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Non-Marketability and One-Day Selling Lockup

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This Version: December, 2017

For helpful comments, we thank Yakov Amihud, Darwin Choi, Joel Hasbrouck, Jennifer Huang, Gang Li, Laura Liu, Yu-Jane Liu, Lin Peng, Robert Schwartz, Gordon Tang, Wilson Tong, Steven X. Wei, Xinzhong Xu, Hong Yan, Jialin Yu, Chu Zhang, seminar participants at Baruch College, Florida International University, Hong Kong Baptist University, Hong Kong Polytechnic University, Hong Kong University of Science and Technology, University of Miami, the Shanghai Stock Exchange, and Peking University, and participants at the China International Conference in Finance, TCFA annual meeting, FMA annual meeting, EFA annual meeting, and Asian Finance Association annual meeting. We thank Tianyi Wang for programming help. Bian is grateful for the support from the Social Science Foundation of Ministry of Education of China (Project no. 12YJC790001), the National Social Science Foundation of China (Project no. 12CJY117). Wang gratefully acknowledges the financial support from Bert W. Wasserman Endowment. All errors are our own.

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ABSTRACT

We examine a unique one day lockup constraint in stock markets in China and contribute to the understanding of impact of non-marketability on asset prices. Buyers of Chinese stocks are subject to a one day lockup and cannot sell their shares until the next day, but warrant traders are free of such restrictions. We demonstrate that the lockup creates a price discount relative to stock value implied by warrants. We show that the discount decreases throughout the trading day and that investors tend to purchase stocks when the lockup becomes less binding. The paper provides implications to value illiquid assets.

Keywords: non-marketability discount, liquidity, selling lockup

JEL number: G12, G14, G18

"… discounts for lack of marketability can potentially be large even when the illiquidity period is very short."

Francis A. Longstaff

How much can marketability affect security values? Journal of Finance, v(50), 1995

The risk factors of liquidity and marketability are among the most important determinants of asset prices. There are many examples of potentially liquid assets that are, at least temporarily, non-marketable. When first allocated to an investor, some IPO shares may carry a certain lockup period. Employee performance shares may be purchased by a corporate employee potentially at a discount via a stock purchase plan. Employees who purchase these shares are generally required to hold the shares for a fixed period of time before they can sell these shares, which creates temporary non-marketability in the shares they hold. When first awarded to employees and executives, Employee Stock Options (ESOs) are usually not fully vested. Even when they are later fully vested, these ESOs are not tradable and hence not marketable. Security holdings in a hedge fund may not be redeemed without advanced written requests to hedge fund managers and shares may be liquidated only after redemption-notice periods have lapsed. Consequently, to the holders of hedge funds, shares are temporarily non-marketable. Even in the case of the most popular open-ended mutual funds, shares of mutual funds are restricted from trading until market close, thus creating non-marketability during trading hours prior to market close. Finally, in the case of actively traded stocks, bonds, and derivative contracts, when security markets are closed these liquid securities temporarily lose their marketability.

In this paper, we examine the impact of a unique non-marketability constraint on security prices. This constraint is the result of a very short trading lockup period (less than one trading day) embedded in the underlying stocks. We are not aware of any studies that examine a short-lived trading constraint.[1] Previous research has focused on examining the non-marketability over relatively long horizons and clearly found that a security with a long-term marketability constraint would be priced at a discount from an otherwise-identical security without such a marketability constraint. However, understanding the effect of a short-term trading lockup is important to both

[1]For the effect of non-marketability over the long-run, see Silber (1991), Kahl, Liu, and Longstaff (2003), Brenner, Eldor, and Hauser (2001), Aragon (2007), Khandani and Lo (2011), and Huang and Xu (2009).

academics and securities regulatory departments. For example, a line of research in the stock market regulatory policy is the impact of the temporary trading lockups, such as the trading halts or circuit breakers in the NYSE and NASDAQ (see Greenwald and Stein (1991), Lauterbach and Ben-Zion (1993), Subrahmanyam (1994), and Goldstein and Kavajecz (2004)). Regulators and SEC have also discussed the circuit breakers on individual stocks as effective regulatory methods to curb the unwanted consequence from the prevailing high frequency trading, such as the flash crash (Angstadt (2010)). More studies on the effect of short-term trading lockup are thus highly needed.

Compared to the effect of long-term trading lockup, there is much less consensus in the theoretical literature on the impact of the short-lived trading lockup. Longstaff (1995) derives an analytical upper bound on the value of marketability and states that "… discounts for lack of marketability can potentially be large even when the illiquidity period is very short." Hong and Wang (2000) show that periodic trading lockup can generate rich patterns of time variation in returns. On the other hand, we may treat the temporary loss of marketability over a short-term as a form a transaction cost. Constantinides (1986) shows that in a static equilibrium model proportional transaction costs have only a small effect on asset prices. Yet Lo, Mamaysky, and Wang (2004) and Jang, Koo, Liu, and Loewenstein (2007) both extend Constantinides' model and reach opposite conclusions that even small transaction costs can significantly affect asset prices. Longstaff (2001, 2009) further uses theoretical analyses to show that even small trading lockup can not only adversely affect asset prices, but also impact investors' optimal portfolio choices. It is thus of tremendous interest to academic financial economists as well as industry practitioners to accurately measure the size of the discount attributable to non-marketability over a short-term.

This paper complements previous studies by providing evidence that a repeated, yet individually very short-lived non-marketability constraint significantly and adversely affect stock prices. To investigate this, we need a market in which two identical securities, one with a short marketability constraint and one without, are simultaneously traded by potentially the same investors. The stock market in China provides an ideal setting. As we explain in the next section, two securities, a stock and its equity call warrant, are simultaneously traded by domestic investors in the Chinese market. Yet the stock buyer is not allowed to sell his shares on the same day he buys them, while the warrant buyer can buy and sell a warrant multiple times on any trading day. Because the warrant is priced based on the underlying stock, we infer the price of the underlying stock without the one-day selling lockup. The ability to observe market prices of both the restricted stock and the unrestricted stock at the same time makes it possible for us to directly and accurately isolate the price impact due to non-marketability, and to do so without unrealistic model assumptions on the price of non-marketable securities.

Our paper uses the unique feature of coexistence of both restricted stocks and unrestricted stocks. Computing a non-marketability discount requires the price of both stocks. In this case, the restricted stock price is the observed market stock price. We obtain the unrestricted stock price by three different methods. The first method is totally free of any option pricing models, the second method is based on the Black-Scholes (Black and Scholes (1973)) option pricing model, and the third method is based on the Heston-Nandi (Heston and Nandi (2003)) GARCH option pricing model. All three methods impute the implied stock prices from observed market warrant prices. We then treat an implied stock price as the unrestricted stock price and subtract the restricted stock price from it to obtain the non-marketability discount caused by a short non-marketability window of less than one trading day. This discount provides a clean measure of price impact that is entirely due to a short-term selling lockup. We find that the non-marketability discount in the Chinese stock market is both statistically and economically significant. Given the total market capitalization of Chinese equity in 2011, our result amounts to nearly US$90 billion lost due to the trading restriction.

The features that distinguish our paper from other studies on non-marketability are the analyses of the size of non-marketability and investor behaviors during the lockup period. These analyses shed light on how the non-marketability discount evolves. At the intraday level, the non-marketability discount shrinks in size from the market open to the market close. This result matches the idea that the selling lockup becomes less binding as the market close approaches. All else equal, there is clearly less need and fewer incentives to sell shares just acquired as the trading day moves to its daily close. We observe non-marketability discounts decrease over time during the trading day, yet the discount remains both statistically and economically significant at the market close, which is due to the permanent impact of trading lockup to investors (Longstaff (2009)). Similar to the intraday pattern in the discount, we find the stock market depth and buyer-initiated order imbalance measures to increase from the market open to the market close. We also observe these intraday patterns of investor behaviors for the stocks that do not issue warrants. This observation suggests that Chinese investors tend to purchase more stocks when there is weaker liquidity constraint. Our findings indicate that one channel through which the non-marketability constraint leads to price discount is that the restriction on asset liquidity or marketability may adversely affect investor demand, thus lowering the equilibrium price. This rationale is consistent with classic liquidity-based asset pricing theories.

While we consider implied stock price from warrants as the price free of trading restrictions, other researchers who study Chinese warrant mispricing have argued that Chinese warrant prices may be speculative and inflated.[2] However, the samples of Chinese warrants in those papers are different from ours. Xiong and Yu (2011) focus on the put warrants, while Li, Liao, Wang, and Zhu (2010) and Liu, Zhang, and Zhao (2014) study all call warrants and put warrants. The warrants in our sample are all deep in-the-money call warrants, which are the least speculative compared to other warrants. This sample helps us best isolate the impact due to the selling lockup from speculation influences. We show that the prices of the warrants in our sample track the price movement of stocks quite well. Consequently, we conclude that the warrant prices in our sample are indicative of the true underlying stock prices.

We aim to make several contributions to literature on the effect of non-marketability on asset prices. First, we provide arguably the first empirical evidence that a repeated and individually very short non-marketability window is able to significantly affect stock price. The second is methodological in nature. We design our procedures to produce a clean unrestricted benchmark, based on which we accurately compute a non-marketability discount. Because of difficulty of obtaining both restricted and unrestricted asset prices, to calculate the discount most prior research makes additional model assumptions. However, the coexistence of different trading rules in the Chinese stock and warrant markets gives us a unique advantage that is not available in other financial markets. This rare feature means that we can measure a price discount entirely due to non-marketability, and do so at a precision level

[2] Xiong and Yu (2011) document the put warrants bubble in Chinese market. Li, Liao, Wang, and Zhu (2010) show that warrants created by securities institutions help mitigate the overheated warrant prices. Liu, Zhang, and Zhao (2014) show that the investors' trading activities in the underlying stocks are associated with warrant price inflations. Chang, Luo, Shi, and Zhang (2013) conclude that hedging motives cannot fully explain warrant pricing in China. Powers and Xiao (2014) show that investors in Chinese put and call warrant markets trade for different motives. Bian and Su (2010, a manuscript in Chinese) show that the absence of selling lockup contributes to the warrant premium in China.

that is previously unattainable. Finally, given the increasing importance of the Chinese market to the world economy, understanding the effect of special trading mechanism in China is an informative exercise in and of itself.

This paper is organized as follows: Section 1 explains why the Chinese stock market makes an ideal experiment for our study. Section 2 presents the data sample, computes the non-marketability discount measure using various methods, and shows that these discounts are not the result of speculative trading in our sample. Section 3 further explores the possible causes of the price discount and performs robustness checks. Section 4 concludes.

1. One-Day Trading Lockup

Chinese stock market follows a unique trading rule: when an investor purchases some common equity shares, he is not allowed to sell these shares on the same day; he must wait till at least the next trading day to sell. This rule prohibits day trading and creates an artificial short-term lockup. This selling lockup and non-marketability are removed at the market open of the following trading day. This procedure is repeated every trading day and is known to all market participants.[3] This trading lockup has been enforced all the way from when the Chinese stock markets first set up to the present (with the exception in early years from 1993-1995). Although researchers and industry practitioners have discussed the costs and benefits of this one-day selling lockup in stock market for a long time, CSRC (China Securities Regulatory Commission, Chinese SEC) has not made any substantial efforts towards lifting this lockup.

To measure the impact of this unique short-lived trading restriction on stock prices, researchers hope to find an alternative stock that is identical to the stock traded and yet have different level of marketability. However, it is difficult to find a market in which both a marketable security and an otherwise identical non-marketable security are traded simultaneously. Nearly all previous empirical research efforts in this area make strong model assumptions.

