbles begin with exogenous shocks, in their case fundamental cash flow shocks, that result in price changes that interact with

[1] In addition to proposing an extrapolative model, Liao and Peng (2019) also use brokerage account records that include trading during the 2014-2015 run-up and collapse in Chinese stock prices to provide evidence that trading during that period was consistent with the predictions of their model.

extrapolation by some investors to create bubbles. There is less of a role for precipitating events in the resale option theory.[2]

Our results are also consistent with the bubble process described by Shiller (2014, 2015) in which a bubble is created by the interaction of a precipitating event and feedback trading that magnifies the impact of the event.

The next section of the paper provides some background about the put warrants and also describes the data we use, focusing on the brokerage account records. Section 3 shows that the shock that precipitated the bubble occurred on May 30, 2007, and identifies the shock as the tax change. Section 4 presents the results about positive feedback trading, and Section 5 shows that estimates of the trading volume due to positive feedback trading explain put warrant prices and returns during the bubble. Section 6 discusses some events related to the financial crisis that appear to have contributed to the bubble's extended life, and Section 7 briefly concludes.

2. Background and data

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 we study. The put warrants were issued between November 2005 and June 2007,

[2] Volatility plays an important role in the resale option theory, and a shock to volatility can plausibly interact with the resale option to create a bubble. Volatility was high after May 30, which might suggest that an increase in volatility caused the bubble. However, in the Chinese put warrants bubble volatility increased only after the exogenous shock started the bubble, indicating that the bubble was not created by a change in volatility.

had maturities of between six months and two years, and gave their holders the right to sell the issuing companies' stocks at predetermined strike prices during specified exercise periods. 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 the difference 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.

The 2006–2007 boom in Chinese stock prices caused most of the 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, leading many to interpret the warrant trading as a speculative bubble, and Xiong and Yu (2011) build a compelling case that it was a bubble.[3] Their most compelling evidence is that two of the warrants at times traded at market prices greater than their strike prices, and that toward the end of their lives, some of the 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. Xiong and Yu (2011) also show that many of the put warrants frequently traded at prices far in excess of estimates of their values computed using the Black-Scholes formula, and that return

[3] 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). Gong, Pan and Shi (2017) provide evidence that the BaoGang call warrant was consistently overvalued.

volatility averaged 271% per day during the zero-fundamental period. They also argue that the put warrants bubble cannot be explained by traditional bubble theories such as those due to Blanchard and Watson (1983), Allen and Gorton (1993), and Allen and Gale (2000).

One can also reject any argument that Chinese investors were willing to pay high prices for the put warrants because they were concerned about the possibility of a sustained decline in stock prices. This argument implies that the investors should have bought and *held* the put warrants as hedges. But Xiong and Yu (2011) emphasize the very high turnover, averaging 328% per day during the zero-fundamental period (Xiong and Yu 2011, Table 2). These high rates of turnover indicate very short holding periods, and are inconsistent with investors buying and holding the warrants as long-term hedges (or bets) that would benefit from the possibility of a sustained decline in Chinese stock prices.[4] Xiong and Yu (2011) also address the possibility that investors might have used the warrants as short-term hedges by noting that between the returns of the put warrants and their underlying stocks was only –0.081, and not significantly different from zero (Xiong and Yu 2011, Table 2).[5]

Due to Xiong and Yu (2011) one can be confident that the investor trades we study are bubble phenomenon and not some mixture of bubble behavior and rationally motivated trading based on fundamental information. For example, because the prices of the put warrants cannot be rationalized in terms of fundamentals one can be confident that the relations between trades and lagged returns we estimate are not caused by rational learning or updating of beliefs about

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[4] In the brokerage firm data we describe below the median holding period was one hour, and 90% of warrant investors closed their positions within five days (see Table 3 below).

[5] Even if one accepts the insignificant point estimate of –0.081, with a correlation this small a "hedged" position of warrant and stock would have a greater volatility than a stand-alone stock position. From the brokerage account records we can also determine that only a very small fraction of the warrant investors held the underlying stocks at the same time they held the warrants. Specifically, from May 30, 2007, among investors who held a warrant at any time during a day, only 1.26% of them held the underlying stock at the close of trading on either that day or the prior day. Given the Chinese market practice in which a stock must be held for at least one overnight period, this implies that at most 1.26% of warrant investors held the underlying stock while they held the warrant.

fundamental information. In contrast, most other bubbles are controversial, with some scholars offering arguments that they were not bubbles. For example, Hall (2001), Pastór and Veronesi (2006), 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 updating of beliefs about possible future technology shocks. Garber (1989, 1990, 2000) offers explanations of the Dutch Tulipmania, the Mississippi Bubble, and South Sea Bubble in terms of fundamentals.

2.2 Warrant and stock information

We focus on the 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 the China Securities Market and Accounting Research (CSMAR) database. We obtain daily and intra-day stock price and trading volumes from the same source. We also checked some of the CSMAR data by obtaining data from Resset, another Chinese financial data vendor. Panels A and B of Table 1 provide some information about the put warrants, include the beginning and end of their trading periods, their terms, and their average prices, daily turnover, and daily trading volume. Panel A reveals that most of the warrants were either in-the-money or not far out-of-the-money when they began trading, but all expired out-of-the-money because the prices of their underlying stocks exceeded the warrant strike prices at the end of trading. Panel B shows that all of the put warrants had very high turnover. The cross-sectional minimum of their average daily turnover is 65%, and 12 of the 18 warrants had turnover exceeding 1,000% on at least one day.

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. These data are from a comprehensive set of brokerage account records obtained 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. We address this by combining 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 linked 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 put warrant was listed, to December 31, 2009, the last date for which we have the brokerage account data.[6] There were 81,811 investors who traded put warrants, consisting of 80,089 individual investors and 1,722 institutional investors. These "institutional investors" are not large financial institutions such as mutual funds, because in China at this time large institutional investors typically had direct access to the exchanges and did not trade through

[6] Trading records from February 28, 2008 are missing from the dataset. This impacts only one of the put warrants, because all but one of the put warrants had expired by this date.

brokerage firms. 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 who traded at least one put warrant traded an average of 4.9 different warrants. Individuals who traded the put warrants executed a total of 69.3 purchase transactions, on average, slightly lower than the institutional investors' average of 79.8.

Due to our interest in feedback trading, on each date we use the data on the investors who have previously purchased at least one put warrant because those are the investors for whom we can compute one or more past returns. Specifically, we hypothesize that if an investor experiences a gain from previous warrant trading, the probability that the investor reenters the market and buys another warrant is larger. But in actual data, an investor might use multiple buy orders 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 grouping together transactions on a single day is that in our main empirical analyses the unit of observation is an investor-warrant-date. We use a daily interval because we include date fixed effects in the hazard rate and logistic regressions to capture the effect of the May 30 tax change and also the effects of other possible market-wide shocks, resulting in a large number of parameters to estimate in the non-linear optimizations. Any smaller time interval, combined with the date fixed effects and the large number of combinations of investor-warrant-dates, makes computation extremely burdensome.

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

Table 1 Panel C reports the numbers of investors trading each of the 18 put warrants and the average lengths of the transaction cycles in the various warrants. The majority of transaction cycles are completed and there are only a few uncompleted cycles, which occur when investors open a position and hold it through either the warrant expiration day or the last date for which we have data. Of the completed cycles, the average cycle length ranges from 1.70 days for the Jiafei warrant to 8.96 days for the Maotai warrant. These mean cycle lengths are long compared to the median cycle length of one hour reported in footnote 4 because the cycle lengths in Panel C are based on the above definition of a transaction cycle in which all transactions occurring within a single day are grouped together and also because the distribution of cycle lengths is skewed to the right so that the mean length is much greater than the median.

3. The May 30, 2007 tax change

Of the 18 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, right-hand axis) and turnover (dashed blue line, left-hand axis) of these five warrants for a six-month period roughly centered on May 30, 2007, specifically 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 turnover on May 30 to turnover on May 29 are 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 more than 12-fold increase in turnover on May 30, 2007. The visual impression is of discontinuous changes on that date. Turnover remained high after May 30; while the turnovers of the Hualing, Wuliang, and Zhongji put warrants declined from their peaks in early June, their 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 date 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 were highly volatile after May 30. The prices of Hualing, Wuliang, and Zhongji 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 investors increased their trading on May 30, 2007. Specifically, each panel shows the daily closing price (black line, right-hand axis) and the number of investors who have previously purchased at least one put warrant on each date (dotted red line, left-hand axis). Similar to the changes in turnover shown in Figure 1, the five panels show that for all five put warrants the numbers of such investors jumped sharply on May 30. The visual impression again is of discontinuous changes.[7] Figure 2 also shows that the number of new investors in each warrant also jumped sharply on May 30, where a new investor in warrant *k* on date *t* is one who has not previously traded any warrant. However, the five panels also make clear that the numbers of new investors were small relative to the numbers of investors who have previously traded put warrants, which explains why they are not the focus of our analysis.

Table 2 provides additional evidence to verify that the bubble was more pronounced after May 30, 2007 than before. The three panels report several 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 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 both before and 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 show 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

[7] Section 4 below reports the results of various regression models that provide evidence of positive feedback trading. 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, controlling for the impact of other covariates.

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). The average daily turnover and volatility are also much greater after May 30 than before.

Something important happened on May 30, 2007. The more than 12-fold increase in turnover on May 30, and the jump in the purchases by both returning and new investors, pin down the date exactly. The fact that put warrant trading volume and volatility were high starting from the opening of trading on May 30 indicates that the precipitating event happened sometime between the close of trading on May 29 and the opening on May 30. What happened before the opening of trading on May 30?

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 the requirement that a stock be held for at least one overnight period, 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 about midnight on May 30 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.[8]

The transaction tax was clearly important for the stock market. It had an immediate and substantial negative impact, with the Shanghai and Shenzhen stock indexes falling by 6.15% and 5.78%, respectively, on May 30. The tax change did not directly impact the warrants, as the

[8] See http://www.mof.gov.cn/zhengwuxinxi/caizhengxinwen/200805/t20080519_26343.html (website of the Ministry of Finance).

transaction tax on warrant trades was always zero. But the increase in the tax on stock trades increased the relative attractiveness of the warrants for short term speculation, because they (along with the call warrants) were the only listed financial instruments that were exempt from the tax. It may also have brought attention to the put warrants, because at the time they were the only instruments with payoffs negatively related to stock prices that were available for trading.[9] The seemingly discontinuous change in trading and turnover on May 30, 2007, combined with the lack of other market news relevant to the put warrants, makes it clear that this was the precipitating event that caused the put warrants bubble.[10]

The combination of dramatic warrant price increases on the same date as a precipitous decline in Chinese stock prices and the fact that the put warrants were the only financial instruments with payoffs negatively related to stock prices might suggest the hypothesis that investors were willing to pay high prices for the warrants to insure against the tail risk of a very large stock price decline. While Xiong and Yu (2011; pp. 2739-2740) have already considered and rejected this hypothesis, our brokerage account data allow us to bring additional evidence to bear. Specifically, from May 30 2007, among investors who held a warrant at any time during a day, only 1.26% of them held the underlying stock at close of trading on either that day or the prior day. Given the Chinese market practice in which a stock must be held for at least one overnight period, this implies that at most 1.26% of warrant investors held the underlying stock while they held the warrant, eliminating the possibility that more than a small fraction of the warrant investors held the warrants to hedge the underlying stocks. In addition, Table 3 shows

[9] The decline in stock prices increased the put warrants fundamental values, but only by small amounts—the warrants were so far out of the money on May 29 that any plausible estimates of the Black-Scholes fundamental values of the put warrants were still very small even after the decline in stock prices.

[10] Powers and Xiao (2014) hypothesize and provide evidence that the May 30, 2007 tax change impacted warrant pricing, but do not attribute to it a key role in starting the bubble.

that the warrant holding periods were generally short: 50% were less than or equal to one hour, 75% were less than or equal to one day, and almost 97% less than or equal to 20 days. The short holding periods eliminate the possibility that investors bought and held the warrants as long-term hedges against declines in either the prices of their underlying stock or the overall stock market. It also is difficult to argue that investors traded the warrants to hedge short-term stock price changes. This alternative is rejected by the fact that during the entire period of warrant trading the correlation between the returns of the put warrants and their underlying stocks was only −0.081, and not significantly different from zero (Xiong and Yu 2011, Table 2), making it "difficult to argue that investors traded these warrants to hedge daily fluctuations of the underlying stocks" (Xiong and Yu 2011; p. 2724). Using pooled return data from after May 30, 2007 we find that the correlations between the warrant returns and percentage changes in the Shanghai and Shenzhen stock market indexes were −0.059 and −0.047 and also not statistically significantly different from zero. With such small correlations, the warrants could not have been useful hedges of short-term fluctuations in stock prices.

4. Positive feedback trading

We estimate Cox proportional hazard rate models to provide evidence that the probability that an investor buys a put warrant is related to his or her past warrant returns. We use these models because they take account of the time that has elapsed since an investor completed his or her last transaction cycle. In addition to estimating the standard (Cox 1972) version we also allow for the possibility of unobserved individual heterogeneity by using the stratified partial likelihood method described by Ridder and Tunali (1999). In our implementation of the stratified model each investor is a stratum, allowing for individual specific baseline hazard rates.

We also verify that the main results are robust to the choice of the hazard rate specification by estimating logistic regression models that include investor fixed effects.

4.1 Samples and covariates

Since we are interested in feedback trading, we estimate the models using on each date only the investors who have previously purchased at least one put warrant because these are the investors for whom we can compute at least one past realized or unrealized return. Thus, in modeling the purchase of warrant k on date t we consider the investors who do not hold warrant k as of the close of trading on date $t-1$ and have previously purchased and sold warrant k or previously purchased (but not necessarily sold) one of the other put warrants. We exclude the investors who hold warrant k as of the close of trading on date $t-1$ because, as discussed in Section 2, we equate "purchase" with beginning a new transaction cycle, and an investor cannot begin a new transaction cycle in warrant k on date t if he or she holds warrant k as of the close of trading on date $t-1$. For each warrant k and date t, we divide the sample into three groups depending on the availability of the return variables. The three groups consist of investors who have previously completed one transaction cycle in warrant k ("one-cycle investors"), those who have completed two or more transaction cycles in warrant k ("two-cycle investors"), and those who have not previously traded warrant k but have purchased some other warrant ("inexperienced investors").

The proportional hazards model specifies that $\lambda_{i,k,t}(\tau)$, the hazard function of starting a new transaction cycle by investor i in warrant k on date t, τ trading days after the end of the investor's last transaction cycle, takes the 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 the investors who have previously completed one transaction cycle in warrant k (the one-cycle investors) the term $x_{i,k,t}\beta$ includes the following covariates: $RetLag1_{i.k,t}$, the realized return of the most recent transaction cycle of investor i in warrant k before date t; $I(RetLag1_{i.k,t} > 0)$, an indicator variable that takes the value one if $RetLag1_{i.k,t}$ is positive; $OtherRetLag1_{i.k,t}$, the realized return of the most recent transaction cycle of investor i in a warrant other than warrant k before date t; $I(OtherRetLag1_{i.k,t} > 0)$, an indicator variable that takes the value one if the return on the other warrant is positive; $NoOtherRetLag1_{i.k,t}$, an indicator variable that takes the value one if the investor has not previously traded another warrant so that $OtherRetLag1_{i.k,t}$ is not available; $OtherRetLag2_{i.k,t}$, the average realized returns of all completed transaction cycles in other warrants prior to the most recent transaction cycle in warrant k ; $I(OtherRetLag2_{i.k,t} > 0)$ and $NoOtherRetLag2_{i.k,t}$, which are constructed similarly to $I(OtherRetLag1_{i.k,t} > 0)$ and $NoOtherRetLag1_{i.k,t}$; $UnRealizedRet_{i.k,t}$, the unrealized return of the most recently opened but not completed transaction cycle of investor i in a warrant other than warrant k; $I(UnRealizedRet_{i.k,t} > 0)$, an indicator variable that takes the value one if the unrealized return is positive; and $NoUnRealizedRet_{i.k,t}$, an indicator variable that takes the value one if $UnRealizedRet_{i.k,t}$ is not available because the investor does not currently have an open transaction in another warrant. We are primarily interested in the estimates of the coefficients on these return variables.

We are also interested in the impact of publicly observed market returns and thus include three market return variables: $MktRet1Day_{k,t}$, the close-to-close market return on warrant k from the close of trading on date $t-2$ to the close of trading on date $t-1$; $MktRet4Day_{k,t}$, the return from date $t-6$ to date $t-2$, and $MktRet3Week_{k,t}$, the return from date $t-21$ to date $t-6$.

We include turnover on date $t-1$, denoted $TurnoverDay_{k,t}$; average turnover over dates t –

5 to $t-2$, denoted *Turnover*4*Day*$_{k,t}$; and average turnover over dates $t-20$ to $t-6$, denoted *Turnover*3*Week*$_{k,t}$, as control variables. We also include a measure of the moneyness of the warrant, *Fundamental*$_{k,t}$, computed as

$$Fundamental_{k,t} = \left(\frac{Stock\ Price_{k,t} - Strike\ Price_k}{Stock\ Price_{k,t}}\right) / Maturity_{k,t}. \tag{2}$$

We use this measure rather than the Black-Scholes value because we hypothesize that investors are more sensitive to the difference between the underlying stock price and the strike price when making an investment decision in warrant *k* than the warrant's Black-Scholes value, which is less accessible to investors.

Finally, we include calendar date, time-to-maturity, and warrant fixed effects, denoted α_t, α_m, and α_k, respectively. The results in the previous section indicate that date fixed effects are important around and shortly after May 30, 2007; we include them for all dates to allow for the possibility that they are important on other dates as well. Time-to-maturity fixed effects are included because, as noted by Xiong and Yu (2011), warrant turnover tends to increase as the maturity date approaches, which suggests that hazard rates become larger as the maturity date approaches. The warrant fixed effects allow for the possibility that hazard rates differ across warrants for reasons that are not captured by the other variables.

The specification for investors who have previously completed two or more transaction cycles in warrant *k* (the two-cycle investors) is similar to the specification for the one-cycle investors, except that we capture the returns on the earlier transaction cycles in warrant *k* by adding the variables $RetLag2_{i,k,t}$ and $I(RetLag2_{i,k,t} > 0)$, where $RetLag2_{i,k,t}$ is the average return of the transaction cycles of investor *i* in warrant *k* prior to the most recent transaction cycle before date *t*.

For the investors who have not previously traded warrant *k* (the inexperienced investors), the model is the same except that the variables $RetLag1_{i,k,t}$, $I(RetLag1_{i,k,t} > 0)$, $RetLag2_{i,k,t}$, and $I(RetLag2_{i,k,t} > 0)$ are not included because they are not available.

4.2 Possible unobserved individual heterogeneity

There might be unobserved time-invariant individual heterogeneity that is positively correlated with both the purchase probability and investors' past performance, for example investors' abilities. In this case ignoring the unobserved individual heterogeneity among individuals will bias the estimates of the baseline hazard function (Cameron and Trivedi 2005, Seru, Shumway and Stoffman 2010). Cox hazard model specifications that do not take account of the heterogeneity can also result in biased estimates of the impact of past performance on the probability of buying (Ivković, Poterba, and Weisbenner, 2005). For example, if there is time-invariant unobserved heterogeneity that is positively correlated with both the probability of reentry and investors' past performance, perhaps due to variation in investors' investment skill, one might overestimate the impact of past performance on the probability of another warrant purchase.

One possible approach to address this is to include individual fixed effects in the hazard rate specification in equation (1). The hazard function would take the form

$$\lambda_{i,k,t}(\tau) = \lambda(\tau) \times e^{x_{i,k,t}\beta + u_i}, \tag{3}$$

where u_i is the individual fixed effect for investor i. However, we have a large number of investors and thus a large number of individual fixed effects to estimate. For example, we have about 30,000 one-cycle investors, and maximizing the partial likelihood function with 30,000 parameters is not computationally feasible.[11] As a result, we use the stratified partial likelihood

[11] We also tried using a 10% sample of our population (about 3,000 investors) and were unable to get the optimization of the log likelihood to converge.

method described by Ridder and Tunalı (1999). In this method, the hazard function takes the form

$$\lambda_{i,k,t}(\tau) = \lambda_i(\tau) \times e^{x_{i,k,t}\beta}, \tag{4}$$

where each investor i is a stratum and has his or her own baseline hazard function $\lambda_i(\tau)$. This model allows for an unobserved stratum-specific effect in the hazard function; because in our case each stratum is an investor, it allows for unobserved individual effects.

In the conventional Cox model, estimation of the coefficient vector β in equation (1) is feasible because the nonparametric hazard function $\lambda(\tau)$ is cancelled out in the partial likelihood function. But in equation (4), the individual fixed effects would not be cancelled out, greatly increasing the number of parameters. Ridder and Tunalı (1999) overcome this difficulty by introducing the stratified partial likelihood estimator. Instead of constructing the partial likelihood function by pooling all individuals together, the stratified method first constructs the partial likelihood function in the conventional way within each stratum, in our case, within each investor, so the individual-specific baseline hazard function $\lambda_i(\tau)$ is cancelled out. Then, it estimates the coefficient vector β by maximizing the stratified partial likelihood function, which combines together the stratum-specific partial likelihood functions. Thus, the estimation is feasible as the large number of investor-specific parameters are cancelled out by construction.

Incorporating large numbers of individual fixed effects is feasible in logistic regression models, so in addition we pursue the estimation of logistic regression models with individual fixed effects. These additional logistic regression results are discussed in Section 4.4 below.

Unobserved time-varying individual heterogeneity is another potential concern. This might arise due to changes in investors' access to information or changes in their skill. For example, during a period when investors have better access to information their returns might tend to be positive and they might also be more likely to trade again. It seems unlikely that there can be many changes in investors' access to information or trading skill at the time scale of the warrant trading.[12] Furthermore, alternative hypotheses about time-varying changes in access to information or skill have difficulty explain the discontinuities at zero in the relation between past returns and the probability of trading that we find.

4.3 Hazard rate model results

Table 4 Panel A reports the estimated coefficients and *p*-values for tests of the hypotheses that the coefficients are zero for the three groups of investors using the standard Cox model. Panel B reports the corresponding results for the stratified version of the model. The results for the two versions of the model in Panels A and B are similar for all three groups of investors. For the one- and two-cycle investors (all of whom have completed at least one transaction cycle in the same warrant), the coefficients on both *RetLag*1 and the indicator variable $I(RetLag1 > 0)$ are large and highly significant, with *p*-values less than 0.0001, For the stratified version the coefficients on *RetLag*1 are larger and those on $I(RetLag1 > 0)$ are slightly smaller, but these differences do not affect the conclusion that both variables are strongly related to the probability of subsequent warrant purchases. Given the magnitudes of the variables, that is *RetLag*1 is a decimal return while $I(RetLag1 > 0)$ is either zero or one, the dummy variable has a more important impact on the probability of buying than *RetLag*1 even though the coefficients on *RetLag*1 are larger in both versions of the model. In the model for two-cycle investors that

[12] The median holding period is one hour (see Table 3), investors who re-enter the market typically do so within a few days of their most recent warrant trade, and the typical investor participates in put warrant trading for 160 days. However, the evidence in the literature is that learning by trading occurs slowly: Seru, Shumway, and Stoffman (2010), p. 708 find that "after accounting for survivorship, an extra 100 trades is associated with an improvement in average returns of approximately 3.6 basis points (bp) over a 30-day horizon (or about 30 bp per year)." This suggests that it is unlikely that the warrant investors engaged in significant learning during the time when they were trading.

includes *RetLag*2 and *I*(*RetLag*2 > 0) the coefficients on *RetLag*2 and *I*(*RetLag*2 > 0) are smaller than the coefficients on *RetLag*1 and *I*(*RetLag*1 > 0), as expected, but are still highly significant with *p*-values less than 0.0001.

Calculations of the marginal effects of changes in the covariates reveal that the coefficient estimates are large enough for feedback trading to be economically important. Consider an investor *i* who closed his or her last transaction cycle in warrant k a days ago at date $t - a$, where $a \geq 1$, and has not traded warrant k for $a - 1$ days since the closing of that cycle. Using one-cycle investors as an example and evaluating the marginal effects at the mean values of the covariates and baseline hazard functions, for the duration interval $(a - 1, a]$ with a equal to one day the marginal effect of a 1% increase in the one-cycle return *RetLag*1 is a 0.12% increase in the conditional reentry probability. Given that the standard deviation of *RetLag*1 is 19.01%, a one standard deviation increase in this variable implies an increase in the reentry probability of 2.28 percentage points. When $a = 1$, the sample conditional reentry probability during the duration interval $(0,1]$ is 16.82%, so the 2.28 percentage point increase in the reentry probability implies a 13.55% = 2.28/16.82 increase in the sample reentry conditional probability. The relative changes in the reentry probabilities for $a = 2, 3, 4$, and 5 are similar and actually slightly larger.

Considering the impact of a gain versus a loss (the impact of the indicator variable *I*(*RetLag1*>0)) when $a = 1$, having *I*(*RetLag1*>0) = 1 implies a large increase in the reentry probability of 3.48 percentage points, which corresponds to a 20.68% increase in the sample conditional reentry probability. Similar to the marginal impact of *RetLag*1, the relative changes in the reentry probabilities for $a = 2, 3, 4$, and 5 are similar and actually slightly larger. The calculations of these impacts and the corresponding results for two-cycle investors are detailed in the internet appendix.[13] The impacts for two-cycle investors are not as large as those for one-cycle investors, but are still economically significant.

For both one and two-cycle investors the estimated coefficients on the realized return of the most recent completed transaction cycle in another warrant, *OtherRetLag*1, are highly significant but smaller than the coefficients on *RetLag*1. This is unsurprising. Similarly, the estimated coefficients on the unrealized return on a position in another warrant that is still open, *UnrealizedRet*, are highly significant but smaller than the coefficients on *RetLag*1. The coefficients on the dummy variables for whether these returns are positive are also positive and significant, though in one case, the coefficient on the variable *I*(*OtherRetLag*1 > 0) in the model for two-cycle investors in Panel A, the estimate is only 0.0103 and not particularly significant (*p*-value of 0.0219). In contrast, the corresponding coefficient for the stratified version in Panel B is 0.0614 and highly significant.

These results are as expected. The probability of a purchase of warrant *k* is very strongly related to the return on the most recently completed transaction cycle in warrant *k*; it is also strongly, though less so, related to the returns of earlier transactions in warrant *k*, the realized return of the most recently completed transaction cycle in another warrant, and the unrealized return on a currently open position in another warrant. The only slightly anomalous results for the variables capturing the returns on the previous trades are that in Panel A reporting the results for the conventional version of the Cox model the coefficient on the dummy variable *I*(*OtherRetLag*2 > 0) is negative and highly significant for both one and two-cycle investors, though the point estimates are not large (only –0.0646 and –0.0548 for one and two-cycle

[13] The internet appendix also presents results showing that an investor who traded for say 20 transactions cycles and then left the market typically traded profitably for the first 17 of the 20 cycles, and then experienced losses on his 18th, 19th, and 20th cycles before leaving the market. This is also consistent with feedback trading.

investors, respectively). Also, for the two-cycle investors the coefficient on *OtherRetLag*2 is larger than the coefficient on *OtherRetLag*1, though this can be rationalized by the observation that *OtherRetLag*2 is an average of the return on all transactions in warrants other than warrant *k* prior to the most recent transaction in a warrant other than *k*, and thus might be expected to receive more weight. Regardless, such slightly anomalous results are not found in Panel B reporting the estimates of the stratified version of the model that allows for unobserved individual heterogeneity.

Turning to the close-to-close market return variables, *MktRet*4*Day* and *MktRet*3*Week* are significantly related to the probability of warrant purchases, though the coefficients are considerably smaller than those on the return variables capturing the investors' own experience. The coefficient estimates on *MktRet*1*Day* are small, and insignificant in Panel B reporting the results for the stratified version of the model. These results showing that the returns experienced by the investors are important are consistent with the results in the experiential literature showing that investors' own experience is important (Kaustia and Knüpfer 2008, Chiang, Hirshleifer, Qian, and Sherman 2011, Malmendier, Tate, and Yan 2011, Malmendier and Nagel 2011, 2015).

The results differ in the expected ways for the investors who have not previously purchased warrant *k*. Because these investors have never experienced a return on a transaction in warrant *k*, one should expect that the returns on their trades in other warrants will be more strongly related to the probability of purchasing warrant *k* than they are for the one and two-cycle investors who have previously purchased warrant *k*. With one small exception, this is shown in the results for the new investors in the right-hand part of Table 4. Specifically for the new investors the coefficients on *OtherRetLag*1, $I(\mathit{OtherRetLag}1 > 0)$, *UnrealizedRet* and $I(\mathit{UnrealizedRet} > 0)$ are larger for the new investors than for the one and two-cycle investors.

The one case in which the coefficient for the new investors is not larger is that in Panel A for the two-cycle investors the coefficient on *OtherRetLag*2 is greater than the corresponding coefficient for the new investors. This anomalously large coefficient on *OtherRetLag*2 for the two-cycle investors in Panel A was mentioned above, and is not found in the Panel B results for the stratified version of the model.