The Chinese market provides the researchers with a natural experiment that overcomes this barrier. China started its warrant market in 2005. A strikingly different trading rule in the warrant market is that investors can

[3]Previous studies examining this trading rule obtain mixed findings. Guo, Li, and Tu (2012) show that trading lockup discourages investors to trade and encourages traders to follow trends. Chan, Tong, and Zhang (2012) show that the lockup helps eliminate excessive trading and improve market liquidity.

perform day trade. There is no one-day selling lockup in the trading of Chinese warrants. Both common stock shares and their equity warrants are listed on the same exchanges and traded by domestic investors. We examine the Chinese stock market and the associated equity warrant market simultaneously. The difference in trading restrictions provides us with a perfect laboratory to address questions in asset liquidity and marketability that previous research is unable to resolve.

2. Data and the Non-Marketability Measure

In this section, we describe our data and define variables of interest. We describes in detail how we construct the data sample in this study, and why our sample is particularly suitable to examine the impact on asset prices due to lack of marketability and liquidity.

2.1 Data and Preliminary Statistics

Our stock and warrant data consist of all daily open and close prices, trading volume, yuan (the Chinese currency unit) trading volume, and intraday time-stamped trade and quote records for all stocks and warrants traded on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). The two exchanges operate in the same way, but list stocks of different companies. We acquire our data from Resset Data Inc. in Beijing, China.[4]

We focus on firms that have both stocks and call warrants listed on either the SSE or the SZSE.[5]These warrants are essentially financial options issued by listed companies and are European-style in nature. We study the difference between the stock price implied from the deep in-the-money call warrant's market price and the observed market stock price. Although the price movements of call warrants are usually positively correlated with the price movements of the underlying stocks, the leverage and price exposures provided by holding call warrants are not the same as those from holding the underlying stocks. Thus, some investors may buy call warrants to increase leverage rather than buy them for marketability reasons. Deep in-the-money call warrants mitigate this concern. Because

[4]For more information, please see http://www.resset.cn/enindex.
[5]A few firms also have put warrants listed on the exchanges. The focus of this paper is to analyze the marketability differences between a call warrant and its underlying stock. We exclude put warrants. For those interested in the Chinese put warrants market, see Xiong and Yu (2011).

short selling is not allowed in Chinese markets, investors cannot arbitrage the price differences between warrants and stocks. However, both stocks and deep in-the-money warrants are based on the same fundamentals – the firm's expected future cash flows. In the paper, we attempt to identify a persistent pricing difference between these two assets and attribute this pricing difference to marketability and liquidity.

We select deep in-the-money call warrants based on a warrant's delta. To compute the deltas of all call warrants by the Black-Scholes (1973) model, for every trading day we use the closing prices of call warrants and the underlying stock, the historical 120-day stock return volatility, the short-term risk-free interest rate, and the strike price of the call warrant. Our sample retains all warrants with a delta of 0.9 or higher. The threshold of 0.9 is not critical to our results. For robustness, we use cut-off values of 0.85 and 0.95. We find that our results do not change qualitatively.

We apply several filters to our data sample. First, the Chinese Securities Regulatory Commission (CSRC), which is the equivalent of the U.S. SEC, imposes a 10% limit on the daily price increase or decrease of any stock traded on either of the two stock exchanges. Once the price limit is reached, prices are not allowed to move beyond that limit and hence the transaction volume typically drops substantially. But the size of the daily permissible price percentage change of a warrant is much larger. It is equal to the product of daily permissible price change limit of the underlying stock (10%), a factor of 1.25, and the warrant's conversion ratio. The difference in the sizes of daily price limit allows a wider range of daily warrant returns than daily stock returns. There is a small portion (less than 1%) of the observations in which the stock prices hit the 10% limit within a trading day, yet warrant prices do not hit their price limits. Because the differences in price limits may contribute to the price differences between these two markets in addition to marketability, we remove these observations from our sample.[6]

Further, we remove observations when there is either no trading, or very limited trading, in either the underlying stock or its warrant. Extremely low volume may occur if a stock reaches the price limit right after the market opens, or if the CSRC halts the trading for inspection of abnormal activity. We remove stale quotes, which are easily recognized by their zero depth, or observations with zero trading volumes. Because traders tend to show

[6]We add these observations back to our sample and repeat all the empirical analyses. The results are not qualitatively different.

irrational trading behaviors when warrants approach their expirations, we remove observations that are within two weeks of expiration dates. There are three call warrants that have changed their conversion ratios, which are the number of shares of stock warrant holders are entitled to purchase per warrant exercised at warrants' expirations. Because such changes in conversion ratios are likely to confuse less experienced investors in the valuation of warrants, we remove these three warrants from our sample. Thus, our final sample contains 16 pairs of call warrants and their underlying stocks, from August 22, 2005 to June 30, 2008.

Insert Table 1 about Here

Table 1 presents summary statistics of our sample. The average time to maturity of the warrants in our sample is 0.56 years. The annualized 120-day historical volatility of the stock returns averages to 54.8% per year. We define the moneyness of the warrants as the difference between the ratio of stock price to warrant strike price and one. Hence, the average moneyness of 1.72 indicates that the stock prices are 272% of warrant exercise prices on average. The average delta of the sample is 0.979 and the medium is 0.991. These results indicate that our warrant sample consists of deep in-the-money call warrants and that they should be close trading alternatives of their corresponding underlying stocks, given the fact that deep in-the-money warrants carry very small time value. The average theta of the warrants is 0.51, which indicates that a warrant loses a value of ¥0.51 (yuan) over a year. Further, if we assume 250 trading days per year, this theta suggests an average daily time value decay of about ¥0.002. Hence, we can ignore the intraday time value decay in the sample. We note that our deep-in-the-money sample also includes a few observations where stock prices are not much higher than the strike prices. For example, the lowest warrant moneyness is 0.126. In our robustness sections later on in this study, we show that our conclusion remains the same even if we remove these warrants observations.

In Table 1, we include the market capitalization of the stocks and the total market value of warrants and the daily close prices of stocks and warrants. The average market capitalization of the stocks is over ¥39 billion and the average total market value of the warrants is over ¥2.5 billion. Although the total market value of warrants is significantly smaller than that of the underlying stocks, the warrant market is nevertheless sufficiently large to attract investors. The average closing prices of stocks and warrants are ¥20.97 and ¥13.63, respectively. Most of the prices are in the same magnitude, hence there is no concern for large price differences.

2.2 Comparisons between the Stock and the Warrant Markets

Although the deep in-the-money call warrants and their underlying stocks are similar assets, warrants are much more actively traded. Table 2 reports additional statistics in the stock and warrant markets. The table also demonstrates that the warrant market enjoys much higher trading volume. The average daily trading volume of the stocks in our sample is nearly 30 million shares, but the average daily trading volume of the warrants is about six times higher at 205 million warrants per day. After accounting for price differences in stock and their corresponding warrants, the warrant market is still more active in terms of average daily yuan trading volume. The average daily yuan trading volume of the stocks in our sample is nearly ¥430 million, while the counterpart of the warrants is ¥1,264 million. (We note that the exchange rate between yuan and the U.S. dollar during our sample period is within the range from US$1 = ¥8 to US$1 = ¥7.5, with small variations.)

Insert Table 2 about Here

Next, we compute two liquidity measures on every trading day. The first measure is the Amihud (2002) measure. We calculate our Amihud measure for each security on a daily basis. However, unlike Amihud, who multiplies his measure by 10^6, we multiply ours by 10^7.

$$Amihud_{i,t} = \frac{|R_{i,t}|}{Dvol_{i,t}} \tag{1}$$

$R_{i,t}$ is the holding period return of stock *i* on day *t*, and $Dvol_{i,t}$ is the yuan trading volume (in ¥10,000) of stock *i* on day *t*. The Amihud measure assesses liquidity in the form of price impact. It is the absolute return per yuan in daily trading volume. A large Amihud measure is an indication of low liquidity because it suggests that the daily movement of the security given one yuan in trading volume is large. On the other hand, a low Amihud measure is an indication of high liquidity.

The second liquidity measure we calculate is the turnover ratio, which we define as the total daily trading volume (in shares) divided by the number of tradable shares outstanding. The higher the turnover ratio, the more actively traded the stock, and the higher liquidity the stock market exhibits. Li and Zhang (2011) use turnover ratio to account for a considerable part of the warrant price premium in the Hong Kong market. An alternative interpretation of turnover ratio, proposed by Mei, Scheinkman, and Xiong (2009), is that it is a proxy of intensity of speculative trading in the Chinese stock market. Later in the robustness sections, we show that using turnover ratio as a measure for the speculative trading does not change the conclusion of this paper.

We note that we do not use the bid-ask spread as a liquidity measure. Because the Chinese market is an order-driven market and because there are no explicit market makers, the bid-ask spread does not vary significantly, and in most cases does not vary at all. In our sample, almost 80% of stock quoted spreads and over 50% of warrant quoted spreads stay at their tick-size without any variations. Consequently, we use only the Amihud measure and turnover ratio as proxies of liquidity.

Panel B of Table 2 shows the two liquidity measures in the two markets. All results indicate that the warrant market is much more liquid. It has a lower Amihud measure and a higher turnover ratio than the stock market. All the differences between the two markets are statistically significant. The stock market has lower liquidity than the corresponding warrant market.

We find that on average, the warrant turnover ratio is more than 20 times greater than its counterpart in the stock market. This finding, although striking, is consistent with Longstaff (2009), who shows that the introduction of new illiquid assets may result in frenzy trading of liquid assets. In later sections, we further show this point using account-level brokerage data.

Panel C of Table 2 presents statistics of additional control variables. One set of control variables is the logarithm of the stock market capitalization and warrant total market value measured at the end of each month. We interpret market capitalization as a measure for either liquidity or information asymmetry, because the liquidity level is usually higher and the information costs are typically lower for large firms. The other control variable is a return momentum measure. We compute the cumulative return of each stock and that of its paired warrant in the prior calendar month. According to Karolyi and Li (2003), the cumulative return proxies for security momentum and may be associated with risk. Table 2 shows that the market capitalization in the stock market is much higher than the warrant total market value, but the return momentum is greater in the warrant market than in the stock market. We control for these variables in our regression analysis.

2.3 The Non-Marketability Discount Measure

In this subsection, we compute our measure of the one-day non-marketability discount. Because deep in-the-money call warrants and the underlying stocks are similar financial assets based on the same fundamental factor (the expected future cash flows of the company), investors with a short time horizon might consider the two assets as close substitutes. The main difference between the two assets is marketability: the warrant has no trading restrictions, but the stock cannot be sold on the same day when it is bought. We argue that differences in marketability result in a differences in prices.

To precisely measure the non-marketability discount in the underlying stocks, we infer the price of a fully marketable stock from observed warrant price. We achieve this goal in three ways.

In the first method, we compute the implied stock price as the sum of deep in-the-money call warrant price and the warrant's strike price. We call this stock price the model-free implied stock price. This price ignores the time value embedded in the warrant price, hence is upward biased. We note that the time value of a deep in-the-money warrant is small. The time value is generally the highest when warrants/options are at-the-money. The advantage of this method is its simplicity and independence of any option pricing models and their assumptions. We do not need to validate and apply the option pricing model, nor do we need to estimate input parameters such as stock return volatility. Despite the popularity and extensive application of various option pricing models, no option pricing models can fully capture the underlying process of stock return dynamics and it may produce biased prices as evidenced in the volatility smile reported in prior research. Our model-free implied stock price avoids this complication. Furthermore, given that the warrants in our sample are all deep in-the-money, the time value of these warrants is minimal.

In the second method, we use the Black-Scholes model to back out an implied stock price as in Chakravarty, Gulen, and Mayhew (2004). We obtain the strike price and the time to maturity from the warrant contract. We obtain the risk-free interest rate from Resset Data Inc. For volatility, we take the historical volatility of the returns of the underlying stock in the past 120 days.[7] Because Chinese warrants are all dividend-protected in that their strike prices are adjusted downward automatically by the amount of cash dividend on ex-dividend days, we do not make any additional adjustments on the prices of the underlying stocks for dividend payments. Hence, we have five out of the six parameters needed for the Black-Scholes model. Given the market warrant price, we back out the only remaining parameter – the stock price that equates the Black-Scholes model output to the observed market warrant price. (Chinese warrants do not have dilution effects. When warrants expire, issuers convert non-tradable shares into tradable shares. By doing so they are able to fulfill the exercise of warrant holders. No new shares are created.) We call this stock price the Black-Scholes implied stock price. Because the warrants are fully marketable and free of the one-day lockup, the implied stock price represents the stock price had there been no lockup.

In the third method, we adopt the model developed by Heston and Nandi (2003). Heston-Nandi model provides a computable formula for the mean-reverting volatility model that approximates the continuous-time stochastic volatility model in Heston (1993), yet can be estimated using only the historical stock return data. We use the returns of the underlying stock in the past 120 days to estimate the discrete-time GARCH model for the volatility input, and then compute the implied stock prices. Other model parameters are similarly defined as in Black-Scholes model approach.

We report results on the model-free, Black-Scholes, and Heston-Nandi implied stock prices to demonstrate that our results are robust to various specifications. Because the warrants in our sample are European style, investors cannot exercise their warrants prior to the maturity dates. An alternative of the model-free implied stock price is the sum of deep in-the-money call warrant price and the present value of the warrant's strike price. In unreported tables, we repeat all the empirical tests in the paper using this alternative specification and find the results do not change qualitatively.

Once we have the implied stock price from the warrant market, we compare it with the observed stock price in the stock market. We calculate the non-marketability discount (*DISC*) as the difference between the implied stock

[7] Another way is to use the implied volatility from the previous trading day as the volatility parameter input for the current trading day (Chakravarty, Gulen, and Mayhew, 2004). However, we find the daily implied volatility in our sample to be very volatile and thus it is too noisy to be useful in our estimation procedures.

price and the observed stock price divided by the implied stock price. The three implied stock prices yield three discount measures as defined in (2)

$$DISC = \frac{IMPLIED\ STOCK\ PRICE\ -\ OBSERVED\ STOCK\ PRICE}{IMPLIED\ STOCK\ PRICE} \tag{2}$$

Because buyers of stocks are subject to the one-day selling lockup, we expect the stock price to be lower than it would be without the lockup. Hence, we expect the non-marketability discount to be positive.

We report both the discounts at the market open and at the market close from our sample. We expect them to be different. At the market close, the lockup restriction does not place any constraint on trading activities for that particular trading day, because any stock bought at the market close cannot be sold in the same trading day anyway. At the market open, the lockup is the most restrictive because any stock bought at the open is restricted from being sold for the longest time. The restriction covers all trading hours subsequent to market open during the same trading day. Consequently, if prices in both warrant and stock markets are determined by the same marginal investors, we expect to see that there is a positive non-marketability discount at the market open, but that the discount becomes smaller or even vanishes at the market close. However, Longstaff (2009) presents an asset pricing model with heterogeneous investors and shows that it is possible for the non-marketability discount to exist at the market close because the lack of marketability may affect investors' long-term wealth allocation. Longstaff (2009) shows that there may be a permanent shift in investor clientele between two otherwise similar assets with different levels of liquidity, and that the difference in liquidity may induce significant differences in equilibrium prices of liquid and illiquid assets.

Insert Table 3 about Here

In Table 3, we report summary statistics of the non-marketability discount at both the market open and market close. The mean discount at the market open is 0.041 (model-free approach), 0.030 (Black-Scholes model), and 0.023 (Heston-Nandi model). The discounts are statistically significant from zero. The discounts at the market close are smaller than those at the market open, but they are still significantly positive, with a mean of 0.037 (model-free approach), 0.026 (Black-Scholes model), and 0.020 (Heston-Nandi). These results are consistent with our prior conjecture. Note that the discount is economically significant. By removing marketability for as little as one trading day, the asset loses as much as 3% in its market value. Given the total Chinese equity capitalization of around 3 trillion US$ at the end of 2011, this result amounts to US$90 billion lost due to lack of marketability.

We further examine the differences between the discounts at the market open and at the market close. Based on the argument that the lockup restriction is more binding at the market open, we expect the differences to be positive. Because we have three methods to compute the discounts, we have three differences in discounts between the market open and the market close. The means of the differences are 0.004 (model-free approach), 0.005 (Black-Scholes model), and 0.003 (Heston-Nandi model), respectively, while the medians of the differences are either 0.003 or 0.004 for various methods. All of these statistics are significant and positive at the 0.01 level.

We note that the non-marketability discounts reported in Table 3 show a pattern of cross-sectional variation. For example, the standard deviation of the discount using model free approach is roughly 0.09, with the minimum being negative at -0.27. This result suggests that a portion of the discounts in the sample are negative. The finding is not very surprising because we do not claim that the price impact caused by the non-marketability discount is the only factor affecting price differentials between stocks and warrants. Other factors (such as speculation) might take effects as well, resulting in the cross-stock variation of the discount. However, the significantly positive mean and median of the discounts in all three methods provide clear evidence that, for this sample, the illiquidity price impact due to the non-marketability, on average, dominates the price differentials. Results in Table 3 also suggest that further analyses (such as regression analyses) are needed to confirm the existence of the non-marketability discount.

2.4 Is There Excessive Speculation in Our Warrant Sample?

We claim that investors who prefer marketability and liquidity would gravitate toward the warrant market. However, it is also possible that investors choose warrant market due to speculation. Xiong and Yu (2011) show that the Chinese put warrant market is highly speculative and irrational. Their paper examines only put warrants in China. Most of these put warrants represent highly leveraged speculative positions and their pricing can be extremely sensitive to changes in market sentiment and potentially irrational trading behavior. We note that our sample contains only deep in-the-money call warrants, which are the least speculative among all warrants. To further contrast our sample with the sample in Xiong and Yu (2001), we run several regressions using the warrant price at market close as the dependent variable. Our goal is to investigate the determinants of the warrant price in our sample and to demonstrate that the call warrants in our sample are much less speculative than put warrants in Xiong and Yu (2001) sample.

Insert Table 4 about Here

In column 1 of Table 4, we regress the warrant close price on the corresponding stock close price with monthly time-to-maturity fixed effects. We include the monthly time-to-maturity fixed effects to account for time value decay of warrants over time. In this regression, the coefficient of the stock close price is positive and highly significant. Moreover, the R-squared of the regression is 0.95, indicating that 95% of the variation of the warrant close price is explained by the stock price and time-to-maturity fixed effects. In the next three regression models, we switch the control variable from the stock price to the daily warrant turnover, warrant return volatility, and warrant float (number of tradable shares), respectively. Xiong and Yu (2011) use these same three regressions to show that the put warrants in their sample behave like bubbles. Scheinkman and Xiong (2003) develop a model based on asset resale options to show that the size of the bubble is positively correlated with the trading volume and the volatility. Our results are quite the opposite. For the daily warrant turnover, the coefficient is significantly negative. If the call warrant price in our sample contains a large bubble component, one would expect a positive coefficient for the daily warrant turnover. The negative coefficient in column 2 of Table 4 indicates that our sample of deep in-the-money call warrants does not have as much speculative trading as the sample in Xiong and Yu (2011).

In column 3 of Table 4, the coefficient for the volatility is negative but insignificant. The negative sign is at least consistent with the rational prediction from the tradeoff between risk and expected returns. Again, our result is opposite to that of Xiong and Yu (2011). In column 4 of Table 4, we regress the warrant price on its warrant float, the number of tradable warrants. In column 6, we regress the warrant price on the total number of warrants issued by the underlying firms and the net total number of warrant issued by brokerage firms. Both regressions are to connect the warrant price to the warrant float. In these two regressions, our results are similar to Xiong and Yu (2011). However, when we include the stock close price together with other control variables in columns 5 and 7, the only significant variable is the stock price. All other variables become insignificant. In addition, the R-squared of regressions 5 and 7 remains 0.95, the same as regression 1, although we include more control variables in regressions 5 and 7. All these results demonstrate that the main driving factor of the warrant price in our sample is the stock price. In summary, our sample of deep in-the-money call warrants is not overly speculative and hence it is reasonable for us to explore the link between these warrants and stocks to uncover valuation difference in marketability and liquidity.

We do not rule out the possibility that speculation could contribute to the price difference between the stock and warrant markets. However, the preference of marketability and liquidity, similar to speculation, is also important in driving traders to the warrants market (Xiong and Yu (2011)). The influence of speculation is different between call warrants and put warrants, and different during the lifetime of a warrant. By carefully selecting a data sample with only deep in-the-money call warrants, we lower the price impact of speculation on warrants to the most extent. In the appendix, as a controlled experiment, we apply our methods to estimate the difference between stock price from the market and implied stock price from options market to a group of U.S. Dow Jones Industrial Average index stocks. Consistent with the fact that there is no trading restriction between the two markets in the U.S., we do not find any significant difference between the two prices.

3. Possible Economic Mechanisms: Empirical Analysis

Our analysis in the previous section documents the existence of the discount in the Chinese stock market. The fact that this discount is significantly higher at the market open than market close provides evidence that the discount is due to the short-term non-marketability caused by the one-day selling lockup. In this section, we further explore this economic mechanism for the cause of the non-marketability discount. We also examine a set of alternative possible causes to conduct robustness checks.

3.1 Investors' Preference to Liquidity: Intraday Evidence

If the discount is mainly driven by marketability in the stock market, we should expect this discount to show a predictable trend as the liquidity constraint improves intra-daily. In this subsection, we provide evidence that this constraint has a significant impact on several other market variables, and infer from the variation of these variables the economic forces that lead to the formation and intra-daily evolution of the non-marketability discount.

A. Intraday Patterns of the Non-Marketability Discount

If the discount is driven by marketability in the stock market, we expect the discount to decrease from the market open to the market close as the liquidity constraint becomes less binding. To test this idea, we compute the discount every 30 minutes during the time when the market is open. That is, we calculate the discount at the market open (9:30 a.m.), 10:00 a.m., 10:30 a.m., 11:00 a.m., 11:30 a.m., 1:00 p.m., 1:30 p.m., 2:00 p.m., 2:30 p.m., and the market close (3:00 p.m.). Figure 1 plots the medians of non-marketability discounts at the end of each 30-minute interval over a trading day. We use the Black-Scholes model, the Heston-Nandi model, and the model-free approach. In all the three approaches, the discount displays a clear downward trend over the course of a trading day. However, the level of the discount using the model-free approach is slightly higher. This result is consistent with the upward bias induced by omitting warrants' time value in the model-free approach.