In addition, in the inexperienced investor results in both panels the coefficient on the most recent close-to-close market return is much larger than the estimate for the one and two-cycle investors, which is unsurprising. The coefficient estimates on the other market return variables *MktRet*4*Day* and *MktRet*3*Week* are similar for all three groups of investors.

Figure 3 plots the calendar date fixed effects from the stratified version of the model for a four-month window approximately centered on May 30, 2007, the date of the tax change. One can see an obvious jump on May 30, consistent with the conclusion in the preceding section that the tripling of the stock transaction tax had an important effect on the warrant market.

4.4 Logistic regression models

Logistic regression models with individual fixed effects are an alternative to the stratified Cox hazard rate model for addressing unobservable individual heterogeneity. Thus, we also estimate logistic regression models that explain the probability of buying using the same samples of one-cycle, two-cycle, and new investors for which we estimated the hazard rate models. We use the same covariates as in the corresponding Cox hazard models, and account for the duration dependence by introducing an additional duration fixed-effect α_τ, where τ is the number of trading days since the end of the investor's last transaction cycle. The duration fixed effects provide a flexible specification of the duration dependence.

Table 5 reports the coefficient estimates for the one-cycle, two-cycle, and inexperienced investors. The point estimates of the coefficients of course differ due to the different functional form, but the patterns in the coefficient estimates are similar. The return on the most recent transaction cycle in the same warrant and the dummy variable for a positive return, *RetLag*1 and *I*(*RetLag*1 > 0), are large and highly significant for the one and two-cycle investors for which these variables are available. For those investors the coefficient estimates on the other return variables are smaller than the coefficient estimates on *RetLag*1, and the coefficient estimates on the dummy variables for other positive returns are smaller than the coefficient estimates on *I*(*RetLag1* > 0). For both one and two-cycle investors the coefficients on *MktRet*1*Day* are very small. For the two-cycle investors the coefficients on the other market return variables are smaller than all of the coefficients on the variables that measure the returns experienced by the investors. For the one-cycle investors the coefficients on the market return variables *MktRet*2*Day* and *MktRet*3*Week* are smaller than all of the coefficients on the variables that measure the returns experienced by the investors except for the coefficient on *OtherRetLag*2.

Turning to the inexperienced investors for whom lagged returns on completed transaction cycles in the same warrant are not available, the estimates of the coefficients on the other return variables are larger than the corresponding estimates for the one and two-cycle investors, just as with the hazard rate regressions. Also consistent with the results for the hazard rate regressions, the estimated coefficient on *MktRet*1*Day* is now large. These logistic regression results show that the conclusions about the importance of the various return variables are not sensitive to the regression specification.

5. Does feedback trading explain put warrant prices during the bubble?

The immediate large increase in warrant prices on May 30, 2007 due to the transaction tax, combined with the positive coefficients on returns in the hazard rate model, suggest that positive feedback trading might have been important during the days following May 30. We present two kinds of evidence to show that it was important and also consistent with the hypothesis that feedback trading explained put warrant prices during the bubble. First, we sum the estimates of the buying attributable to feedback trading and show graphically that for each of the five put warrants the time pattern of volume due to feedback trading closely corresponds to the time pattern of put warrant prices during the bubble. Second, we revisit the panel regressions that Xiong and Yu (2011) use to provide support for the resale option theory by including the estimates of feedback trading volume and a dummy variable for the dates after the tax change as additional covariates to explain prices. We find that the additional covariates explain put warrant prices, and once we include them in the panel regressions the turnover and return volatility variables considered by Xiong and Yu (2011) are no longer significantly related to warrant prices.

5.1 Dynamics of feedback trading volume and put warrant prices around the May 30, 2007 tax change

We use the estimated hazard rate and logistic regression models to compute estimates of trading volume due to feedback trading. Specifically, for each investor *i*, warrant *k*, and trading date *t* the investor's buying is described by either the one-cycle, two-cycle, or inexperienced investor version of the hazard rate or logit model depending on the warrant trades that the investor has previously executed. We use the coefficient estimates from the appropriate model and the covariates to calculate the fitted probability that investor *i* purchases warrant *k* on date *t* and call the result $\hat{P}_{i,k,t}$. The variables *RetLag*1, *I*(*RetLag*1 > 0), *RetLag*2, *I*(*RetLag*2 > 0), *OtherRetLag*1, *I*(*OtherRetLag*1 > 0), *OtherRetLag*2, *I*(*OtherRetLag*2 > 0), *UnrealizedRet*, and *I*(*UnrealizedRet* > 0) capture the investor's own return experience. We set the coefficient estimates on these return variables equal to zero and recalculate the buying probability for each investor *i*, warrant k, and date *t*, calling the result $\bar{P}_{i,k,t}$. The difference $\hat{P}_{i,k,t} - \bar{P}_{i,k,t}$ is the part of the buying probability that is due to the investor's own past returns. Letting $\bar{Q}_{i,k}$ be the average trade size of investor *i* in warrant *k* in the previous cycles, the product $(\hat{P}_{i,k,t} - \bar{P}_{i,k,t})\bar{Q}_{i,k}$ measures the effect of positive feedback from own returns on the trading volume of investor *i* in warrant *k* on date *t*. Then for each warrant, on each trading date, we sum the terms $(\hat{P}_{i,k,t} - \bar{P}_{i,k,t})\bar{Q}_{i,k}$ over investors *i*, yielding an estimate of the total trading volume $F_{k,t}$ that is due to positive feedback trading for each warrant and date. The appendix provides a more detailed description of the calculations.

These estimates $F_{k,t}$ are only for the feedback trading of the customers of the brokerage firm that provided the data. In order to scale them up to the market level, for each warrant and date we scale the estimate $F_{k,t}$ by the ratio of total market trading volume to the trading volume of the brokerage firm customers, that is we compute an estimate

$$FeedbackVolume_{k,t} = F_{k,t} \times \left(\frac{Volume_{k,t}^{Market}}{Volume_{k,t}^{Brokerage}}\right), \tag{5}$$

where $Volume_{k,t}^{Market}$ is the market trading volume in warrant k on date t and $Volume_{k,t}^{Brokerage}$ is the corresponding trading volume of the brokerage firm customers.

We perform these calculations using the estimates from the standard and stratified versions of the Cox hazard rate model and the logistic regression model. The five panels in Figure 4 plot the estimates of feedback trading volume based on the stratified Cox model (dashed blue line, left axis) and the warrant prices (solid black line, right axis) for the five warrants during a four month window surrounding the May 30, 2007 tax change.[14] One can see clearly that feedback trading volume becomes important starting from May 30, 2007. The hypothesis that feedback trading is important in driving the bubble predicts that the estimates of it should be highly correlated with put warrant prices. The five panels reveal striking similarities between the time patterns of the volume estimates and the put warrant prices. For example, for Hualing the peaks of both the price and volume series are achieved on June 15, both series achieve local minima on June 20, and both reach local maxima on either June 25 or June 26. Wuliang, Zhongli, and Zhaohang display similar patterns. Jiafei differs from the other four warrants because its last trading date is June 22, but the price and estimated volume series for Jiafei are nonetheless strikingly similar to each other. For example, the maxima are on either May 31 or June 1, and both series achieve local minima on either June 5 or June 6. For three of the warrants (Hualing, Zhongji, and Zhaohang), the estimates of feedback trading volume appear to lead the run-up in prices that occurred starting on May 30, 2007. Examining Figure 4, it is difficult to escape the conclusion that feedback trading played an important role in the put warrants bubble.

5.2 Panel regressions showing that feedback trading explains put warrant prices

We now turn to providing more formal evidence consistent with the hypothesis that feedback trading contributed to the bubble. For each of the 18 put warrants, Xiong and Yu (2011) determine a zero-fundamental period in which either an estimate of the fundamental value of the warrants computed using the Black-Scholes formula and historical volatility is less than ¥0.005, or, for the cash settled Nanhang warrant, the settlement price will exceed the strike price even if the stock trades limit down every day until the expiration date. Using data from the zero-

[14] Figures showing estimates based on the standard Cox hazard rate model and the logistic regression model are similar and are not shown.

fundamental period, they estimate unbalanced panel regressions in which they regress the daily warrant prices (which measure the bubble size as the fundamental value is nearly zero) on turnover, an estimate of the daily volatility computed from intraday five-minute returns, the warrant float, and remaining time-to-maturity fixed effects, and obtain positive coefficients on turnover and volatility and a negative coefficient on float. Xiong and Yu (2011) argue that the resale option theory of Scheinkman and Xiong (2003) predicts positive coefficients on turnover and volatility, and Xiong and Yu (2011) interpret their panel regression results as supportive of that theory.

We revisit these panel regressions by adding the estimates of trading volume due to feedback trading to the regression models. We want to see whether feedback trading helps explain the bubble size, controlling for the turnover and volatility variables used in the Xiong and Yu (2011) panel regressions.

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 clustered by date, as in Xiong and Yu (2011). The first three columns each report the results of regressions that include the variables *Turnover*, *Volatility*, and *Float* one at a time, while column (4) presents the results of a specification that includes all three variables. The coefficient point estimates and *t*-statistics in Panel A are very similar, but not quite identical, to those reported in the corresponding columns of Xiong and Yu (2011) Table 5.

Panel B reports the results of the same set of regression models but also adding a transaction tax dummy variable (*TransactionTax*) that is equal to one for May 30, 2007 and later dates and equal to zero for dates before May 30. The results in Panel B for the regression specifications that include the dummy variable are quite different than those in Panel A that do not. In the specification that includes *Turnover* by itself (without *Volatility* or *Float*) the point estimate of the coefficient on *Turnover* is now negative, though not significantly different from zero, in contrast to the positive coefficient in Panel A. In the specification that includes all three variables *Turnover* is significantly negatively related to the warrant price, whereas the relation in Panel A was positive. *Volatility* remains significantly positively related to the size of the put warrants bubble, consistent with the resale option theory, though the point estimates are smaller than in Panel A.[15] The coefficient on *Float* is always negative and highly significant, which is consistent with the resale option theory and also with other theories of security valuation. It is also consistent with short sale constraints playing an important role in the bubble. The coefficient on the transaction tax dummy is positive and significant in all specifications, consistent with our earlier claim that the tripling of the transaction tax was an important event for the warrant market.

To test the hypothesis that feedback trading contributes to the size of the bubble we add an estimate of feedback trading volume as an additional covariate in the panel regressions. The measure of positive feedback trading for warrant *k* on date *t* consists of the estimates of feedback trading volume described above based on either the standard or stratified Cox hazard rate model or the logistic regression model, but now scaled by the number of warrants outstanding on date *t*.

Table 7 Panel A reports the means, medians, and standard deviations of the estimates of feedback trading volume from the three models, denoted $FeedbackVolume^{\mathrm{Cox}}$, $FeedbackVolume^{\mathrm{stratified}}$, and $FeedbackVolume^{\mathrm{logit}}$. These variables are on average equal to

[15] In untabulated results we add date fixed effects to the regressions instead of the transaction tax dummy variable. The calendar date fixed effects show a pronounced change around May 30, and the change in the significance of *Turnover* and *Volatility* is similar to that shown in Panel B of Table 6.

8.68%, 13.72%, and 15.29% of shares outstanding, respectively. While the medians are smaller, 3.90%, 8.59%, and 8.14%, respectively, these proportions are still large enough for feedback volume to have an important impact on prices. Below the statistics for feedback trading volume the panel reports the same statistics for three variables $Volume^{\mathrm{Cox}}$, $Volume^{\mathrm{stratified}}$, *and* $Volume^{\mathrm{logit}}$, which are estimates of the of the total volume predicted by the hazard rate and logistic regression models, also scaled by shares outstanding. Across warrant-dates, the medians of these three variables are 53%, 56%, and 67% for the standard Cox, stratified Cox, and logistic regression models, respectively. The means of the volumes explained by the three models are larger, between 76% and 94%.

Table 7 Panel A also includes the same statistics for *Volatility*, *Turnover*, and *Float*. Panel B reports the correlation matrix of these nine variables and shows that the various estimates of feedback trading volume are very highly correlated.

Table 8 reports the results of various panel regressions that include one of the three estimates of feedback trading volume, either *Volatility*, *Turnover*, or both, *Float*, and the transaction tax dummy variable. The coefficient on the estimate of feedback trading volume is positive and highly significant in every specification. Once we include a measure of feedback volume in the regression specification the estimated coefficient on *Volatility* becomes insignificant in every specification in which it appears. The point estimate of the coefficient on *Turnover* is negative in all six specifications in which this variable appears, and significant at the 1% level in two and at the 10% level in one.

These panel regressions are very successful in explaining warrant prices. Across the specifications that include a measure of feedback volume along with the transaction tax dummy, the lowest adjusted R^2 is 0.683, and the largest is 0.711. The *TransactionTax* dummy makes an important contribution to these good fits, which can be seen by comparing Panels A and B of Table 7. But *FeedbackVolume* also makes an important contribution, which can be seen by comparing the R^2s of the regressions with *FeedbackVolume* reported in Table 8 to the R^2s of the regressions with the *TransactionTax* dummy but without *FeedbackVolume* reported in Table 7 Panel B. These good fits are not driven by the time to maturity fixed effects. When we omit the time to maturity fixed effects, in untabulated results we find that the adjusted R^2's in the specifications that include one of the estimates of feedback volume are almost as large, ranging from 0.521 to 0.600. For comparison, the maximal adjusted R^2 in the Xiong and Yu (2011) panel regressions replicated in Table 6 is 0.332. When we omit the time to maturity fixed effects the adjusted R^2 in this specification falls to 0.069, and the maximal adjusted R^2 across all Xiong and Yu (2011) specifications that do not include time to maturity fixed effects is 0.081. Thus, our panel regressions are much more successful in explaining warrant prices than the Xiong and Yu (2011) specifications.

We interpret the failure of *Volatility* to be related to warrant prices once an estimate of feedback volume is included in the panel regressions as evidence against the resale option theory, as volatility plays a central role in that theory. The results for *Turnover* are also inconsistent with that theory, as *Turnover* is either not significantly related to warrant prices or significantly related to them but with a sign opposite to that predicted by the theory. We conjecture that the sometimes significantly negative coefficients are due to the fact that feedback trading is not the only determinant of warrant prices, and that turnover is correlated with those other determinants. Regardless, the negative coefficient on *Turnover* is not a robust result as the coefficient estimate is not statistically significant in three of the six specifications in which that variable appears.