Insert Figure 1 about Here

To quantitatively identify the intraday trend in the non-marketability discount, we regress the discount on intraday dummies and control variables in equation (3).

$$DISC_{i,j,t} = \alpha_t + \sum_{j=1}^{9} \beta_j I_j + \beta_C CONTROL_{i,t} + WARRANT \quad FIXED \quad EFFECT + \varepsilon_{i,j,t} \tag{3}$$

$DISC_{i,j,t}$ is the non-marketability discount of stock *i* at the j^{th} 30-minute starting from 9:30 a.m. to 2:30 p.m. (with a lunch break from 11:30 a.m. to 1:00 p.m.) on day *t*. I_1 through I_9 are dummy variables for the 30-minute time slots between 9:30 a.m. and 2:30 p.m. (We do not include the dummy variable at the market close.) $CONTROL_{i,t}$ is a vector of control variables of stock *i* on day *t*.

We include two sets of control variables to control for other factors that could explain the intraday price differences between the stock and warrant markets. The first set of control variables is the stock turnover ratio and warrant turnover ratio. We use turnover as our proxy for the level of trading activity and liquidity. The second set of control variables is the log of stock market capitalization and the log of warrant total market value at the end of previous month. Market capitalization can be a proxy for information asymmetry, because information costs are typically lower for large firms. Market capitalization can also be a proxy for domestic share supply, because firms with larger market capitalization usually issue more domestic shares. According to Chan and Kwok (2005), Chan, Menkveld, and Yang (2008), and Mei, Scheinkman, and Xiong (2009), the price difference from twin Chinese shares based on the same fundamental asset could result from differences in trading frenzy, liquidity, supply of domestic shares, and information asymmetry between these two stocks.

Additionally, we include fixed effect for each warrant in the regression. The coefficients of interest are the $\beta_j's$ for variables I_1 through I_9. If the non-marketability discount decreases over the course of the day, these coefficients should be statistically significantly positive and show a decreasing trend from market open to market close.

Insert Table 5 about Here

We report the regression results in Table 5. Our results are consistent with the trend in Figure 1. Coefficients β_1 to β_9 represent the mean differences in the discount between the reporting time and the market close. All these coefficients are significantly positive, indicating that the non-marketability discounts are all significantly greater than that at the market close. Note that the statistical significance reported below the coefficients is based on robust standard errors that allow for clustering by each warrant. The trend also generally decreases from the morning to the afternoon, with the coefficients of dummy variables going down from 0.047 to 0.019 using Black-Scholes model or Heston-Nandi model, and from 0.046 to 0.018 using the model-free approach.

It should be noted that the higher discount towards the market close might be due to the higher stock volatility around the market close, in case the intraday volatility of stocks is not constant. To eliminate the impact of the variation of intraday stock volatility, in unreported tables for robustness checks, we add stock return volatility for the 30 minutes prior to each discount as an independent variable. The stock return volatility is computed as either the standard deviation of the 1- minute return of stocks or the summation of the squared 1-minute returns over the 30-minute interval. For this regression, we have fewer independent variables. We remove the dummy variables for 9:30 AM and 13:00 PM because there are no prior 30-minute stock volatility for these discounts. We repeat our regression in equation (3), and find our results very similar to the results in Table 5. The coefficients of intraday dummy variable show a clearly decreasing trend towards the market close, with the coefficient for coefficient of the 30-minute stock return volatility is not statistically significant. This result shows the intraday variation of the discount is not driven by the variation of intraday stock return volatility (The results are available from authors).

B. Intraday Patterns of the Market Depth

We then study the intraday pattern of the market depth in the two markets to gain more insights. Investors rationally prefer a market with a higher level of marketability and liquidity to a market with a lower level of marketability and liquidity. Consequently, given the level marketability is higher towards market close, we expect more investors to submit orders in the stock market at the market close. As a result, we expect stock market depth to display an increasing pattern throughout a trading day.

We measure market depth in millions of yuan. For both stocks and warrants, we compute the ask depth as the sum of products of the five best ask prices and the corresponding ask share volume, and the bid depth as the sum of products of the five best bid prices and the corresponding bid share volume. We then calculate the market depth as the average of the ask depth and the bid depth in equation (4).

$$MDEPTH_i = \frac{1}{2}\left[\sum_{j=1}^{5} Ask\,\mathrm{Pr}_{i,j} \times AskSize_{i,j} + \sum_{j=1}^{5} Bid\,\mathrm{Pr}_{i,j} \times BidSize_{i,j}\right] \tag{4}$$

At any time, $Ask\,\mathrm{Pr}_{i,j}$ is the j^{th} ask price for stock *i*, and $AskSize_{i,j}$ is the j^{th} ask size (in share volume) for stock *i*. $Bid\,\mathrm{Pr}_{i,j}$ is the j^{th} bid price for stock *i*, and $BidSize_{i,j}$ is the j^{th} bid size (in share volume) for stock *i*. We do not use only the best quoted price and order share volume to calculate market depth. We choose the five best quoted bid and ask for two reasons. First, Huang (2002) suggests that inside quotes are more informative of the market quality than the best quote alone in electronic limit order market such as the one in China; and second, the five best quoted prices and order sizes are observable to all investors. In unreported tables, we switch to calculating the market depth as using only the best ask and bid price and order share volume, and find the results consistent with what we present in the paper. We take the time-weighted average of all the market depths to obtain the market depth for every 30-minute interval and then take log of the depths. We plot the intraday trend of the log depth in Figure 2.

Insert Figure 2 about Here

Figure 2 shows that the market depth of stocks displays an overall upward trend, with the market depth at the market close being the greatest. In the stock market, the median of the log market depth starts at the level around 1.9 at the interval from the market opens at 9:30 a.m. to 10:00 a.m., to the level around 3.0 at the market close. However, the median log market depth in the warrant market does not have a clear intraday pattern and stays around the level of 1.0 throughout the entire trading day.

Similar to equation (3), equation (5) regresses the log market depth on intraday time interval dummies and control variables to confirm the trend observed in Figure 2.

$$DEPTH_{i,j,t} = \alpha + \sum_{j=1}^{7} \beta_j I_j + \beta_C CONTROL_{i,t} + WARRANT\ FIXED\ EFFECT + \varepsilon_{i,j,t} \tag{5}$$

$Depth_{i,j,t}$ is the log market depth of the stock *i* or warrant *i* during the j^{th} 30-minute interval between 9:30 a.m. (the market open) and 2:30 p.m. on day *t*. I_1 through I_7 are dummy variables for the 30-minute interval within this period. (We do not include the dummy variable of the last 30-minute interval of the trading day.) $CONTROL_{i,t}$ is a vector of control variables of stock *i* on day *t*. As in equation (3), we include four control variables of stock turnover ratio, warrant turnover ratio, the log of stock market capitalization, and the log of warrant total market value. We include these control variables to control for any effects on the variations of market depths that could be attributed to the differences between the trading frenzy, liquidity levels, and domestic share supply. We also include fixed effects for each warrant in the regression. The coefficients of interest are the β_j's for variables I_1 through I_7, which denote the amount of log market depth in excess of the log market depth at the interval from 2:30 p.m. to 3:00 p.m. To be consistent with the intraday pattern in Figure 2, these coefficients should be statistically significant, and show an increasing trend from morning to afternoon.

The regression results are reported in the "market depth" columns of Table 6. The results are consistent with an upward trend in the market depth in the stock market but not in the warrant market. The coefficients β_1 through

β_7 show an upward trend, increasing from -1.528 to -0.252. However, the corresponding coefficients in the warrant market do not show any clear trend. The difference in the two markets demonstrates that the restriction on marketability has a profound trading impact in the stock market.

The regression results reported in Table 6 strongly support the pattern identified in Figures 1 and 2, as well as our intuition that investor participation is positively correlated with marketability and liquidity. We note that theoretically, the non-marketability discount pattern could be due to the intraday time value decay of the warrants. However, given the small time value embedded in the deep in-the-money call warrants and the small warrant thetas summarized in Table 1, it is unlikely that the time value decay is the reason of decrease in the non-marketability discount over a trading day.

In addition to market depth, we compute the price impact coefficients following the method by Breen, Hodrick, and Korajczyk (2002). We divide every trading day into morning and afternoon sessions. For each session, we regress the five-minute returns on the net trading volumes in the same five-minute interval. The regression coefficient on the net trading volume is the price impact coefficient. We obtain morning and afternoon price impact coefficients for the stock market and the warrant market separately. Because the level of stock marketability increases when the time approaches the market close, we expect that more investors participate in the stock market in the afternoon. Consequently, we expect that the price impact in stock trading is lower in the afternoon. We indeed find that the average price impact in the afternoon is significantly smaller than that in the morning in stock trading. On the other hand, the average price impact for the warrants in the afternoon is not statistically different from that in the morning.[8] The results in the warrant market are consistent with the absence of changing in level of marketability in the warrant market.

C. Intraday Patterns of the Trading Imbalance

How does level of marketability affect trading? Because investors tend to hold assets with high level of marketability and liquidity, we expect increasing buying pressure in stock market as time approaches market close.

[8]The results are available from the authors.

This conjecture is consistent with Longstaff (2009) who shows that during periods when both liquid and illiquid assets are present, investors give up diversification strategies and put non-proportional weights on assets according to their liquidity preferences.

We examine the buying and selling activities from the intraday time-stamped data. Using an algorithm first developed by Lee and Ready (1991), and later refined by Lee and Radhakrishna (2000), Odders-White (2000), and Ellis, Michaely, and O'Hara (2000), we identify each trade as either buyer or seller-initiated. The quote rule identifies a trade as buyer-initiated if the transaction price is above the midpoint of the most recent bid-ask quote, and seller-initiated if the transaction price is below the midpoint. The tick rule identifies a trade as buyer-initiated if the price is above the last executed trade price and seller-initiated otherwise. We use the tick rule for trades that are executed between the posted bid and ask prices, and the quote rule otherwise. We drop trades that cannot be identified by using the rules specified above. This approach is adopted by Chan, Menkveld, and Yang (2008) in classifying trades in the Chinese A and B share markets.

We compute several measures of buy-sell imbalance over the course of a trading day. The first measure is the difference between the share volume of buy and sell trades during a period divided by the total share trading volume in the day. We call this measure the share volume imbalance. The second measure is the difference between the yuan volume of buy and sell trades during a period divided by the total yuan volume in the day. We label this measure the yuan volume imbalance. The third measure is the difference between the numbers of buy and sell trades during a period divided by the total number of trades in the day. We designate this measure as the trade number imbalance.

Insert Figure 3 about Here

We calculate each trade imbalance measure in both the warrant market and the stock market in every 30-minute interval during a trading session. Figure 3 plots the medians of these trade imbalance measures during the day. In the warrant market, the largest net buying activity happens immediately after the market open. Then the net buying decreases during the day and ticks up in the last 30-minute interval before market close. In the stock market, there is net selling during most of the day. Only during the last 30 minutes before the market close is there some net buying. This result is expected if investors recognize the effect of marketability constraints. Investors optimally choose to buy stocks near the market close, when the discount due to non-marketability is the smallest. In contrast, investors in the warrant market, who do not face changes in marketability, buy most at the market open. Their buying strategies might be driven by the fact that most information is released between the previous day's market close and current day's market open. They also tend to buy more at the market close. This trading pattern is the typical U-shaped trading activity documented in the market microstructure literature (McInish and Wood, 1992).

In terms of share volume or yuan volume, the net trading imbalance is not increasing monotonically during the day in the stock market. At the market open, there may be some information-driven buying by investors, hence the trade imbalance at the market open is not quite negative. After about 10:30 a.m., there is less buying activity and the trade imbalance becomes more negative. As the stock market approaches the market close, the buying activity in the stock market picks up and turns the trade imbalance to positive. The general trend of market buying activities supports Longstaff's (2009) hypothesis that investors adjusts their portfolio holdings according to their liquidity preference. In our study, investors increase their stock holdings when the adverse effects of non-marketability get smaller.

The trade number imbalance in Panel C of Figure 3 gives us a somewhat different picture. In the stock market, the number of net buy orders is positive at both the market open and the market close. The number of net buy orders decreases in the middle of the trading day. Together with the figures for the volume imbalance (Panel A) and the yuan volume imbalance (Panel B), Panel C implies that the buying activity at the market open is driven primarily by small orders that are likely submitted by retail investors, while the buying activity at the market close is driven by large orders potentially submitted by institutional investors. Hence, the evidence appears to support the notion that sophisticated investors understand (lack of) marketability well and trade near the market close when the level of marketability is the highest.

In the warrant market, the trade number imbalance has a generally downward trend over the course of a trading day. The largest number of net buy orders (which we normalized by the total number of orders) appears at the market open. This measure decreases and becomes negative after 10:30 a.m. Because there is no restraint on the warrant buying during the trading day, the imbalance pattern in the warrant market is different from that in the stock market.

Insert Figure 4 about Here

We further explore investors' intraday trading behavior by separately examining large trades and small trades. Similar to Lee (1992), we classify large trades as trades that are more than ¥500,000 in a single transaction and small trades as trades that are less than ¥100,000 in a single transaction. In Figure 4, we plot the net yuan volume imbalance separately for large trades and small trades. The results are consistent with our conjecture that large investors recognize the impact of non-marketability in the stock market and concentrate most of their purchases toward the market close. The net trading imbalance of small investors in the stock market is nearly constant. There is no discernible time when small investors concentrate their purchases. In the warrant market, we find a downward trend in trading imbalance of both large and small investors. There are no differences in the patterns in the buying and selling behavior between these two groups of investors in the warrant market.

Figure 4 suggests that retail investors do not appear to factor in changes in level of marketability when they trade in the stock market. In contrast, investors who make large trades, most likely institutional traders, usually take into consideration of level of marketability (liquidity) to time their trades and formulate their portfolio strategies (Longstaff, 2009).

D. What Can We Learn from Intraday Patterns?

Our intraday results show that aggregate trading patterns in the stock market reflect changes in level of marketability and liquidity. One may argue that such short-term change in marketability has little impact on large portfolio managers because they have a large inventory of long positions from previous purchases and can engage in both buying and selling activities of the same stock on the same day. However, if these large investors anticipate the impact of marketability on other investors, they should react accordingly and their actions affect trading patterns and prices of the assets with marketability constraints, as predicted by Longstaff (2009). Our study provides such an example.

Overall, our results from the intraday analyses shed light on factors contributing to the formation of the non-marketability discount. Our findings show that more investors' presence, as well as more net buying volumes, in the stock market, is connected with lower non-marketability discount. This conclusion is consistent with the fact that the restriction on asset liquidity or marketability may adversely affect investor demand, thus lowering the equilibrium price. Additionally, the non-marketability discount reflects investors' preference to liquidity (Longstaff (2004), Longstaff (2009)). We do not claim that the discount is due to only non-marketability. Other factors might affect asset prices as well. However, the intraday patterns of the multiple aggregate measures provide strong evidence that non-marketability plays an important role in the formation of the discount.

We note that one strategy used by mutual funds and portfolio managers near the end of year or end of quarter to improve the appearance of the portfolio/fund before presenting it to clients or shareholders is "window dressing". In the Chinese context, to window dress, fund managers may purchase in the stock market near the market close to increase the share prices. To eliminate this concern, we remove from our sample the observations of month-end dates and redo all the empirical tests. We find qualitatively very similar results.

In unreported figures, we plot the median of trade imbalances for all stocks in the market and during more recent years when warrants have expired, rather than confine our focus to only those companies that issue warrants. In the larger sample, we continue to observe evidence of buying stocks at the market close.[9] This result demonstrates that our conclusion is robust to the whole Chinese stock market where marketability is restricted.

3.2 Evidence from the Cross-Sectional Regressions

Amihud and Mendelson (1986) derive a positive relation between asset prices and liquidity levels. Assets with high liquidity levels command higher current prices and thus lower expected returns, but assets with low liquidity have lower current prices and higher expected returns. In our case, we have two assets based on the same fundamental value and both assets are actively traded in the same exchange. There is one exogenous trading restriction that causes the stock to have a lower marketability than the warrant. Even though the marketability constraint appears to be nonbinding at the market close, it continues to be enforced when the stock is sold in the subsequent trading days. The next buyer is restricted from selling the shares on the day when she buys the shares. Therefore, the next buyer discounts the stock purchase price due to the non-marketability which applies to her and

[9] The results are available from the authors.

all subsequent traders. In equilibrium, the current stock buyer takes into consideration all the subsequent discounts and would pay only a lower price, even at market close, than the price of an otherwise identical stock without any marketability constraints.

Although the exogenous marketability constraint does not vary in our sample, the ex ante liquidity level, as a proxy for transaction costs, does vary over time and across different firms. Hence, we further propose that the non-marketability discount is correlated with the change in liquidity in the stock and warrant markets, and that the more liquid the stock market is, the smaller is the discount. That is, everything else held constant, high liquidity in the stock market drives up the observed stock price and reduces the difference between the implied stock price and the observed stock price. However, the more liquid the warrant market is, the greater is the warrant price. Consequently the higher is the implied stock price, and the non-marketability discount would increase. The non-marketability discount should be negatively correlated with the liquidity in the stock market, but positively correlated with the liquidity in the warrant market. Our argument is similar to that of Chan, Hong, and Subrahmanyam (2008). They show that the price differential between American Depositary Receipts (ADRs) and their underlying shares in their home countries is related to liquidity in the two markets.

We first run a correlation analysis of all the liquidity measures and other control variables that might explain the non-marketability discount. The two liquidity measures are the ratio of stock Amihud measure to 1,000 times of the warrant Amihud measure (*AMRATIO*), and the ratio of stock turnover to warrant turnover (*TURNRATIO*). These two variables measure the relative liquidity difference between the stock and warrant markets. Our control variables include the log stock market capitalization (*SMCAP*) and log warrant total market value (*WMVAL*) at the end of the previous month. Because Chinese investors are unable to invest globally, it is possible that their trading activities are negatively affected by the supply of domestic shares (Chan and Kwok, 2005). It is also possible that the information cost is typically lower at the stock market, which usually enjoys a much bigger market capitalization than the warrant market (Chan, Menkveld, and Yang, 2008). Both papers suggest that the non-marketability discount should be negatively related to stock market capitalization, and positively related to total warrant market value.

Other control variables include the cumulative return of the underlying stock (*SMOMENTUM*) in the previous month and the cumulative return of the warrant (*WMOMENTUM*) in the previous month. According to Karolyi and Li (2003), the cumulative returns are proxies for stock and warrant market momentums, which can be further associated with different risk levels. If Chinese investors treat warrants and stocks as assets with different risk levels, then we should expect the non-marketability discount to be negatively related to the stock market momentum and positively related to the warrant market momentum. Another control variable is the annualized historical volatility of the underlying stock returns in the previous 120 trading days (*HVOL*). If Chinese investors use call warrants to hedge their position in the stock market, we should expect the non-marketability discount to be positively related to the historical volatility.

Insert Table 6 about Here

The results in Table 6 show that the stocks with low liquidity levels relative to their paired warrants are associated with high cumulative returns in both their stocks and their paired warrants during the previous month. These stocks have a smaller market capitalization and larger total market values for the paired warrants, and have higher historical volatilities. Therefore, we need to control for these potentially explanatory variables when relating the liquidity measures to the non-marketability discount. The two liquidity ratios, *AMRATIO* and *TURNRATIO*, are negatively correlated, which is consistent with the implication that securities with higher Amihud measure should have lower turnover ratios. We believe it is advisable to try both variables in the regressions, because each of them may empirically measure different aspects of liquidity. We find that the two momentum variables are highly correlated, with a correlation coefficient of 0.867. This finding is consistent with the fact that stocks and deep in-the-money call warrants in our sample are close substitutes. For this reason, we report regression results with only the stock cumulative return as the variable to control for momentum effect. When we switch to the warrant momentum factor, the results do not change qualitatively. Chan, Menkveld, and Yang (2008) adopt a similar approach where they regress the Chinese A-B share price differences on explanatory variables.

In equation (6), we regress the non-marketability discount at the market open on the liquidity measures and control variables in both the stock and the warrant markets.

$$DISC_{i,t} = \alpha_t + \beta_L LIQ_{i,t} + \beta_C CONTROL_{i,t} + WARRANT \quad FIXED \quad EFFECT + \varepsilon_{i,t} \qquad (6)$$

$DISC_{i,t}$ is the non-marketability discount of stock *i* on day *t*. $LIQ_{i,t}$ is the liquidity ratio measure variable, including either *AMRATIO* or *TURNRATIO*. $CONTROL_{i,t}$ is a vector of control variables of stock *i* on day *t*. We use four control variables, *SMCAP*, *WMVAL*, *SMOMENTUM*, and *HVOL*, to control for any effect that could attribute to the differences between the market size, information asymmetry in the stock and warrant markets, and differences in historical volatility. We also include warrant fixed effects in the regression. The coefficients of interest are the β_L for the liquidity measure variables. Our premise is that the low liquidity in the stock market or high liquidity in the warrant market leads to a large non-marketability discount. We expect the coefficients of β_L to be positive for *AMRATIO* and negative for *TURNRATIO*. To control for the possible serial correlation in our sample, we report the standard errors that allow for the clustering among each warrant.

Insert Table 7 about Here

Table 7 presents the results of regressions in which the dependent variable is the non-marketability discount at the market open. The analyses of the regressions generate further support for our hypothesis that the marketability constraints contributes to the non-marketability discount in the stock market. For example, the coefficient on *AMRATIO* is 0.036 when we compute the non-marketability discount using the Black-Scholes model, 0.034 using the Heston-Nandi model, and 0.037 using the model-free approach. All coefficients are positive and statistically significant at the 5% level based on robust standard errors that allow for clustering by each warrant. The coefficients are also economically significant: a one standard deviation change in the *AMRATIO* causes the non-marketability discount to increase by about 0.003, which is roughly 10% of the average non-marketability discount at the market open. The coefficients for *TURNRATIO* in Table 7 are significant and negative, which indicates that high liquidity in the warrant market or low liquidity in the stock market leads to large non-marketability discount. This result further supports our argument.

In unreported tables, we regress the non-marketability discount at the market close on the liquidity measures and control variables, and find qualitatively similar results as in Table 7. We control for other competing explanatory variables in the regressions. For example, the regressions results reported in Tables 7 show that the coefficient for stock market capitalization is significantly negative, and that the coefficient for the stock momentums is significantly negative. In line with our explanations, the results suggest that the information asymmetry in the stock market contributes to the observed non-marketability discounts, and that investors may be more risk tolerant towards those stocks that experienced higher cumulative returns during the previous months and willing to accept higher prices. The coefficients for other variables are in general not statistically significant. The coefficients of liquidity measures in Tables 7 suggest that the liquidity difference within the stock and warrant markets contribute significantly to the non-marketability discount at both the market open and the market close, even after controlling effects from other possible explanations.

We note that the cross-sectional analysis has some weaknesses. Even if warrant prices are not driven by investors' flight to liquidity / marketability, but by speculation, we may still be able to observe the patterns in Table 7. However, one merit of introducing the cross-sectional analysis is that we may use this framework to rule out several alternative hypotheses, which are conducted in the next subsection.