Finally, we verify the robustness of the results by re-estimating the specifications in Table 8 replacing the estimates of feedback volume with the variables $Volume^{\text{Cox}}$, $Volume^{\text{stratified}}$, and $Volume^{\text{logit}}$, which are estimates of the total volume predicted by the hazard rate and logistic regression models, scaled by shares outstanding. These variables differ from the estimates of feedback volume in that the estimates of feedback volume are the differences between volume estimates intended to capture the effect of the lagged return variables, while $Volume^{\text{Cox}}$, $Volume^{\text{stratified}}$ and $Volume^{\text{logit}}$ are the volumes predicted by the models and not the differences between two estimates. We expect the results using these alternative estimates of volume to be similar to those in Table 8 because most of the variability in the predictions from the regression equations comes from the effect of the lagged return variables, implying that these variables are highly correlated with the estimates of feedback volume. This is confirmed by the correlations reported in Table 7 Panel B.

Table 9 presents the results using the variables $Volume^{\text{Cox}}$, $Volume^{\text{stratified}}$, *and* $Volume^{\text{logit}}$. As expected, the results are similar to those in Table 8. The variables $Volume^{\text{Cox}}$, $Volume^{\text{stratified}}$, *and* $Volume^{\text{logit}}$ are positively and significantly related to put warrant prices in all specifications in which they appear, with coefficient point estimates that are similar to the coefficients on the estimates of feedback volume in Table 8. These results provide comfort that the estimated relations between buying due to feedback trading and social contagion are robust.

5.3 Panel regressions showing that feedback trading explains put warrant returns

Another test of whether feedback trading helps explain the bubble is to examine whether changes in feedback volume are related to put warrant returns.[16] Recall that $F_{k,t}$ is the estimate of the feedback trading volume on date t of the customers of the brokerage firm that provided the

[16] We thank David Hirshleifer for suggesting this analysis.

data; it is computed using information from date $t - 1$ and earlier dates. The first difference $F_{k,t} - F_{k,t-1}$ of course is also computed using information from date $t - 1$ and earlier dates. We scale these first differences up to the market level by multiplying each first difference $F_{k,t} - F_{k,t-1}$ by the ratio of market trading volume to that of the brokerage firm customers on date $t - 1$, and then divide them by the number of warrants outstanding on date $t - 1$. We call the result $\Delta FeedbackVolume_t$ and examine whether it and first differences of other variables predict put warrant returns $R_t = (P_t - P_{t-1})/P_{t-1}$ in panel regressions using data from the Xiong and Yu (2011) zero-fundamental period.

The first three columns of Table 10 Panel A report the results of regressions that do not include $\Delta FeedbackVolume_t$ but rather use lagged first differences in turnover and volatility defined as $\Delta Turnover_{t-1} = Turnover_{t-1} - Turnover_{t-2}$ and $\Delta Volatility_{t-1} = Volatility_{t-1} - Volatility_{t-2}$ to try to explain warrant returns. We also include first difference of the transaction tax dummy defined as $\Delta TransactionTax_t = TransactionTax_t - TransactionTax_{t-1}$; because the transaction tax dummy takes the value one for May 30, 2007 and later dates, its first difference $\Delta TransactionTax_t$ equals one only on May 30. These results in columns (1)-(3) show that when $\Delta FeedbackVolume_t$ is not included in the specification the lagged change in turnover $\Delta Turnover_{t-1}$ is significantly positively related to R_t in both specifications that include this variable, but the lagged change in volatility $\Delta Volatility_{t-1}$ is not significantly related to the return. The coefficients on $\Delta TransactionTax_t$ are large and highly significant, consistent with previous results showing that the change in the transaction tax had an important impact on warrant prices.

The remaining columns of Table 10 report the results of specifications that include estimates of the change in feedback volume $\Delta FeedbackVolume_t$ based on the standard and stratified Cox hazard rate models and the logistic regression model, along with other covariates.

The estimated coefficients on $\Delta FeedbackVolume_t$ are significantly different from zero in all nine specifications in which this variable appears, with t-statistics ranging from 2.06 to 4.24. When this variable is included in the regression specifications the coefficients on $\Delta Turnover_{t-1}$ and $\Delta Volatility_{t-1}$ are no longer significant. As expected, the estimated coefficients on $\Delta TransactionTax_t$ are large and highly significant in all specifications; in our preferred specifications, those in columns (7)-(9) in which $\Delta FeedbackVolume_t$ is computed from the estimates of the stratified Cox model, the estimated coefficients on $\Delta TransactionTax_t$ are almost exactly equal to the average put warrant return on May 30, 2007. These results showing that $\Delta FeedbackVolume_t$ explains warrant returns are additional evidence consistent with the hypothesis that feedback trading played an important role in the put warrants bubble, and thus additional evidence consistent with the implications of extrapolative theories of speculative asset price bubbles.

6. Why did the bubble last so long?

The bubble lasted for an extended period. For example, the turnover of the Wuliang put warrant was elevated and its price was well above any reasonable estimate of its fundamental value from the beginning of the bubble on May 30, 2007 until the warrant's expiration in late March 2008. Related to this, Figure 2 shows that there were several subsequent smaller spikes in put warrant prices in addition to the large price spike that started on May 30, 2007. Looking across the various panels, one can see that these subsequent spikes in the prices of the different warrants occurred on the same dates, suggesting common causes. Consistent with this, we find that there were additional common shocks during 2007, and that each of the subsequent spikes in put warrant prices is preceded by one of these additional shocks.

Because the spikes occur on the same dates and thus appear to have common causes we focus on only one warrant and select Wuliang because of the five warrants that traded both before and after May 30, 2007, it is the one that expired last.[17] Figure 5 plots the calendar date fixed effects (left axis) from the stratified Cox hazard rate regressions estimated using the sample of two-cycle investors, who comprise most of the investors, along with the Shanghai stock exchange (SHSE) composite index (right axis), through the expiration of the Wuliang put warrant.[18] These calendar date fixed effects capture the buying that is not explained by the other covariates and thus capture the impact of any shocks that are exogenous to the warrant market. Figure 6 plots the same fixed effects (left axis) along with the price of the Wuliang put warrant (right axis). Figure 6 reveals one large spike in warrant prices labelled "A" following the May 30 tax change and three subsequent smaller spikes labelled "B", "C", and "D". It also shows that each of the spikes in warrant prices labelled "A", "B", "C", and "D" is preceded by a large fixed effect labelled "a", "b", "c", or "d" in both Figures 5 and 6.

The largest fixed effect is for May 30, 2007, the date of the tripling of the transaction tax, and is labelled "a" in both Figures 5 and 6. Figure 5 shows that this was followed by a (temporary) decline in the SHSE index and preceded the peak in warrant prices that occurred in June 2007 labelled "A" in Figure 6. The second largest fixed effect is labelled "b" and is from August 15, 2007, when the European and Japanese central banks announced the provision of additional liquidity to the financial system in response to the developing financial crisis and the People's Bank of China (PBOC) announced an increase in the required reserve ratio by 0.5% to 12%. Figure 2 reveals that this fixed effect was also associated with a sharp (though temporary)

[17] The prices of Hualing and Zhongji are similar (see Figure 1, Panel A), and Jiafei and Zhanghang expired during the summer or early fall of 2007 and thus do not have prices after the summer of 2007.
[18] These fixed effects are from the model whose coefficient estimates are reported in Table 4, Panel B. These estimates are computed using data on trades in all 18 put warrants during the entire period when the warrants traded.

decline in the SHSE index. There are several other large fixed effects for dates shortly before August 15, the largest of which is on the same date (July 10) that both Moody's and S&P announced a mass downgrading of the ratings of subprime mortgaged back securities. This set of fixed effects is followed by the spike in warrant prices labelled B in Figure 6.

The third largest fixed effect labelled "c" is from September 25, 2007 when the PBOC announced another change in the reserved ratio, Deutsche Bank announced a large decline in profit due to the subprime mortgage crises, and there was news that the U.S. Federal Reserve might further reduce the Federal Funds rate to avoid a possible recession. Figure 6 reveals that this large fixed effect is followed by the spike in warrant prices labelled "C". Then there is another large fixed effect labelled "d" on November 26, 2007, when the PBOC announced another change in the reserve requirement. Fixed effects on some nearby dates were also large, and the SHSE indexed dipped. This fixed effect precedes the spike in warrant prices labelled "D" in Panel B.

Thus, each of the significant spikes in warrant prices labelled "A", "B", "C", and "D" in Figure 6 is preceded by a fixed effect labelled "a", "b", "c", or "d". Each of these fixed effects coincides with a release of significant news and a (temporary) decline in the SHSE index that may have brought additional attention to the put warrants, because as we pointed out above during 2007 the put warrants were the only financial instruments with payoffs negatively related to stock prices that were available for trading.[19] While the importance of the additional shocks "b", "c", and "d" is less clear than the importance of the tax change—for example, we do not find anything like the 12-fold increase in turnover caused by the tax change—the pattern of spikes in warrant prices occurring several days to a week or so after the shocks to trading

[19] The news releases may have been caused by the stock market declines. For example, the PBOC announcements may have been in reaction to market events rather than the cause of market events.

captured by the fixed effects is similar to what happened following the tax change, and exactly what one would expect if feedback trading drives warrant prices. These additional market shocks appear to have contributed to the extended life of the put warrants bubble.

7. Conclusion

We show how positive feedback trading based on investors' experienced returns interacted with the May 30, 2007 tripling of the transaction tax imposed on stock trades to drive the Chinese put warrants bubble. The tax change appears to have been necessary for the bubble—feedback trading existed through the entire period of warrant trading, but did not create a bubble until the tax change precipitated it.

The results regarding feedback trading are consistent with extrapolative models such as Barberis et al (2018) because past returns play an important role in such models. Our finding that the precipitating event was important is also consistent with the Barberis et al (2018) model, as in that model bubbles are started by exogenous shocks that interact with investors' extrapolative beliefs to create bubbles, consistent with what we find during the Chinese put warrants bubble.

We revisit the panel regression specifications that Xiong and Yu (2011) use to explain put warrant prices during the bubble and find that estimates of the trading volume due to positive feedback based on investors' experienced returns explains the bubble very well and drive out the turnover and volatility variables that Xiong and Yu (2011) use to provide support for the resale option theory. The finding that volatility is no longer related to returns once we include measures of feedback trading in the regressions is inconsistent with the resale option theory because volatility plays a central role in that theory.

We also find that changes in feedback trading volume explain warrant returns during the bubble, which is additional evidence consistent with the implications of extrapolative models of asset price bubbles.

Appendix. Estimates of the warrant buying due to positive feedback trading

We estimate the warrant trading volume due to positive feedback from investors' experienced returns using the procedure described below. We describe it in the context of the conventional and stratified versions of the Cox hazard rate model, and we use a similar approach for the fixed-effects logistic regression model.

We are interested in the impact of the variables *RetLag*1, *I*(*RetLag*1 > 0), *RetLag*2, *I*(*RetLag*2 > 0), *OtherRetLag*1, *I*(*OtherRetLag*1 > 0), *OtherRetLag*2, *I*(*OtherRetLag*2 > 0), *UnrealizedRet*, and *I*(*UnrealizedRet* > 0), which capture the investors' own return experience. For each investor *i*, warrant *k*, and date *t* we denote the vector of these variables by $x_{i,k,t}^{P}$; the coefficients on these variables are β^P. Similarly, we use $x_{i,k,t}^{M}$ to denote the vector formed from the market return variables $MktRet1Day_{k,t}$, $MktRet4Day_{k,t}$, and $MktRet3Week_{k,t}$, and use β^M to denote the vector of coefficients on these variables. All the other controls, including the fixed effects, are denoted by $x_{i,k,t}^{Z}$ with coefficient vector β^Z. Let $\beta = (\beta^P; \beta^M; \beta^Z)$ and $x = (x^P; x^M; x^Z)$. Then the hazard function for the standard Cox hazard model equation (1) can be restated as

$$\lambda_{i,k,t}(\tau) = \lambda(\tau) \times e^{x'_{i,k,t}\beta} = \lambda(\tau) \times e^{x_{i,k,t}^{P}{}'\beta^P + x_{i,k,t}^{M}{}'\beta^M + x_{i,k,t}^{Z}{}'\beta^Z}. \quad \text{(A.1)}$$

On calendar date *t*, we are interested in the expected trading volume in warrant *k* due to investor *i* who has not held warrant *k* for τ trading days after finishing his last transaction cycle in warrant *k*, given investor *i*'s state at the close of trading on the previous trading date *t* −1. We are also interested in the part of volume that can be attributed to the investor's experienced returns $x_{i,k,t}^{P}$. In our model, the state is represented by $x_{i,k,t}$ which contains lagged variables. Let $buy_{i,k,t}$ be an indicator variable that equals one if investor *i* buys warrant *k* on date *t*. The expected trading volume $V_{i,k,t}$ can be decomposed into

$$E(V_{i,k,t} | x_{i,k,t}) = \Pr[buy_{i,k,t} = 1 \text{ on date } t | x_{i,k,t}] \times E(V_{i,k,t} | buy_{i,k,t} = 1 \text{ on date } t, x_{i,k,t}). \quad \text{(A.2)}$$

The conditioning on no reentry before date *t* is suppressed for simplicity of notation. The first term, denoted by $\hat{P}_{i,k,t} = \Pr[buy_{i,k,t} = 1 \text{ on date } t | x_{i,k,t}]$, represents the probability of investor *i*'s reentry into warrant *k* on date *t* given his previous state and is given by the Cox hazard model. The second term is estimated as the average reentry trading volume averaged across investor *i*'s trades in all warrants on all dates before date *t*; that is, $E\left(V_{i,k,t}\middle|buy_{i,k,t} = 1\ in\ date\ t, x_{i,k,t}\right)$ is estimated as

$$E\left(V_{i,k,t}\middle|buy_{i,k,t} = 1\ on\ date\ t, x_{i,k,t}\right) = \frac{\sum_{\kappa\in K}\sum_{s=1}^{t-1} V_{i,\kappa,s}\times I(buy_{i,\kappa,s}=1)}{\sum_{\kappa\in K}\sum_{s=1}^{t-1} I\left(buy_{i,\kappa,s}=1\right)}, \quad \text{(A.3)}$$

where $I(buy_{i,k,t} = 1)$ is an indicator variable that equals one if the volume traded on date *t* is the beginning of a new transaction cycle for investor *i* in warrant *k* and *K* is the set of the five warrants of interest.

If the past private performance has no impact on investors' reentry decisions, then the expected trading volume without positive feedback from investors' experienced returns would be

$$\bar{E}\left(V_{i,k,t}\middle|x_{i,k,t}\right) = \bar{P}_{i,k,t} \times E\left(V_{i,k,t}\middle|buy_{i,k,t} = 1 \text{ on date } t, x_{i,k,t}\right). \quad \text{(A.5)}$$

where $\bar{P}_{i,k,t}$ is the probability of reentry assuming that there was no positive feedback. Then the difference

$$\begin{aligned} D_{i,k,t} &= E\left(V_{i,k,t}\middle|x_{i,k,t}\right) - \bar{E}\left(V_{i,k,t}\middle|x_{i,k,t}\right) \\ &= (\hat{P}_{i,k,t} - \bar{P}_{i,k,t}) \times E\left(V_{i,k,t}\middle|buy_{i,k,t} = 1 \text{ on date } t\right) \end{aligned} \quad \text{(A.6)}$$

is the part of the trading volume that is due to positive feedback from investors' experienced returns. Then for each of the five warrants, on each calendar date *t*, we sum the differences $D_{i,k,t}$ over all existing one-cycle investors *i*, yielding an estimate of the total trading volume of one-cycle investors that is due to positive feedback from own return, that is,

$$D_{k,t} = \sum_{i\in I} D_{i,k,t},$$

where *I* is the set of one-cycle investors. We carry out similar calculations for the two-cycle investors and the inexperienced investors.

The first term in Equation (A.2) is calculated from our models using the following approach (see also Cameron and Trivedi 2005). Suppose the distribution of duration lengths follows a nonnegative random variable *T* with cumulative probability function $F(\tau)$ and density function $f(\tau)$, such that $f(\tau) = \frac{dF(\tau)}{d\tau}$. The survival function is

$$S(\tau) = \Pr[T > \tau] = 1 - F(\tau).$$

By definition, the hazard rate function $\lambda(\tau)$ in a continuous-time setting is the probability density of event occurrence within duration time $[\tau, \tau + \Delta\tau)$, conditional on the event not having occurred prior to time τ; more formally,

$$\lambda(\tau|\boldsymbol{x}) \equiv \lim_{\Delta\tau\to 0} \frac{\Pr[\tau \le T < \tau + \Delta\tau | T \ge \tau, \boldsymbol{x}]}{\Delta\tau} = \frac{f(\tau|\boldsymbol{x})}{S(\tau|\boldsymbol{x})}.$$

The cumulative hazard function is defined as

$$\Lambda(\tau|\boldsymbol{x}) = \int_0^\tau \lambda(s|\boldsymbol{x})ds.$$

After some algebra, it can be shown that

$$\Lambda(\tau|\boldsymbol{x}) = -\ln S(\tau|\boldsymbol{x}).$$

For discrete-time data, which is the case at hand, with time interval $[\tau_{a-1}, \tau_a), a = 1,2,\cdots,A$, the discrete-time hazard rate function

$$\lambda^d(\tau_a|\boldsymbol{x}) \equiv \Pr[\tau_{a-1} \le T < \tau_a | T \ge \tau_{a-1}, \boldsymbol{x}(\tau_{a-1})]$$
$$= \frac{s(\tau_{a-1}|\boldsymbol{x}) - s(\tau_a|\boldsymbol{x})}{s(\tau_{a-1}|\boldsymbol{x})},$$

where $S(\tau|\boldsymbol{x})$ is the survival function in the continuous proportional hazard model. Since

$$S(\tau|\boldsymbol{x}) = \exp\left[-\int_0^\tau \lambda(s|\boldsymbol{x})ds\right],$$

then with some algebra, the discrete-time hazard function becomes

$$\lambda^d(\tau_a|\boldsymbol{x}) = 1 - \exp\left[-\int_{\tau_{a-1}}^{\tau_a} \lambda(s|\boldsymbol{x})ds\right],$$

where $\lambda(t)$ is the continuous hazard rate function. Assuming that the covariates are constant within the time interval,

$$\lambda\big(\tau|\boldsymbol{x}(\tau)\big) = \lambda_0(\tau) \times \exp[\boldsymbol{x}(\tau_{a-1})\beta]$$

for all τ in $[\tau_{a-1}, \tau_a)$. Then the discrete-time hazard function becomes

$$\lambda^d(\tau_a|\boldsymbol{x}) = 1 - \exp\left[-\exp[\boldsymbol{x}(\tau_{a-1})\beta] \times \int_{\tau_{a-1}}^{\tau_a} \lambda_0(s)ds\right].$$

This is for the standard Cox hazard rate model.

For the stratified Cox model, following Ridder and Tunalı (1999), after obtaining the estimated coefficients $\hat{\beta}$ from the stratified partial likelihood function, a nonparametric estimator of the continuous-time hazard rate function can be derived using Breslow’s (1972) approach:

$$\int_{\tau_{a-1}}^{\tau_a} \hat{\lambda}_0(s)ds = \frac{d_a}{\sum_{j\in R(\tau_a)} \exp\big(\boldsymbol{x}_j\beta\big)} \triangleq \lambda_a,$$

where the summation is over the individuals in the risk set at time τ_a, that is, the set of individuals whose lengths of durations are no shorter than τ_a. By definition, the estimated probability of failure during $[\tau_{a-1}, \tau_a)$ (i.e. date *t*) given that the subject has survival at τ_{a-1} is

$$\begin{aligned}\hat{P}_{i,k,t} &= \Pr\left[buy_{i,k,t} = 1 \; during \; [\tau_{a-1}, \tau_a) \middle| x(\tau_{a-1})\right] \\ &= \Pr[\tau_{a-1} \leq T < \tau_a | T \geq \tau_{a-1}, x(\tau_{a-1})] = \lambda^d(\tau|x) \\ &= 1 - \exp\left[-\exp\left[x(\tau_{a-1})\hat{\beta}\right] \times \lambda_a\right].\end{aligned}$$

For both the standard and stratified Cox models we derive the first term in Equation (A.5) under the assumption of no positive feedback from own returns by setting all the coefficients on the variables measuring investors' experienced returns to zero, i.e. we set $\beta^P = 0$, and then recalculate the probability using the above formula

$$\bar{P}^P_{i,k,t} = 1 - \exp\left[-\exp\left[x(\tau_{a-1})(0; \hat{\beta}^M; \hat{\beta}^Z)\right] \times \lambda_a\right].$$

We then use equation (A.6) above to compute the trading volume due to feedback from investors' experienced returns.

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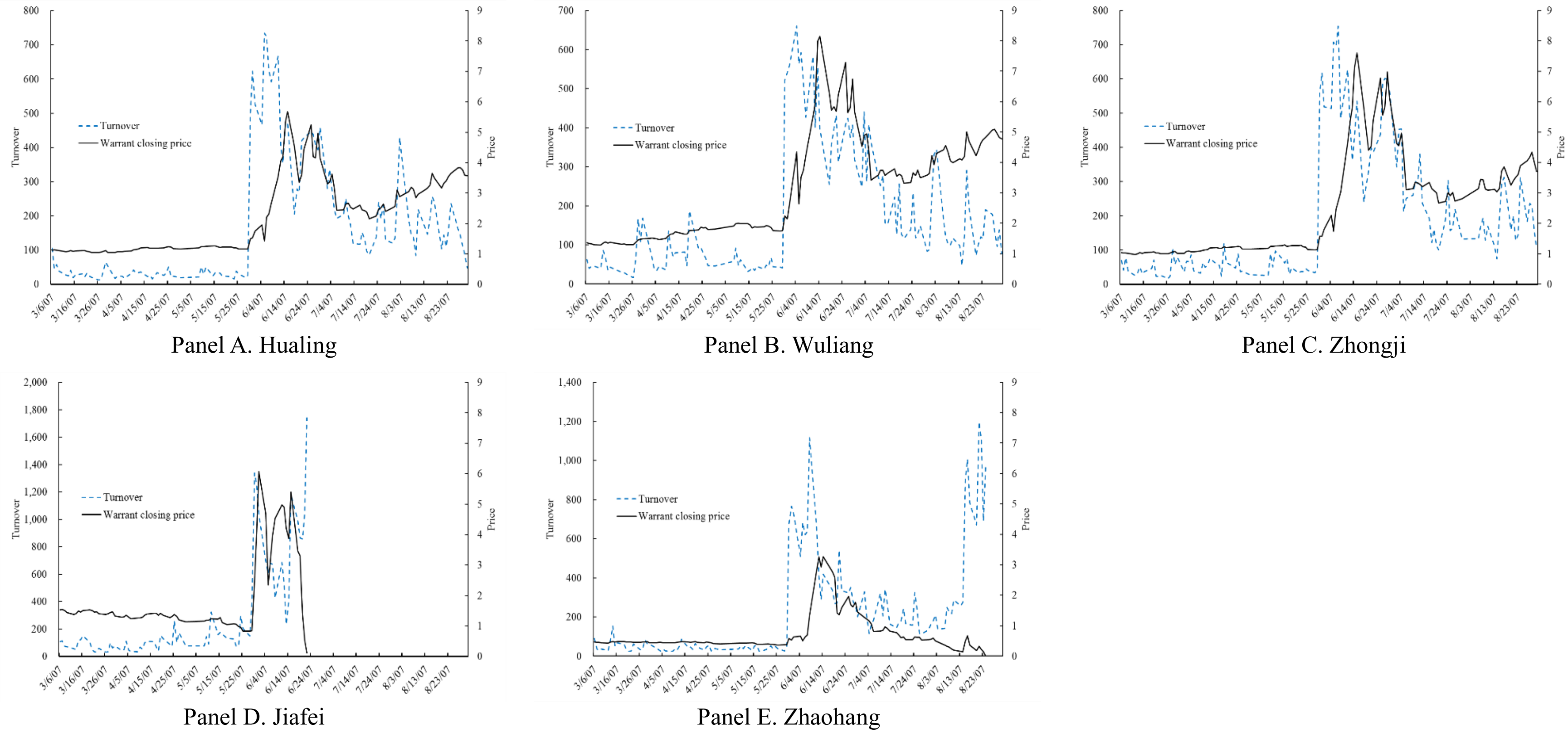
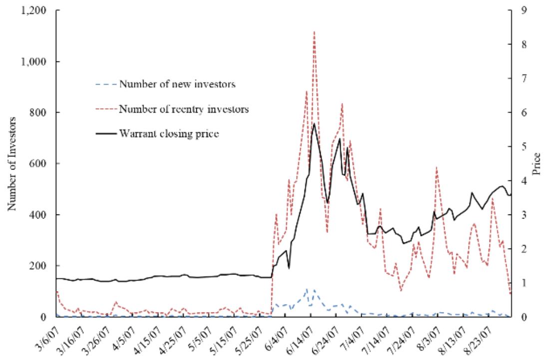
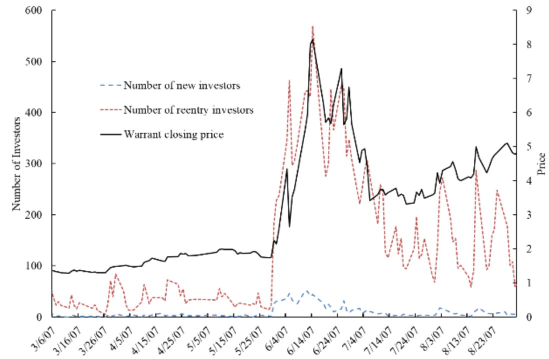


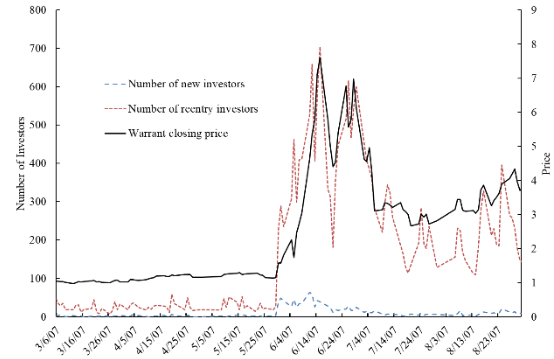
Figure 1. Price and turnover of 5 put warrants. Daily closing price (solid black line, right-hand axis) and turnover (dotted blue line, left-hand axis) of the five put warrants that traded both before and after the tripling of the stock transaction tax that took effect on May 30, 2007. The series are shown from March 2007 to August 2007, a six-month window approximately centered on May 30, 2007. The five panels show that for all five put warrants the turnover jumped sharply on May 30 and prices rose sharply either on or shortly after May 30.



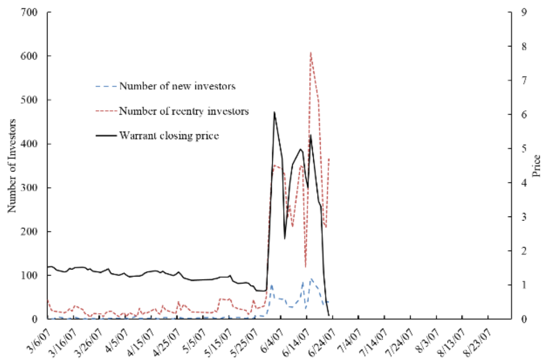
Panel A. Hualing



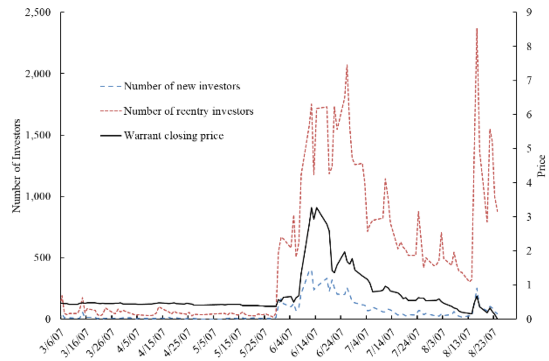
Panel B. Wuliang



Panel C. Zhongji

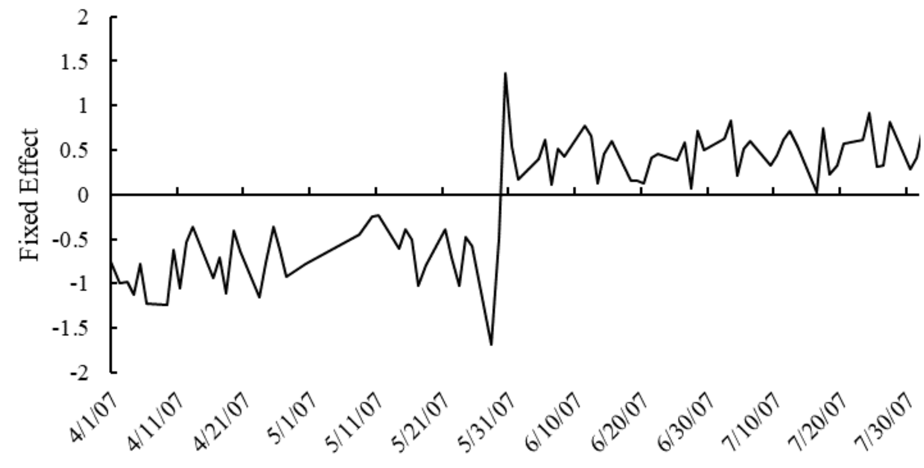


Panel D. Jiafei

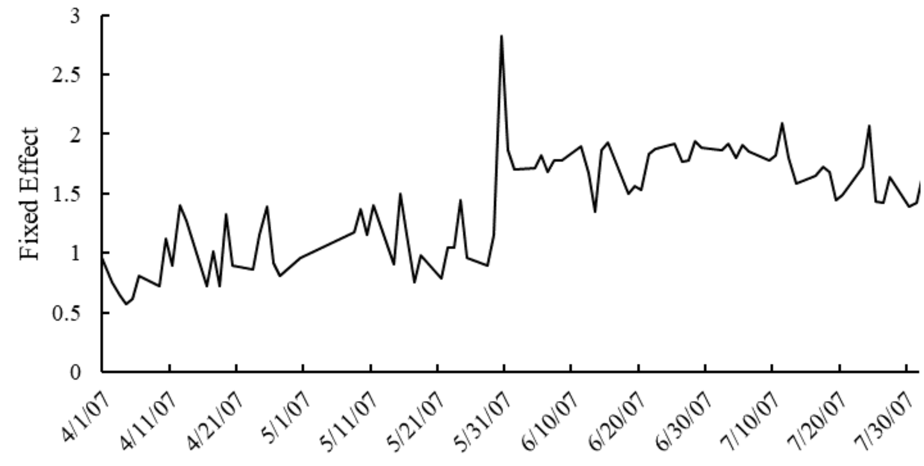


Panel E. Zhaohang

Figure 2. Price of and number of investors buying each of 5 put warrants. Each panel shows the daily closing price (black line, right-hand axis), the number of new investors (dashed blue line, left-hand axis), and the number of returning investors (dotted red line, left-hand axis) on each date for the five put warrants that traded both before and after the tripling of the transaction tax on May 30, 2007. A new investor in warrant *k* on date *t* is one who has not previously traded any warrant, while a returning investor is one who has previously traded at least one warrant. The five panels show that for all five put warrants the numbers of both new and returning investors jumped sharply on May 30.