3.3. Robustness Checks and Discussion

We argue that the key difference between the warrant market and the stock market is the marketability constraint in the stock market but not in the warrant market, and that level of marketability drives our results. There may be alternative explanations of the non-marketability discount. We investigate several alternative explanations.

A. Transaction Tax Effect.

One alternative hypothesis is that the non-marketability discount may be caused by lower transaction costs in the warrant market. When investors trade Chinese stocks, they must pay a transaction tax to the government, but this tax is not levied on warrant investors. Given its lower transaction cost, investors may prefer to trade in the warrant market and thus drive up the warrant price and non-marketability discount. During our sample period, the transaction cost does not change in the warrant market, but it does change in the stock market. The transaction tax rate, which the government applies to the total yuan transaction volume, goes from 0.1% to 0.3% on May 30, 2007, and back to 0.1% on April 24, 2008. We compare and contrast the sizes of the non-marketability discount over these two periods. If the non-marketability discount is driven by the difference in transaction tax, we expect that the non-marketability discount to be greater in a high transaction tax period when the transaction tax rate is 0.3% in the stock market.

Insert Table 8 about Here

Panel A of Table 8 summarizes results under high and low transaction taxes, separately. Contrary to the previous transaction tax based explanation, we find that the non-marketability discount is actually greater when the transaction tax rate is lower. Thus, the transaction tax alone does not explain the non-marketability discount.

We run separate regressions of the non-marketability discount on liquidity measures for the two periods of different transaction tax rates. Table 9 presents the regression results. The results do not change qualitatively when we partition the sample into two periods based on different transaction tax rates in the stock market.

Insert Table 9 about Here

B. Speculative Trading Concern

In previous sections, we regress the daily warrant close prices on the stock close prices and other control variables to show that the call warrant prices in our sample are not driven by the behavioral biases in the warrants market, as in the put warrants sample depicted by Xiong and Yu (2011). We now further examine the possibility that the non-marketability discount is related to speculative trading.

If speculative activities drive up the price of one asset (warrant) more than the other asset (stock), researchers would also observe the discount. The common variable to measure speculative activity is the turnover ratio (Mei, Scheinkman, and Xiong, 2009). Although we interpret the turnover ratio as a measure of liquidity in this paper, our result that the non-marketability discount is positively correlated with the warrant turnover is also consistent with the speculative trading explanation. To explore this issue further, we split the sample into two subsamples based on the level of stock turnover. If speculative trading drives our results, we should observe some impact from speculative trading in the stock because the stock and warrant are close substitutes for each other. Panel B of Table 8 presents the comparison between the two subsamples and Table 9 presents the regression results using the two subsamples separately. We do not observe a significant difference in the non-marketability discounts of the two subsamples. All regression results do not change qualitatively. Hence, our results do not appear to be attributable to speculative trading. Instead, we believe that the difference in marketability contributes directly to the non-marketability discount.

C. Information Asymmetry

The third alternative explanation for the non-marketability discount is related to the information asymmetry. Easley, O'Hara, and Srinivas (1998) show that informed traders tend to concentrate their trading in the option markets, because options markets allow them to maximize the value of their private information. Amin and Lee (1997) show that informed traders tend to trade in the option market around the firms' earnings announcement dates. Applying this insight to the Chinese market, one could argue that traders in the Chinese warrant market might have better access to private information. Because short selling is not allowed in China, informed traders are more likely to explore positive news and bid the prices higher. If there are informed traders in the warrant market, the warrant price may be bid up and result in the discount we observe.

Chan, Menkveld, and Yang (2008) propose a similar hypothesis to explain the A-B share price premium. They argue that there is more information asymmetry in the B share market and thus B shares are traded at a discount to the corresponding A shares of the same company. We explore this alternative explanation by splitting the sample into two subsamples. One subsample includes the observations within 10 days of the earnings announcement dates of the companies; the other subsample includes all the remaining observations. Because Amin and Lee (1997) report a higher percentage of informed trading around the earnings announcement dates in the options market, we denote the former subsample with high information asymmetry, and latter subsample with low information asymmetry. We compare the summary statistics of the non-marketability discount in these two subsamples, and rerun all cross-sectional regressions. The results are reported in Panel C of Table 8 and columns 5 and 6 of Table 9.

The non-marketability discount is greater in the low information asymmetry sample. This result is opposite to the alternative explanation. In addition, if there is more informed trading in the derivative market during the high information asymmetry time, we should expect to observe more trading activities in the warrant market around the earnings announcement dates. However, when we examine the turnover ratio in both the high and low information asymmetry subsamples, we find exactly the opposite. The warrant turnover ratios in the two subsamples are not statistically different, and the stock turnover ratio is significantly higher in the high information asymmetry period than in the low information asymmetry period. This result suggests that it is not the informed trading in the warrant market, but the clustering of noise trading around the earnings announcement dates in the stock market that drives up the stock prices and generates smaller non-marketability discounts. Regressions using each subsample generate qualitatively similar results. Hence, we do not find evidence to support the alternative explanation that non-marketability discount is caused by informed trading.

D. Bias in the Model-Free Approach and Sample Selection

Our model-free approach has some systematic biases. We ignore the time value of the warrants, hence our implied stock price estimates and our discount estimates are upward biased. Because the time value of call warrants decreases with the time to maturity, this bias is larger when the time to maturity is long. We examine the impact of this bias by splitting the sample into two sub-samples, one with long time to maturity and one with short time to maturity. If this bias is significant, we would expect that the discounts, especially the model-free discounts, in the long time to maturity sample are larger than those in the short time to maturity sample. Panel D of Table 8 shows that all discounts are larger in the short time to maturity instead. In addition, the results are virtually identical for discounts derived from the model-free approach, Black-Scholes model, and the Heston-Nandi model. Because both Black-Scholes and Heston-Nandi models account for the time value of call warrants, and the model-free approach does not, the fact that we get similar results between the different time to maturity samples show that the bias in our model-free approach is not significant. We also run the same regressions in the two sub-samples and all the regression results are qualitatively unchanged as shown in columns 7 and 8 of Table 9. It appears that omitting the time value in our model-free approach does not have a large impact to our results.

As we have explained in section 3.1, our sample includes some warrants observations with relatively lower moneyness measures. To eliminate effects from the low moneyness warrants, we remove observations from our sample with moneyness less than 0.5. There are about only 7% of the observations eliminated. We find all our empirical results qualitatively remained for the reduced sample.

4. Conclusion

In this paper, we extend previous studies on the effect of non-marketability on stock prices, and examine a unique short-lived non-marketability that lasts for only less than one day in China. We examine two similar assets in the Chinese equity market, the deep in-the-money call warrant and the common stock of the same company. Although the fundamental values of the two assets are the same, there is a difference in marketability in the two assets. The common stock is subject to a one-day selling lockup, while the warrant is not. Unlike other studies on impact of price illiquidity, in our paper both assets are traded in the same market to potentially the same investors. Furthermore, both assets are highly liquid with large transaction volumes and turnover. Nevertheless, we illustrate that lack of marketability in the stock market contributes to the non-marketability discount in the stock price and that this non-marketability discount exists even at the market close when the non-marketability restriction does not appear to be directly binding. We also find this discount decreases from market open to market close. The net trade imbalance over the course of a trading day shows that investors tend to concentrate buying in the stock market near the market close. In terms of market depth, we find that the average market depth increases over the course of a trading day, indicating that more investors trade toward the market close to minimize impact of non-marketability. We do not see similar patterns in the warrant market, either in the net trade imbalance or in the market depth.

Our study provides evidence that even a short-term (i.e., measured in hours) lockup restrictions can generate a significant non-marketability discount. It provides clean supporting evidence to the liquidity-based asset pricing theories of Longstaff (2009) that the restriction on asset liquidity or marketability may adversely affect investor demand, thus lower the equilibrium price. Our findings help evaluate the potential impact of policy proposals suggesting the widespread use of trading lockups to curb excessive high frequency trading (such as the circuit breakers on individual stocks). Lockup can also be viewed as an alternative transaction cost. Lo, Mamaysky, and Wang (2004) conclude that small fixed transaction costs may produce a significant non-marketability discount. Our investigation suggests that even though each individual lockup restriction may not seem to produce a strong impact on asset prices, the fact that the lockup is a "repeated game" permanently reduces the marketability and liquidity of assets. Hence, the non-marketability discount not only exists, it is also significant. Our results suggest that omissions of small but repetitive transaction costs (such as the transaction tax) may significantly affect asset prices. The conclusions in this paper are fully consistent with those of Longstaff (1995) who states that small illiquidity periods may produce large negative price impacts.

Appendix

In this appendix, we apply the same methods to examine the difference between the option implied stock price and the observed stock price in the U.S. stock market. Compared with the Chinese stock market, the U.S. market allows investors to sell stocks at any time after their purchases. We therefore do not expect the non-marketability discount to exist in the U.S. market.

We obtain the option data from the OptionMetrics database, and the corresponding stock data from CRSP. The time period is from January 2007 to June 2008. We apply a few filters to our dataset. First, we select stocks in CRSP that also have options listed in CBOE from January 2007 to June 2008. We calculate the market capitalization for each stock at the end of each month and then take the time series average from each stock. We then sort the stocks based on their average end of month market capitalizations. Because our sample in the Chinese market includes 16 warrants, we choose 16 U.S. stocks with the largest average market capitalizations. The options of these 16 stocks are in general the most actively traded options in the market, thus carry the least concerns of nonsynchronous trading concerns between the option and the underlying stock markets. These stocks include: American International Group, Inc. (AIG), Bank of America Corporation (BAC), Citigroup, Inc. (C), Cisco System, Inc. (CSCO), Chevron Corporation (CVX), General Electric Company (GE), International Business Machines Corporation (IBM), Johnson & Johnson (JNJ), JPMorgan & Chase Corporation (JPM), Altria Group, Inc. (MO), Microsoft Corporation (MSFT), Pfizer, Inc. (PFE), Procter & Gamble Corporation (PG), AT & T, Inc. (T), Wal-Mart Stores, Inc. (WMT), and Exxon Mobil Corporation (XOM).

Next, for the 16 stocks and their corresponding options, we obtain the daily close prices for both the stocks and their options. We restrict our sample to call options only. For the stocks that have multiple calls in a trading day, we choose the in-the-money call option that has the smallest difference between the close price of the underlying stock and the strike price. For stocks with more than one option that have the same differences between strike price and the corresponding stock close prices, we choose the option with highest trading volume. We further restrict our sample to call options with at least 15 days to maturity, with positive open interest, and when the underlying stocks are not on their ex-dividend days. We also eliminate the stock-option pair if the stock close price is less than $5, or the close option bid price is higher than the close option ask price.

Our final sample has a size of 3426 observations for 16 options and their underlying stocks. We then use the Black-Scholes option pricing model to calculate the implied stock prices (ISP) from option prices. Similar to the computation in the Chinese warrant market, we take the historical volatility of the returns of the underlying stock in the past 120 days as the volatility input. We download the daily risk-free interest rate from Ken French's website.[10]

Similar to the non-marketability discount in the Chinese warrant market, we define the implied stock discount (ISD) in the U.S. market as:

$$ISD = \frac{ISP - Stock\ Close\ \Pr ice}{ISP} \tag{A.1}$$

The average *ISD* in our sample of U.S. stocks is -0.00003. This result is negative and insignificant, with the *t*-value of -1.45. In contrast, the average *ISD* for Chinese market is 0.03. We believe that one main cause for this difference is that the U.S. stock market does not impose the selling lockup.