Panel A. One-cycle investors



Panel B. Two-cycle investors

Figure 3. Date fixed effects from the positive feedback regressions for two groups of investors. Calendar-date fixed effects from the stratified Cox regressions reported in Table IV Panel B that use investors' previous warrant returns to predict reentry into the warrant market. The two panels show the fixed effects from two different regressions estimated using investors who have previously completed one and two or more transaction cycles. The fixed effects are shown for a four-month window approximately centered on May 30, 2007, the date when the stock transaction tax was tripled.

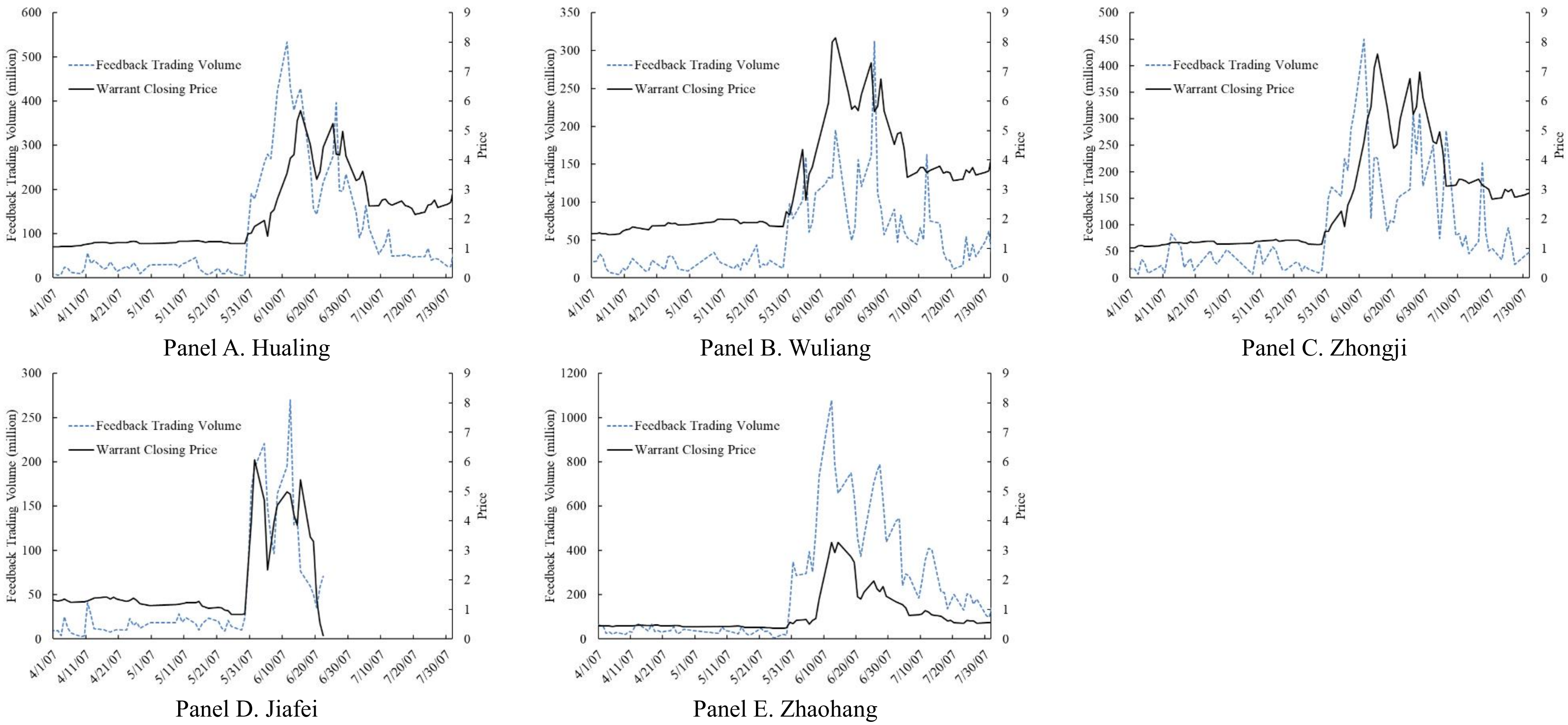


Figure 4. Estimates of trading volume due to positive feedback trading. Estimates of trading volume due to positive feedback trading are shown for the five warrants that traded before and after May 30, 2007. We first use the estimates of the stratified Cox regressions reported in Table 4 Panel B to compute for each investor, warrant, and date the probability that the investor reenters the warrant market. We then recompute these probabilities after setting the coefficients on the variables measuring the investors' own past returns to zero. For each investor, warrant, and date the estimate of the volume due to positive feedback trading is the difference in probabilities multiplied by the investor's previous average trade size when the investor starts a new transaction cycle. For each warrant and date these estimates are summed across investors, yielding estimates of the trading volume due to positive feedback trading of the customers of the brokerage firm that provided the data. Then, these estimates are scaled up to the market level by the ratio of total market trading volume to the trading volume of the brokerage customers. Each panel displays the total estimated feedback trading volume of the returning investors (dashed blue line, left-hand axis) and the warrant daily closing price (solid black line, right-hand axis).

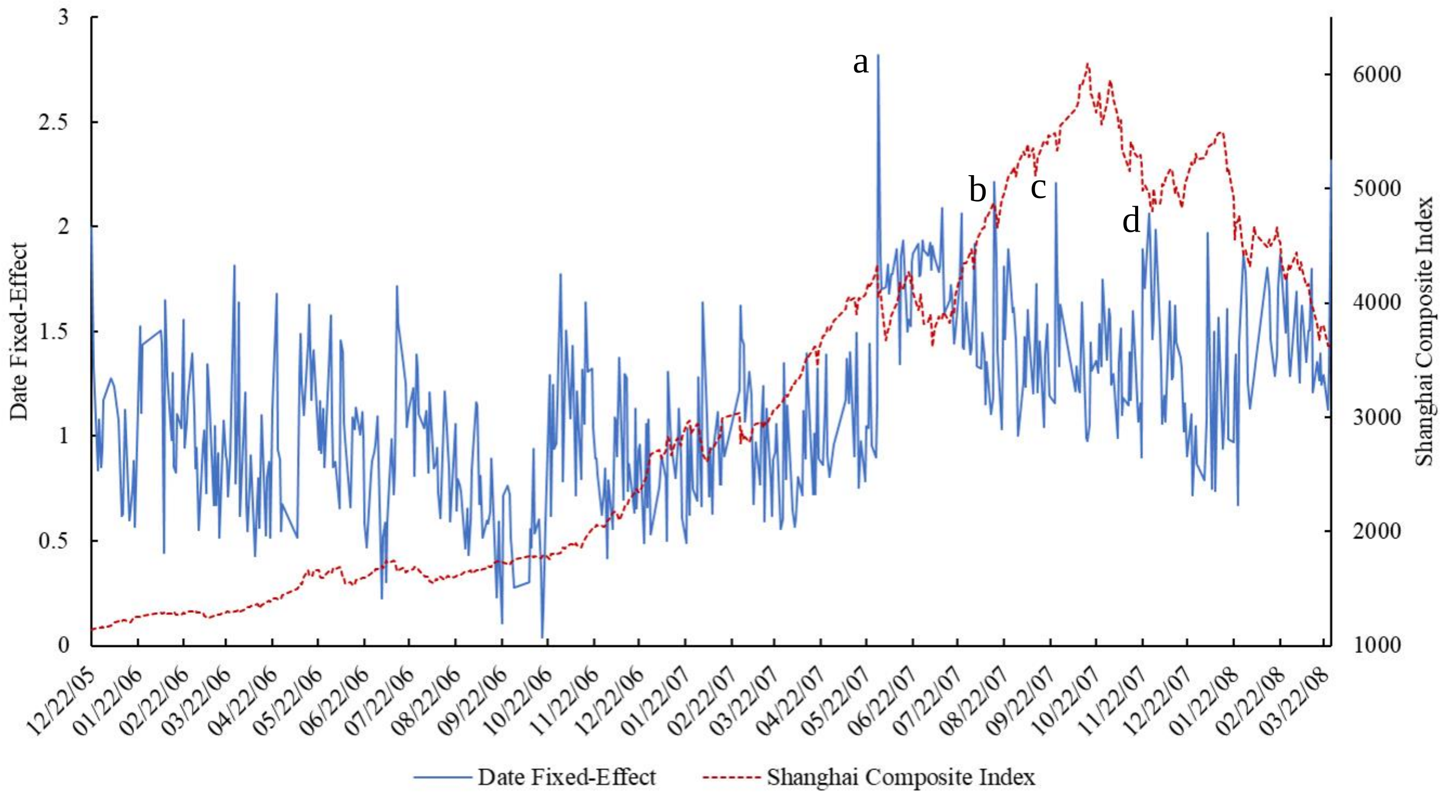


Figure 5. Estimated date fixed effects and SHSE composite index The figure shows the estimated date fixed effects from the stratified Cox hazard model estimated using the sample of two-cycle investors (blue line, left axis) for which coefficient estimates are reported in Table 2, Panel B and the SHSE composite index (dashed red line, right axis). The label "a" indicates the date of the May 30, 2007 transaction tax change, "b" indicates August 15, 2007 when the European and Japanese central banks provided additional liquidity to support the market and the PBOC increased the required reserve ratio to 12%, "c" is September 25, 2007 when the PBOC increased requirement reserve ratio to 12.5%, Deutsche Bank announced a large decline in profit due to the subprime mortgage crises, and there was news that the U.S. Federal Reserve might further reduce the Federal Funds rate to avoid a possible recession, and "d" indicates November 26, 2007 when the PBOC increased the required reserve ratio to 13.5%.

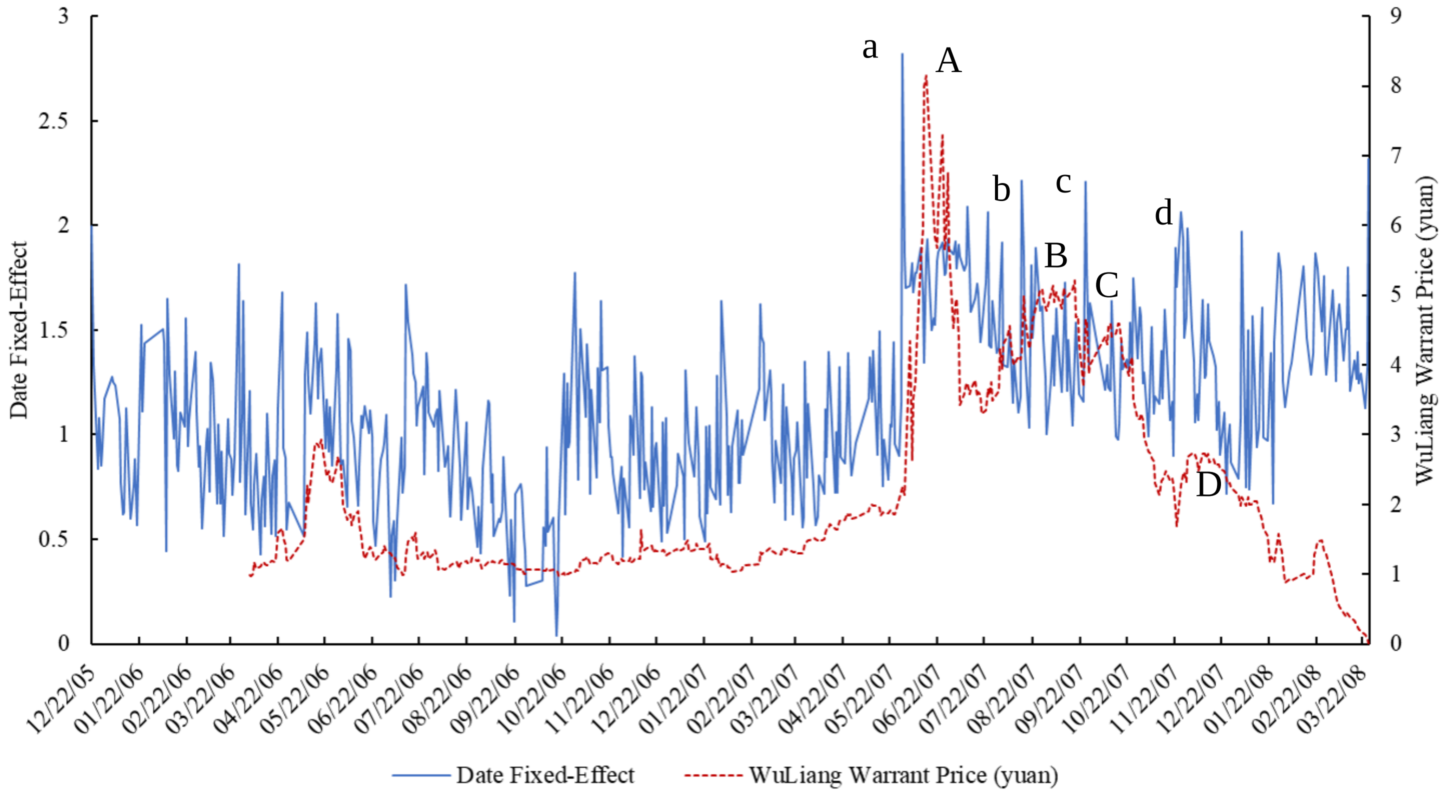


Figure 6. Estimated date fixed effects and prices of the Wuliang put warrant The figure shows the estimated date fixed effects from the stratified Cox hazard model estimated using the sample of two-cycle investors (blue line, left axis) for which coefficient estimates are reported in Table 2, Panel B and the prices of the Wuliang put warrant (dashed red line, right axis). The label "a" indicates the fixed effect on the date of the May 30, 2007 transaction tax change, "b" indicates August 15, 2007 when the European and Japanese central banks provided additional liquidity to support the market and the PBOC increased the required reserve ratio to 12%, "c" is September 25, 2007 when the PBOC increased requirement reserve ratio to 12.5%, Deutsche Bank announced a large decline in profit due to the subprime mortgage crises, and there was news that the U.S. Federal Reserve might further reduce the Federal Funds rate to avoid a possible recession, and "d" indicates November 26, 2007 when the PBOC increased the required reserve ratio to 13.5%. "A", "B", "C", and "D" indicate the subsequent spikes in the warrant price.

Table 1

Summary information and statistics for the 18 put warrants

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

Panel A: Market information

	Trading period			Warrant information at beginning of trading				Warrant information at end of trading			
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 of 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 of brokerage investor trading

		Completed cycles		Uncompleted cycles	
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 2

Statistics related to the bubble during periods before and after May 30, 2007

Time-series average and maximum of daily turnover, bubble size, and volatility of the 18 put warrants during periods before and after May 30, 2007, the date of the tripling of the transaction tax. Daily turnover is daily trading volume divided by the number of outstanding warrants, bubble size is the warrant price minus the Black-Scholes value, and the volatility is computed from intraday 5-minute warrant returns, and then annualized. Panel A reports these statistics for the 12 warrants that expire before May 30, 2007, Panel B reports them for the five warrants that traded both before and after May 30, for the period before May 30, and Panel C reports them for the 6 warrants that traded after May 30, for the period after May 30.

Panel A. 12 warrants that expired before May 30, 2007

	Daily turnover (percent)		Bubble Size		Volatility (percent)	
Name	Average	Maximum	Average	Maximum	Average	Maximum
Wanke	66	547	0.309	0.659	116	2327
Shenneng	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
Yuanshui	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. Five warrants that expired after May 30, 2007, for the period before May 30, 2007

	Daily turnover (percent)		Bubble Size		Volatility (percent)	
Name	Average	Maximum	Average	Maximum	Average	Maximum
Jiafei	74	415	1.188	2.344	68	359
Zhaohang	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. Six warrants that expired after May 30, 2007, for the period after May 30, 2007

	Daily turnover (percent)		Bubble Size		Volatility (percent)	
Name	Average	Maximum	Average	Maximum	Average	Maximum
Jiafei	814	1741	3.410	6.070	729	1623
Zhaohang	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 3
Distribution of investor holding periods
The table shows the frequencies, percentages and cumulative percentages of lengths of the investors' warrant holding periods. For the purposes of this table, a warrant holding period is defined similarly to the transaction cycles we use in the main analyses. Starting from owning zero shares of warrant *k*, the holding period in warrant *k* begins with the first trade of the set of trades that build up a positive position in warrant *k*, and then ends once the investor finishes liquidating the position and does not own any shares of warrant *k*. The holding period lengths in this table differ from the transaction cycle lengths discussed elsewhere because elsewhere we combine an investor's trades on a given day into a single transaction cycle and for this table we do not.

Holding period length	Frequency	Proportion	Cumulative Proportion
Less than 5 minutes	76,512	0.1039	0.1039
5 - 10 minutes	63,031	0.0856	0.1895
10 minutes - 1 hour	228,910	0.3109	0.5004
1 hour -1 day	180,243	0.2448	0.7452
1 - 2 days	39,176	0.0532	0.7984
2 - 5 days	80,701	0.1096	0.9080
5 - 10 days	27,764	0.0377	0.9457
10 - 20 days	17,162	0.0233	0.9691
Longer than 20 days	22,758	0.0309	1.0000
Total transaction cycles	736,258		

Table 4
Positive feedback regressions for three groups of investors
Results of proportional hazard regressions explaining the reentry of investors who have previously traded put warrants using the investors' previous transaction cycle returns for three groups of investors. Panel A reports the estimated coefficients and p-values for tests of the hypotheses that the coefficients are zero for the investors using the standard Cox model. Panel B reports the corresponding results for the stratified ones. For each warrant and date, the three groups of investors are those who have previously completed one and two or more transaction cycles in the warrant, and those who have completed at least one transaction cycles in other warrants. The unit of observation is an investor-warrant-date, and for investor i in warrant k on date t the left-hand side variable takes the value one if investor i begins a new transaction cycle in warrant k on date t, and otherwise is zero. The main explanatory variables are $RetLag1_{i,k,t}$, investor i's return on the most recent transaction cycle in warrant k before date t, $RetLag2_{i,k,t}$, the average return of the transaction cycles before the most recent cycle, dummy variables I($RetLag1_{i,k,t}$ >0) and I($RetLag2_{i,k,t}$ >0) that take the value one if the return is positive, and variables of investor i's transaction cycle returns and unrealized returns in warrants other than warrant k, $OtherRetLag1_{i,k,t}$, $OtherRetLag2_{i,k,t}$, $UnRealizedRet_{i,k,t}$, and the corresponding dummies that are defined in the a similar way. The control variables are $MktRet1Day_{k,t}$, $MktRet4Day_{k,t}$, $MktRet3Week_{k,t}$, the lagged daily market return of warrant k on date t, $TurnoverDay_{k,t}$, $Turnover4Day_{k,t}$, $Turnover3Week_{k,t}$, the lagged market trading volume in warrant k on date t, divided by number of warrants outstanding on date t, and $Fundamental_{k,t}$, a measure of the moneyness of warrant k on date t, which is defined in the text. All specifications include maturity, warrant and date fixed effects.

Panel A. Results for the Cox hazard rate model

	One-cycle investors		Two-cycle investors		Inexperienced investors	
	(1)		(2)		(3)	
Explanatory variable	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
$RetLag1_{i,k,t}$	0.4313	<0.0001	0.5258	<0.0001		
$I(RetLag1_{i,k,t} > 0)$	0.3412	<0.0001	0.2353	<0.0001		
$RetLag2_{i,k,t}$			0.1394	<0.0001		
$I(RetLag2_{i,k,t} > 0)$			0.0233	<0.0001		
$OtherRetLag1_{i,k,t}$	0.1536	<0.0001	0.2310	<0.0001	0.3109	<0.0001
$I(OtherRetLag1_{i,k,t} > 0)$	0.1082	<0.0001	0.0103	0.0219	0.2412	<0.0001
$NoOtherRetLag1_{i,k,t}$	0.0233	0.1425	0.0277	0.0112	-0.1158	<0.0001
$OtherRetLag2_{i,k,t}$	0.0521	0.1152	0.3885	<0.0001	0.2547	<0.0001
$I(OtherRetLag2_{i,k,t} > 0)$	-0.0646	<0.0001	-0.0548	<0.0001	-0.2893	<0.0001
$NoOtherRetLag2_{i,k,t}$	-0.3201	<0.0001	-0.2926	<0.0001	-1.0768	<0.0001
$UnRealizedRet_{i,k,t}$	0.2354	<0.0001	0.2627	<0.0001	0.3612	<0.0001
$I(UnRealizedRet_{i,k,t} > 0)$	0.1832	<0.0001	0.1486	<0.0001	0.2512	<0.0001
$NoUnRealizedRet_{i,k,t}$	-0.0299	0.0132	0.0650	<0.0001	-0.4160	<0.0001
$MktRet1Day_{k,t}$	0.1730	<0.0001	0.1170	<0.0001	0.7447	<0.0001
$MktRet4Day_{k,t}$	0.1067	<0.0001	0.0793	<0.0001	0.1126	<0.0001
$MktRet3Week_{k,t}$	0.0820	<0.0001	0.0639	<0.0001	0.0689	<0.0001
$TurnoverDay_{k,t}$	0.0006	<0.0001	0.0002	<0.0001	0.0011	<0.0001
$Turnover4Day_{k,t}$	-0.0003	0.0134	0.0001	0.2051	-0.0003	0.0041
$Turnover3Week_{k,t}$	-0.0004	0.0302	-0.0004	<0.0001	0.0005	0.0018

$Fundamental_{k,t}$	-2.4471	<0.0001	-2.4499	<0.0001	-1.4357	<0.0001
Maturity fixed effects	Yes		Yes		Yes	
Warrant fixed effects	Yes		Yes		Yes	
Date fixed effects	Yes		Yes		Yes	
No. of observations	8,011,312		10,116,045		55,390,101	

Panel B. Results for the stratified Cox model

	One-cycle investors		Two-cycle investors		Inexperienced investors	
	(1)		(2)		(3)	
Explanatory variable	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
$RetLag1_{i,k,t}$	1.0323	<0.0001	0.6412	<0.0001		
$I(RetLag1_{i,k,t} > 0)$	0.2946	<0.0001	0.2239	<0.0001		
$RetLag2_{i,k,t}$			0.4107	<0.0001		
$I(RetLag2_{i,k,t} > 0)$			0.0979	<0.0001		
$OtherRetLag1_{i,k,t}$	0.1486	0.0015	0.1672	<0.0001	0.0051	0.9360
$I(OtherRetLag1_{i,k,t} > 0)$	0.1417	<0.0001	0.0614	<0.0001	0.3292	<0.0001
$NoOtherRetLag1_{i,k,t}$	-0.2127	<0.0001	0.1103	<0.0001	1.8237	<0.0001
$OtherRetLag2_{i,k,t}$	0.2549	0.0135	0.1432	0.0068	0.1907	0.1459
$I(OtherRetLag2_{i,k,t} > 0)$	0.1215	<0.0001	0.0737	<0.0001	0.3329	<0.0001
$NoOtherRetLag2_{i,k,t}$	0.4897	<0.0001	0.1513	<0.0001	2.2125	<0.0001
$UnRealizedRet_{i,k,t}$	0.3110	<0.0001	0.2430	<0.0001	0.3550	0.0018
$I(UnRealizedRet_{i,k,t} > 0)$	0.1301	<0.0001	0.0737	<0.0001	0.1277	0.0007
$NoUnRealizedRet_{i,k,t}$	0.4286	<0.0001	0.3213	<0.0001	1.6049	<0.0001
$MktRet1Day_{k,t}$	0.0495	0.3783	0.0620	0.2614	0.8879	<0.0001
$MktRet4Day_{k,t}$	0.0876	0.0014	0.0798	0.0023	0.0316	0.5128
$MktRet3Week_{k,t}$	0.0727	0.0001	0.0620	<0.0001	0.0625	0.1259
$TurnoverDay_{k,t}$	0.0008	<0.0001	0.0003	0.0002	0.0011	<0.0001
$Turnover4Day_{k,t}$	-0.0003	0.1341	<0.0001	0.8593	0.0005	0.0457
$Turnover3Week_{k,t}$	-0.0003	0.3781	-0.0005	0.0556	0.0008	0.0324
$Fundamental_{k,t}$	-2.3735	0.0004	-2.5882	<0.0001	-0.3207	0.4565
Maturity fixed effects	Yes		Yes		Yes	
Warrant fixed effects	Yes		Yes		Yes	
Date fixed effects	Yes		Yes		Yes	
No. of observations	8,011,312		10,116,045		55,390,101	

Table 5
Logistic regressions for three groups of investors
Results of logistic regressions explaining the reentry of investors who have previously traded put warrants using the investors' previous transaction cycle returns for three groups of investors. For each warrant and date, the three groups of investors are those who have previously completed one and two or more transaction cycles in the warrant, and those who have completed at least one transaction cycles in other warrants. The unit of observation is an investor-warrant-date, and for investor i in warrant k on date t the left-hand side variable takes the value one if investor i begins a new transaction cycle in warrant k on date t, and otherwise is zero. The main explanatory variables are $RetLag1_{i,k,t}$, investor i's return on the most recent transaction cycle in warrant k before date t, $RetLag2_{i,k,t}$, the average return of the transaction cycles before the most recent cycle, dummy variables I($RetLag1_{i,k,t}$ >0) and I($RetLag2_{i,k,t}$ >0) that take the value one if the return is positive, and variables of investor i's transaction cycle returns and unrealized returns in warrants other than warrant k, $OtherRetLag1_{i,k,t}$, $OtherRetLag2_{i,k,t}$, $UnRealizedRet_{i,k,t}$, and the corresponding dummies that are defined in the a similar way. The control variables are $MktRet1Day_{k,t}$, $MktRet4Day_{k,t}$, $MktRet3Week_{k,t}$, the lagged daily market return of warrant k on date t, $TurnoverDay_{k,t}$, $Turnover4Day_{k,t}$, $Turnover3Week_{k,t}$, the lagged market trading volume in warrant k on date t, divided by number of warrants outstanding on date t, and $Fundamental_{k,t}$, a measure of the moneyness of warrant k on date t, which is defined in the text. All the regressions include maturity, warrant, date and duration fixed effects.