[10] Risk-free interest rates are downloadable at Ken French's website at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

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Table 1

Summary Statistics

This table reports the mean (Mean), standard deviation (Std), median (Median), minimum (Min), and maximum (Max) of variables on warrants and their underlying stocks. Our sample contains daily observations on call warrants and stocks between August 22, 2005 and June 30, 2008. We further restrict the sample to those observations when the warrants have Black-Scholes delta greater than or equal to 0.9. The time to maturity is the time to maturity of the warrants. The historical volatility is the annualized standard deviation of returns for the underlying stock during the previous 120 trading days. We calculate moneyness as the difference between the ratio of stock price to warrant strike price and one. Delta and theta are the delta and theta in the Black-Scholes model. Stock market capitalization and warrant market value are the total market value of the stock and its warrants.

Variable	Mean	Std	Median	Min	Max
Time to maturity (years)	0.560	0.405	0.451	0.042	1.906
Historical volatility	0.548	0.111	0.557	0.238	0.760
Moneyness	1.721	1.372	1.329	0.126	9.040
Delta	0.979	0.026	0.991	0.900	1.000
Theta	0.510	0.620	0.236	0.049	3.728
Stock market capitalization (billion yuan)	39.564	30.861	28.787	8.592	161.934
Warrant market value (billion yuan)	2.550	1.887	1.952	0.273	9.483
Stock closing price (yuan)	20.969	15.657	15.185	2.510	69.860
Warrant closing price (yuan)	13.634	11.329	9.724	0.451	57.100

Table 2
Comparison of Stocks and Warrants

This table presents the mean (Mean), standard deviation (Std), and median (Median) of trading activity measures in the stock and warrant samples. In Panel A, the market trading variables are daily trading volume (Volume), daily yuan trading volume (Yuan Volume). In Panel B, liquidity measures are the Amihud measure (AMIHUD) and the turnover ratio (TURNOVER). AMIHUD is the absolute return per yuan in daily trading volume multiplied by 10^7. TURNOVER is the trading volume divided by the total number of tradable shares outstanding. In Panel C, market control variables include log of the stock and warrant market value (MCAP), and the return momentum factor (MOMENTUM) in each market. MOMENTUM is the one-month cumulative return in the prior calendar month. We perform t-tests on the differences between the means of the stock and warrant populations. The Z-statistics are the Wilcoxon test statistics on whether the medians of the two markets are significantly different.

	Stock			Warrant				
	Mean	Std	Median	Mean	Std	Median	*t*-stat	*Z*-stat
Panel A								
Volume (1,000,000 shares)	29.998	28.708	21.492	205.236	337.141	76.912	-23.80	-33.20
Yuan Volume (1,000,000 Yuan)	429.590	354.087	318.355	1264.259	1403.385	817.660	-26.50	-30.47
Panel B								
AMIHUD	0.001	0.001	0.001	0.0006	0.001	0.0003	12.69	17.71
TURNOVER	0.028	0.020	0.023	0.504	0.432	0.394	-50.57	-56.01
Panel C								
MCAP	24.143	0.709	24.083	21.393	0.770	21.392	120.81	56.25
MOMENTUM	0.142	0.238	0.146	0.180	0.322	0.181	-4.33	-2.01

Table 3
Summary Statistics of the Non-Marketability Discount

This table reports the mean (Mean), standard deviation (Std), median (Median), minimum (Min), and maximum (Max) of the non-marketability discount. Open(BSC), Open(HN), and Open(MF) are the non-marketability discounts at the market open using the Black-Scholes model, the Heston-Nandi model, and the model-free approach, respectively. Close(BSC), Close (HN), and Close(MF) are the non-marketability discounts at the market close. Diff(BSC), Diff (HN), and Diff(MF) are the differences of Open(BSC) and Close(BSC), Open(HN) and Close(HN), Open(MF) and Close(MF), respectively. We use t-tests to determine whether the means are significantly different from zero, and the Wilcoxon Z-tests to test whether the medians are significantly different from zero. The table also reports p-values from the *t*-test and *Z*-test.

	Mean	Std	Median	Min	Max	P-value (t-test)	P-value (Z-test)
Non-Marketability Discount							
Open(MF)	0.041	0.089	0.041	-0.268	0.276	0.00	0.00
Open(BSC)	0.030	0.094	0.032	-0.288	0.272	0.00	0.00
Open(HN)	0.023	0.101	0.030	-0.334	0.269	0.00	0.00
Close(MF)	0.037	0.089	0.037	-0.282	0.277	0.00	0.00
Close(BSC)	0.026	0.095	0.029	-0.302	0.274	0.00	0.00
Close(HN)	0.020	0.097	0.026	-0.313	0.272	0.00	0.00
Diff(MF)	0.004	0.019	0.004	-0.111	0.083	0.00	0.00
Diff(BSC)	0.005	0.019	0.004	-0.113	0.083	0.00	0.00
Diff(HN)	0.003	0.032	0.003	-0.135	0.100	0.00	0.00

Table 4
Determinants of the Warrant Close Price

This table includes the regression results of daily warrant closing prices on various control variables. Control variables include daily stock closing prices (Stock), daily warrant turnover (Turnover), on five-minute warrant return volatility (VOL), the total number of warrants outstanding (Float), the total number of warrants issued by the underlying firms (FirmIssue) and net total warrant issued by brokerage firms (BIssue). All regressions include warrant time to maturity fixed effect by month. Heteroskedasticity-robust *t*-statistics are reported in parentheses below the coefficients, and are based on robust standard errors that allow for clustering by each warrant. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Warrant Close Price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stock	0.71***				0.72***		0.72***
	(15.42)				(12.12)		(12.40)
Turnover		-6.87**			-0.68		-0.77
		(-2.21)			(-0.89)		(-0.98)
VOL			-163.29		66.63		61.16
			(-0.58)		(1.40)		(1.37)
Float				-19.45***	0.92		
				(-6.07)	(0.69)		
FirmIssue						-17.61***	0.88
						(-5.95)	(0.66)
BIssue						-64.36**	5.18
						(-2.35)	(1.05)
R^2	0.95	0.10	0.04	0.39	0.95	0.43	0.95

Table 5

Regressions of Non-Marketability Discount and Market Depth on Intraday Dummy and Control Variables

Column 2 and column3 of the table present the regression results of the non-marketability discount and the market depth on control and intraday dummy variables.

$$DISC_{i,j,t} = \alpha_t + \sum_{j=1}^{9} \beta_j I_j + \beta_C CONTROL_{i,t} + WARRANT \quad FIXED \quad EFFECT + \varepsilon_{i,j,t}$$

$DISC_{i,j,t}$ is the non-marketability discount (multiplied by 10) of stock *i* at the j^{th} 30-minute starting from 9:30 a.m. to 2:30 p.m. (with the lunch break from 11:30 a.m. to 1:00 p.m.) on day *t*. I_1 through I_9 are dummy variables for the 30-minute time spots between 9:30 a.m. and 2:30 p.m. (We do not include the dummy variable at the market close.). I_1 to I_9 equal one if the discount is computed at the market open (9:30 a.m.), 10:00 a.m., 10:30 a.m., 11:00 a.m., 11:30 a.m., 1:00 p.m., 1:30 p.m., 2:00 p.m., and 2:30 p.m., respectively, and equal zero otherwise.

Column 4 and column 5 of the table presents the regression results of the market depth on control and intraday dummy variables.

$$DEPTH_{i,j,t} = \alpha + \sum_{j=1}^{7} \beta_j I_j + \beta_C CONTROL_{i,t} + WARRANT\ FIXED\ EFFECT + \varepsilon_{i,j,t}$$

$Depth_{i,j,t}$ is the log market depth of the stock or warrant *i* during the j^{th} 30-minute interval between 9:30 a.m. (the market open) and 2:30 p.m. on day *t*. I_1 through I_7 are dummy variables for the 30-minute interval within this period. We do not include the dummy variable for the last 30-minute interval of the trading day. I_1 to I_7 equal one if the depth is measured from the market open (9:30 a.m.) to 10:00 a.m., from 10:00 a.m. to 10:30 a.m., from 10:30 a.m. to 11:00 a.m., from 11:00 a.m. to 11:30 a.m., from 1:00 p.m. to 1:30 p.m., from 1:30 p.m. to 2:00 p.m., and from 2:00 p.m. to 2:30 p.m., respectively, and equal zero otherwise.

For both regressions, $CONTROL_{i,t}$ is a vector of control variables of stock *i* on day *t*, which includes daily stock turnover (*STURNOVER*), daily warrant turnover (*WTURNOVER*), the log of stock market capitalization (*SMCAP*), and the log of warrant total market value (*WMVAL*) at the end of previous month. All regressions include warrant fixed effect. Heteroskedasticity-robust *t*-statistics are reported in parentheses below the coefficients, and are based on robust standard errors that allow for clustering by each warrant. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	Non-Marketability Discount			Market Depth	
	Model Free	Black-Scholes	Heston-Nandi	Stock	Warrant
I_1	0.046***	0.047***	0.047***	-1.528***	-0.047
	(11.28)	(10.92)	(10.74)	(-4.90)	(-1.20)
I_2	0.077***	0.078***	0.056***	-0.775***	-0.009
	(5.72)	(5.64)	(9.22)	(-3.91)	(-0.43)
I_3	0.052***	0.053***	0.054***	-0.698***	-0.050**
	(7.91)	(7.79)	(7.70)	(-4.21)	(-2.51)
I_4	0.052***	0.053***	0.054***	-0.717***	-0.090***
	(7.92)	(7.86)	(7.86)	(-4.05)	(-4.61)
I_5	0.046***	0.047***	0.048***	-0.486***	-0.090***
	(8.99)	(8.98)	(9.00)	(-3.72)	(-5.42)
I_6	0.046***	0.047***	0.047***	-0.355***	-0.043***
	(7.01)	(7.04)	(7.11)	(-3.15)	(-3.03)
I_7	0.045***	0.046***	0.046***	-0.252***	-0.079***
	(9.36)	(9.14)	(9.08)	(-3.42)	(-3.61)
I_8	0.030***	0.031***	0.031***		
	(8.41)	(8.27)	(8.22)		
I_9	0.018***	0.019***	0.019***		
	(6.44)	(6.33)	(6.27)		
STURNOVER	-9.816***	-10.116***	-10.841***	54.344***	6.870***
	(-3.15)	(-3.26)	(-3.34)	(4.64)	(3.34)
WTURNOVER	0.370**	0.368**	0.363**	-1.100***	0.760***
	(2.66)	(2.80)	(2.95)	(-4.30)	(4.34)
SMCAP	-1.885***	-0.153***	-1.312**	-2.466*	-1.097**
	(-4.38)	(-3.26)	(-2.60)	(-1.96)	(-2.27)
WMVAL	0.631*	0.431	0.297	2.291**	1.331***
	(2.00)	(1.19)	(0.77)	(2.54)	(3.63)
Intercept	33.389***	27.915***	24.935***	15.934	-0.028
	(5.74)	(4.89)	(4.23)	(0.86)	(-0.01)
Number of observations	20510	20510	20510	16376	16376
Adjusted R^2	0.56	0.61	0.65	0.58	0.63

Table 6
Explanatory Variable Correlations

This table presents the correlations among all explanatory variables for the cross-sectional variation in non-marketability discounts. These explanatory variables include two liquidity ratio measures: the ratio of stock Amihud measure to 1,000 times the warrant Amihud measure (*AMRATIO*) and the ratio of stock turnover to warrant turnover (*TURNRATIO*). The explanatory variables also include the log stock market capitalization (*SMCAP*) and log warrant total market value (*WMVAL*) at the end of the previous month, the cumulative return in the previous month of the underlying stock (*SMOMENTUM*) and of the warrant (*WMOMENTUM*), and the annualized standard deviation of the returns for the underlying stock in the previous 120 trading days (*HVOL*).