	One-cycle investors		Two-cycle investors		Inexperienced investors	
	(1)		(2)		(3)	
Explanatory variable	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
$RetLag1_{i,k,t}$	0.8507	<0.0001	0.9990	<0.0001		
$I(RetLag1_{i,k,t} > 0)$	0.3491	<0.0001	0.2526	<0.0001		
$RetLag2_{i,k,t}$			0.3181	<0.0001		
$I(RetLag2_{i,k,t} > 0)$			0.0517	<0.0001		
$OtherRetLag1_{i,k,t}$	0.2082	<0.0001	0.3338	<0.0001	-0.0286	0.3448
$I(OtherRetLag1_{i,k,t} > 0)$	0.1276	<0.0001	0.0261	<0.0001	0.3784	<0.0001
$NoOtherRetLag1_{i,k,t}$	-0.1306	<0.0001	0.0460	0.0225	0.1163	<0.0001
$OtherRetLag2_{i,k,t}$	0.0702	0.3846	0.2113	0.0001	0.4872	<0.0001
$I(OtherRetLag2_{i,k,t} > 0)$	-0.0331	0.0489	0.0245	0.0014	-0.0973	<0.0001
$NoOtherRetLag2_{i,k,t}$	0.2991	<0.0001	-0.0803	<0.0001	-0.2483	<0.0001
$UnRealizedRet_{i,k,t}$	0.5498	<0.0001	0.4573	<0.0001	0.1863	<0.0001
$I(UnRealizedRet_{i,k,t} > 0)$	0.3663	<0.0001	0.2753	<0.0001	0.8026	<0.0001
$NoUnRealizedRet_{i,k,t}$	-0.0279	0.0629	-0.0004	0.9566	-0.0231	0.1000
$MktRet1Day_{k,t}$	0.6271	<0.0001	0.4646	<0.0001	1.4419	<0.0001
$MktRet4Day_{k,t}$	0.1653	<0.0001	0.0939	<0.0001	0.5340	<0.0001
$MktRet3Week_{k,t}$	0.1061	<0.0001	0.0923	<0.0001	0.2390	<0.0001
$TurnoverDay_{k,t}$	0.0008	<0.0001	0.0004	<0.0001	0.0021	<0.0001
$Turnover4Day_{k,t}$	-0.0002	0.1285	0.0001	0.1230	-0.0002	0.0262
$Turnover3Week_{k,t}$	0.0005	0.0260	0.0004	0.0002	0.0005	0.0124
$Fundamental_{k,t}$	-0.1433	0.7402	-0.1235	0.5895	-0.1757	0.4352
Individual fixed effects	Yes		Yes		Yes	

Maturity fixed effects	Yes	Yes	Yes
Warrant fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Duration fixed effects	Yes	Yes	Yes
No. of observations	8,011,312	10,116,045	55,390,101

Table 6
Panel regressions explaining put warrant prices

Results of regressions of daily warrant closing prices on *Turnover*, *Volatility*, *Float* and a *TransactionTax* dummy using the zero-fundamental sample defined in Xiong and Yu (2011), which is the set of warrant-dates for which the Black-Scholes value is less than ¥0.005 (or for the cash settled Nanhang warrant if the settlement price will exceed the strike price even if the stock trades limit down every day until the expiration date). The zero-fundamental sample contains 863 observations, 42 of which are missing the value of *Volatility*. *Turnover* is market trading volume divided by the number of outstanding warrants, and then divided by 100, *Volatility* is computed from intraday 5-minute returns, and then annualized, *Float* is the daily total number of warrants outstanding, in billions, and the *TransactionTax* dummy takes the value one if the date is May 30, 2007 or later. Columns (1)-(4) of Panel A replicate the results in Xiong and Yu (2011), Table 5. Panel B reports results including the *TransactionTax* dummy. All of the regressions include maturity fixed effects. The *t*-statistics (in parentheses) are based on standard errors clustered by date to account for heteroscedasticity and correlation within a trading day.

Panel A: Without *TransactionTax* dummy

Explanatory Variable	(1)	(2)	(3)	(4)
Turnover	0.212			0.146
	(8.31)			(4.91)
Volatility		21.93		15.06
		(5.19)		(2.78)
Float			-0.301	-0.281
			(-11.38)	(-10.17)
Constant	-2.513	-3.185	0.323	-3.671
	(-6.40)	(-4.59)	(3.26)	(-4.71)
Maturity fixed effects	Yes	Yes	Yes	Yes
No. of observations	863	821	863	821
Adjusted R^2	0.181	0.177	0.209	0.322

Panel B: With *TransactionTax* dummy

Explanatory Variable	(5)	(6)	(7)	(8)
Turnover	-0.0127			-0.0776
	(-0.49)			(-2.41)
Volatility		7.375		17.40
		(2.13)		(4.25)
Float			-0.355	-0.344
			(-20.74)	(-17.83)
TransactionTax	1.677	1.387	1.749	1.588
	(16.92)	(16.64)	(19.54)	(15.28)
Constant	-0.398	-1.534	-0.244	-1.821
	(-1.09)	(-2.66)	(-1.09)	(-3.31)
Maturity fixed effects	Yes	Yes	Yes	Yes
No. of observations	863	821	863	821
Adjusted R^2	0.476	0.450	0.627	0.613

Table 7
Summary statistics of the estimates of feedback trading volume and the predicted reentry volume from three models
Panel A reports the means, medians, and standard deviations of the estimates of feedback trading volumes from the three models, denoted $FeedbackVolume^{\text{Cox}}$, $FeedbackVolume^{\text{stratified}}$, and $FeedbackVolume^{\text{logit}}$, and of the predicted reentry volume from the three models, denoted $Volume^{\text{Cox}}$, $Volume^{\text{stratified}}$, and $Volume^{\text{logit}}$. These estimates are defined in Section 5.1 and are further rescaled by dividing by the number of warrants outstanding on date *t*. The sample is the zero-fundamental sample defined in Xiong and Yu (2011), restricted to the set of five warrants that traded both before and after May 30, 2007, the date when the stock transaction tax tripled. Panel A also includes the same statistics for *Volatility*, *Turnover*, and *Float*. Panel B reports the correlation matrix of the nine variables.

Panel A: Summary statistics of the estimates of feedback trading volume and the predicted reentry volume

Variable	Observations	Mean	Median	Standard Deviation
$FeedbackVolume^{\text{Cox}}$ (%)	509	8.68	3.90	20.21
$FeedbackVolume^{\text{stratified}}$ (%)	509	13.72	8.59	22.54
$FeedbackVolume^{\text{logit}}$ (%)	509	15.29	8.14	31.32
$Volume^{\text{Cox}}$ (%)	509	75.89	53.33	107.96
$Volume^{\text{stratified}}$ (%)	509	76.07	56.03	101.66
$Volume^{\text{logit}}$ (%)	509	93.54	67.23	133.43
Volatility (%)	467	171.77	102.14	221.72
Turnover (%)	509	237.99	141.71	260.77
Float (million)	509	1381.87	424.11	1775.06

Panel B: Correlation matrix

Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	$FeedbackVolume^{\text{Cox}}$	1.0000								
(2)	$FeedbackVolume^{\text{stratified}}$	0.9688	1.0000							
(3)	$FeedbackVolume^{\text{logit}}$	0.9667	0.9740	1.0000						
(4)	$Volume^{\text{Cox}}$	0.8981	0.9644	0.9418	1.0000					
(5)	$Volume^{\text{stratified}}$	0.8632	0.9492	0.9210	0.9908	1.0000				
(6)	$Volume^{\text{logit}}$	0.8347	0.9154	0.9312	0.9639	0.9647	1.0000			
(7)	*Volatility*	0.4072	0.4509	0.4241	0.5239	0.5204	0.4866	1.0000		
(8)	*Turnover*	0.3259	0.4076	0.3583	0.5041	0.5215	0.4693	0.8275	1.0000	
(9)	*Float*	-0.1961	-0.2636	-0.2324	-0.2574	-0.2884	-0.2659	0.0805	-0.0312	1.0000

Table 8

Panel regressions explaining warrant prices using feedback volume from three models

Results of panel regressions explaining daily warrant closing prices using estimates of the volume due to positive feedback trading (*FeedbackVolume*) based on the standard Cox hazard rate model, the stratified Cox model, and the logistic regression model. The sample is the zero-fundamental sample defined in Xiong and Yu (2011), restricted to the set of five warrants that traded both before and after May 30, 2007, the date when the stock transaction tax tripled. The zero-fundamental sample for the five warrants contains 509 observations, of which 42 have missing values for *Volatility*. The main variables of interest *FeedbackVolume* is defined in Section 5.1. Other variables are defined in Table 6. All regressions include maturity fixed effects. The *t*-statistics (in parentheses) are based on standard errors clustered by date to account for heteroscedasticity and correlation within a trading day.

	Cox hazard rate model			Stratified Cox model			Logit regression model		
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FeedbackVolume	3.082***	3.059***	3.036***	3.026***	3.031***	3.027***	2.083***	2.084***	2.075***
	(7.74)	(7.60)	(7.28)	(11.56)	(11.16)	(10.17)	(10.28)	(9.79)	(9.18)
Turnover	-0.0491		-0.0374	-0.0861***		-0.0682*	-0.0745**		-0.0582
	(-1.53)		(-0.82)	(-2.68)		(-1.65)	(-2.40)		(-1.38)
Volatility		-1.401	1.667		-4.959	0.378		-3.890	0.741
		(-0.38)	(0.32)		(-1.18)	(0.07)		(-0.97)	(0.14)
Float	-0.239***	-0.208***	-0.213***	-0.207***	-0.171***	-0.178***	-0.223***	-0.188***	-0.195***
	(-11.60)	(-10.02)	(-9.66)	(-10.02)	(-7.86)	(-7.84)	(-10.68)	(-8.55)	(-8.41)
TransactionTax	2.287***	2.040***	2.066***	2.273***	2.006***	2.053***	2.301***	2.038***	2.079***
	(20.58)	(17.81)	(17.82)	(20.54)	(17.60)	(17.73)	(20.61)	(17.70)	(17.81)
Constant	-1.449**	-1.780***	-1.679***	-1.198*	-1.559**	-1.342*	-1.157**	-1.501**	-1.326**
	(-2.37)	(-3.01)	(-2.77)	(-1.95)	(-2.28)	(-1.96)	(-2.05)	(-2.42)	(-2.15)
Maturity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	509	467	467	509	467	467	509	467	467
Adjusted R^2	0.701	0.683	0.683	0.711	0.694	0.697	0.705	0.687	0.689

Table 9
Panel regressions explaining warrant prices using predicted reentry volume from three models

Results of panel regressions explaining daily warrant closing prices using the predicted reentry volume (*Volume*) computed using the standard Cox hazard rate model, the stratified Cox model, and the logistic regression model. The sample is the zero-fundamental sample defined in Xiong and Yu (2011), restricted to the set of five warrants that traded both before and after May 30, 2007, the date when the stock transaction tax tripled. The zero-fundamental sample for the five warrants contains 509 observations, of which 42 have missing values for *Volatility*. The main variable of interest *Volume* is defined in Section 5.1. Other variables are defined in Table 6. All regressions include maturity fixed effects. The *t*-statistics (in parentheses) are based on standard errors clustered by date to take account of heteroscedasticity and correlation within a trading day.

	Cox Regression Model			Stratified Cox Regression Model			Logit Regression Model		
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Volume	0.614***	0.602***	0.609***	0.669***	0.640***	0.660***	0.460***	0.437***	0.446***
	(12.59)	(10.45)	(9.95)	(12.08)	(10.37)	(9.97)	(8.96)	(7.71)	(7.53)
Turnover	-0.0993***		-0.0904**	-0.116***		-0.111***	-0.0893***		-0.0966**
	(-2.88)		(-2.29)	(-3.18)		(-2.82)	(-2.66)		(-2.44)
Volatility		-4.658	2.085		-4.881	2.959		-1.401	5.683
		(-0.94)	(0.39)		(-0.91)	(0.54)		(-0.28)	(1.04)
Float	-0.211***	-0.177***	-0.185***	-0.195***	-0.163***	-0.170***	-0.216***	-0.187***	-0.195***
	(-9.73)	(-7.38)	(-7.53)	(-8.87)	(-6.55)	(-6.71)	(-9.78)	(-7.52)	(-7.64)
TransactionTax	2.272***	1.989***	2.052***	2.301***	2.005***	2.082***	2.275***	1.981***	2.047***
	(19.53)	(16.50)	(16.70)	(19.98)	(16.57)	(16.98)	(19.34)	(16.13)	(16.41)
Constant	-1.266**	-1.836**	-1.512**	-1.091*	-1.840**	-1.398*	-1.212**	-2.068***	-1.706**
	(-2.08)	(-2.46)	(-2.06)	(-1.79)	(-2.33)	(-1.80)	(-2.20)	(-2.87)	(-2.47)
Maturity fixed effs.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	509	467	467	509	467	467	509	467	467
Adjusted R^2	0.682	0.657	0.663	0.678	0.649	0.659	0.661	0.634	0.641

Table 10

Panel regressions explaining warrant returns using first differences of feedback volume based on three models

Results of panel regressions explaining daily warrant returns using the first differences of volume due to positive feedback trading ($\Delta FeedbackVolume_t$) based on the standard Cox hazard rate model, the stratified Cox model, and the logistic regression model. The differences are first scaled by the ratio of market trading volume to that of the brokerage firm's customers on date $t-1$, and then further scaled by dividing by the number of warrants outstanding on date $t-1$. Other explanatory variables include the first difference of daily turnover on date $t-1$ ($\Delta Turnover_{t-1} = Turnover_{t-1} - Turnover_{t-2}$), the first difference of 5-minute intraday volatility on date $t-1$ ($\Delta Volatility_{t-1} = Volatility_{t-1} - Volatility_{t-2}$), and a dummy variable $\Delta TransactionTax_t$ that equals one on May 30, 2007, the date when the stock transaction tax tripled, and zero on all other trading dates. The sample is the zero-fundamental sample defined in Xiong and Yu (2011), restricted to the set of five warrants that traded both before and after May 30, 2007. The zero-fundamental sample for the five warrants having no missing values for $\Delta FeedbackVolume_t$ contains 499 observations, of which 40 have missing values for $\Delta Volatility_{t-1}$. All of the regressions include maturity fixed effects. The *t*-statistics (in parentheses) are based on standard errors clustered by date to account for heteroscedasticity and correlation within a trading day.

	Without $\Delta FeedbackVolume$			With $\Delta FeedbackVolume$								
				Cox Regression Model			Stratified Cox Regression Model			Logit Regression Model		
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta FeedbackVolume_t$				0.413**	0.454**	0.419**	0.442***	0.460***	0.432***	0.403***	0.410***	0.396***
				(2.09)	(2.39)	(2.06)	(3.03)	(3.16)	(2.79)	(3.98)	(4.24)	(3.76)
$\Delta Turnover_{t-1}$	0.0182**		0.0205**	0.0126		0.00998	0.0132		0.0126	0.00568		0.00719
	(2.21)		(2.04)	(1.39)		(0.91)	(1.53)		(1.19)	(0.63)		(0.69)
$\Delta Volatility_{t-1}$		0.560	-0.527		1.153	0.584		0.851	0.171		0.0562	-0.305
		(0.52)	(-0.45)		(1.25)	(0.53)		(0.82)	(0.14)		(0.06)	(-0.27)
$\Delta TransactionTax_t$	0.899***	0.911***	0.899***	0.756***	0.748***	0.754***	0.584***	0.579***	0.592***	0.494***	0.490***	0.501***
	(9.30)	(9.40)	(9.11)	(8.89)	(8.81)	(8.73)	(5.79)	(5.65)	(5.60)	(4.74)	(4.78)	(4.64)
Maturity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	509	467	467	499	459	459	499	459	459	499	459	459
Adjusted R^2	0.233	0.190	0.201	0.265	0.232	0.233	0.278	0.242	0.244	0.306	0.277	0.276