	AMRATIO	*TURNRATIO*	*SMCAP*	*WMVAL*	*SMOMENTUM*	*WMOMENTUM*	*HVOL*
AMRATIO	1	-0.039	-0.020	0.057	-0.033	-0.026	0.040
TURNRATIO		1	-0.221	0.106	0.124	0.097	-0.038
SMCAP			1	0.400	-0.266	-0.334	0.335
WMVAL				1	-0.227	-0.294	0.630
SMOMENTUM					1	0.867	-0.207
WMOMENTUM						1	-0.334
HVOL							1

Table 7
Regressions of Non-Marketability Discounts at the Market Open on Liquidity Ratio Measures and Control Variables

This table presents regression results of the non-marketability discounts at the market open on liquidity ratio measures and control variables.

$$DISC_{i,t} = \alpha_t + \beta_L LIQ_{i,t} + \beta_C CONTROL_{i,t} + WARRANT \quad FIXED \quad EFFECT + \varepsilon_{i,t}$$

$DISC_{i,t}$ is the non-marketability discount of stock *i* at the market open of day *t*. $LIQ_{i,t}$ is the vector of liquidity ratio measure variables. $CONTROL_{i,t}$ is a vector of control variables of stock *i* on day *t*. The liquidity ratio measures are the ratio of stock Amihud measure to 1,000 times of the warrant Amihud measure (AMRATIO), and the ratio of stock turnover to the warrant turnover (TURNRATIO). There are two missing values for AMRATIO because the warrant Amihud measures are zeros. Control variables are log stock market capitalization (SMCAP) and log warrant total market value (WMVAL) at the end of the previous month, the return in the previous month of the underlying stock (SMOMENTUM), and the annualized standard deviation of the returns for the underlying stock in the previous 120 trading days (HVOL). All regressions include warrant fixed effect. Heteroskedasticity-robust *t*-statistics are reported in parentheses below the coefficients, and are based on robust standard errors that allow for clustering by each warrant. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Non-Marketability Discount at the Market Open					
	Model-Free		Black-Scholes		Heston-Nandi	
AMRATIO	0.037**		0.036**		0.034**	
	(2.71)		(2.86)		(2.82)	
TURNRATIO		-0.197**		-0.203**		-0.299***
		(-2.32)		(-2.46)		(-3.41)
SMCAP	-0.245***	-0.253***	-0.207***	-0.215***	-0.181***	-0.193***
	(-5.18)	(-4.89)	(-5.93)	(-4.74)	(-4.47)	(-4.18)
WMVAL	0.069**	0.074**	0.048*	0.054*	0.030	0.038
	(2.55)	(2.60)	(1.64)	(1.79)	(0.95)	(1.15)
SMOMENTUM	-0.126***	-0.121***	-0.127***	-0.121***	-0.116***	-0.108***
	(-3.88)	(-3.53)	(-3.54)	(-3.74)	(-3.18)	(-3.29)
HVOL	0.069	0.048	0.062	0.040	0.036	0.004
	(0.68)	(0.53)	(0.60)	(0.44)	(0.34)	(0.05)
Intercept	4.652***	4.743***	4.046***	4.140***	3.775***	3.914***
	(4.56)	(4.56)	(4.51)	(4.53)	(4.41)	(4.48)
Number of observations	2110	2112	2110	2112	2110	2112
Adjusted R^2	0.62	0.63	0.67	0.68	0.64	0.66

Table 8
Comparison of Non-Marketability Discount under Different Market Scenarios

This table presents the mean (Mean), standard deviation (Std), and median (Median) of the non-marketability discounts. Open(BSC), Open(HN), and Open(MF) are the non-marketability discounts at the market open using the Black-Scholes model, Heston-Nandi model, and the model-free approach, respectively. Close(BSC), Close(HN), and Close(MF) are the non-marketability discount at the market close. STURNOVER is the stock turnover ratio, and WTURNOVER is the warrant turnover ratio. The *t*-statistic reports the *t*-test statistics of whether the means between the two populations are significantly different. The Z-statistic is the Wilcoxon test statistics that report whether the medians of the two populations are significantly different.

	Mean	Std	Median	Mean	Std	Median	T-stat	Z-stat
Panel A	High Tax			Low Tax				
Open(BSC)	0.001	0.104	0.004	0.057	0.075	0.054	-14.38	-12.63
Open(HN)	-0.012	0.110	-0.002	0.055	0.080	0.056	-16.09	-14.10
Open(MF)	0.016	0.098	0.010	0.064	0.073	0.060	-12.78	-11.64
Close(BSC)	-0.004	0.104	0.001	0.053	0.076	0.050	-14.33	-12.66
Close(HN)	-0.012	0.107	-0.004	0.050	0.077	0.047	-15.38	-13.55
Close(MF)	0.012	0.098	0.007	0.060	0.073	0.056	-12.72	-11.64
Panel B	High Stock Turnover			Low Stock Turnover				
Open(BSC)	0.033	0.091	0.030	0.027	0.098	0.038	1.60	0.84
Open(HN)	0.029	0.099	0.029	0.017	0.103	0.031	2.71	1.98
Open(MF)	0.044	0.086	0.036	0.039	0.092	0.048	1.33	1.00
Close(BSC)	0.027	0.090	0.025	0.024	0.099	0.035	0.86	0.05
Close(HN)	0.022	0.093	0.023	0.017	0.101	0.030	1.13	0.21
Close(MF)	0.038	0.086	0.033	0.036	0.093	0.045	0.53	0.15
Panel C	Low Information Asymmetry			High Information Asymmetry				
Open(BSC)	0.032	0.098	0.040	0.023	0.076	0.017	1.81	3.08
Open(HN)	0.025	0.106	0.037	0.016	0.083	0.014	1.72	3.09
Open(MF)	0.044	0.093	0.048	0.033	0.076	0.024	2.25	2.91
Close(BSC)	0.027	0.099	0.035	0.019	0.075	0.013	1.75	3.09
Close(HN)	0.022	0.103	0.033	0.013	0.076	0.010	1.70	3.35
Close(MF)	0.039	0.093	0.042	0.029	0.075	0.020	2.19	2.88
STURNOVER	0.031	0.022	0.025	0.027	0.019	0.022	-3.46	-3.33
WTURNOVER	0.532	0.556	0.389	0.497	0.392	0.395	-1.51	-0.66
Panel D	Long time to maturity			Short time to maturity				
Open(BSC)	-0.003	0.104	0.009	0.052	0.08	0.047	-13.57	-11.26
Open(HN)	-0.015	0.112	0.002	0.048	0.084	0.046	-14.91	-12.33
Open(MF)	0.02	0.096	0.023	0.055	0.081	0.052	-9.02	-7.91
Close(BSC)	-0.007	0.103	0.005	0.048	0.081	0.042	-13.8	-11.52
Close(HN)	-0.020	0.108	-0.003	0.046	0.080	0.041	-16.06	-13.14
Close(MF)	0.015	0.096	0.020	0.051	0.082	0.046	-9.23	-8.18

Table 9

Regressions of Non-Marketability Discount at the Market Open on Liquidity under Different Market Situations

This table presents regression results of the non-marketability discounts (model free approach) at the market open on the liquidity measures.

$$DISC_{i,t} = \alpha_t + \beta_L LIQ_{i,t} + \beta_C CONTROL_{i,t} + WARRANT \quad FIXED \quad EFFECT + \varepsilon_{i,t}$$

$DISC_{i,t}$ is the non-marketability discount of stock *i* at the market open of day *t*. $LIQ_{i,t}$ is the vector of liquidity ratio measure variables. $CONTROL_{i,t}$ is a vector of control variables of stock *i* on day *t*. The liquidity ratio measures are the ratio of stock Amihud measure to 1,000 times of the warrant Amihud measure (AMRATIO). There are two missing values for AMRATIO because the warrant Amihud measures are zeros. Control variables are log stock market capitalization (SMCAP) and log warrant total market value (WMVAL) at the end of the previous month, the return in the previous month of the underlying stock (SMOMENTUM), and the annualized standard deviation of the returns for the underlying stock in the previous 120 trading days (HVOL). All regressions include warrant fixed effect. Heteroskedasticity-robust *t*-statistics are reported in parentheses below the coefficients, and are based on robust standard errors that allow for clustering by each warrant. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

The regression is performed in three different market situations: First, we split the sample into one high transaction tax subsample and one low transaction tax subsample to examine whether different transaction costs in the stock and warrant markets cause the non-marketability discount. Second, we split the sample into one high stock turnover subsample and one low stock turnover subsample to examine whether speculative trading causes the non-marketability discount. Third, we split the sample into one subsample including the observations within 10 days of the earnings announcement dates of the companies and one subsample including all the remaining observations to examine whether the information asymmetry between the stock and warrant traders causes the non-marketability discount. Fourth, we split the sample into one subsample with short time to maturity and one with long time to maturity to examine whether the warrant time value causes bias in the computation of the warrant implied stock price.

Dependent Variable: Non-Marketability Discount at the Open (model free approach)

	High Tax	Low Tax	High Stock Turnover	Low Stock Turnover	High Information Asymmetry	Low Information Asymmetry	Long Time to Maturity	Short Time to Maturity
AMRATIO	0.021**	0.170***	0.029**	0.086***	0.113	0.037**	0.034**	0.032***
	(2.70)	(3.75)	(2.74)	(4.57)	(1.33)	(2.67)	(2.68)	(2.11)
SMCAP	-0.374**	-0.062***	-0.257**	-0.278***	-0.212**	-0.275***	-0.349**	-0.188***
	(-2.99)	(-3.38)	(-2.79)	(-4.64)	(-2.48)	(-5.10)	(-6.00)	(-2.25)
WMVAL	0.055	-0.069**	0.050**	0.128	-0.030	0.101***	-0.035**	0.033
	(1.12)	(-2.78)	(0.98)	(4.04)	(-0.48)	(3.23)	(-1.43)	(0.68)
SMOMENTUM	-0.186**	-0.112***	-0.166***	-0.066***	-0.186***	-0.126***	-0.153***	-0.176***
	(-2.48)	(-3.41)	(-3.95)	(-3.07)	(-8.74)	(-2.78)	(-3.02)	(-4.90)
HVOL	0.008	0.132	0.096	0.054	-0.152	0.122	0.675	-0.037
	(0.03)	(0.60)	(0.56)	(0.80)	(-1.55)	(1.10)	(3.07)	(-0.27)
Intercept	8.315**	2.980***	5.386***	4.156***	5.850***	4.660***	3.309***	3.852***
	(2.59)	(4.99)	(3.61)	(3.94)	(5.96)	(4.46)	(7.14)	(3.10)
Number of observations	1014	1096	1055	1055	449	1661	844	1266
Adjusted R^2	0.64	0.59	0.59	0.71	0.75	0.63	0.59	0.71

Figure 1
Non-Marketability Discount during a Trading Day

This figure presents the medians of the non-marketability discount at the end of each 30-minute interval during a trading day. Panel A uses the Black-Scholes model to compute the implied stock price. Panel B uses the Heston-Nandi model to compute the implied stock prices. Panel C uses the model-free approach. In all panels, the non-marketability discount decreases in the afternoon trading with the smallest non-marketability discount realized at the market close.

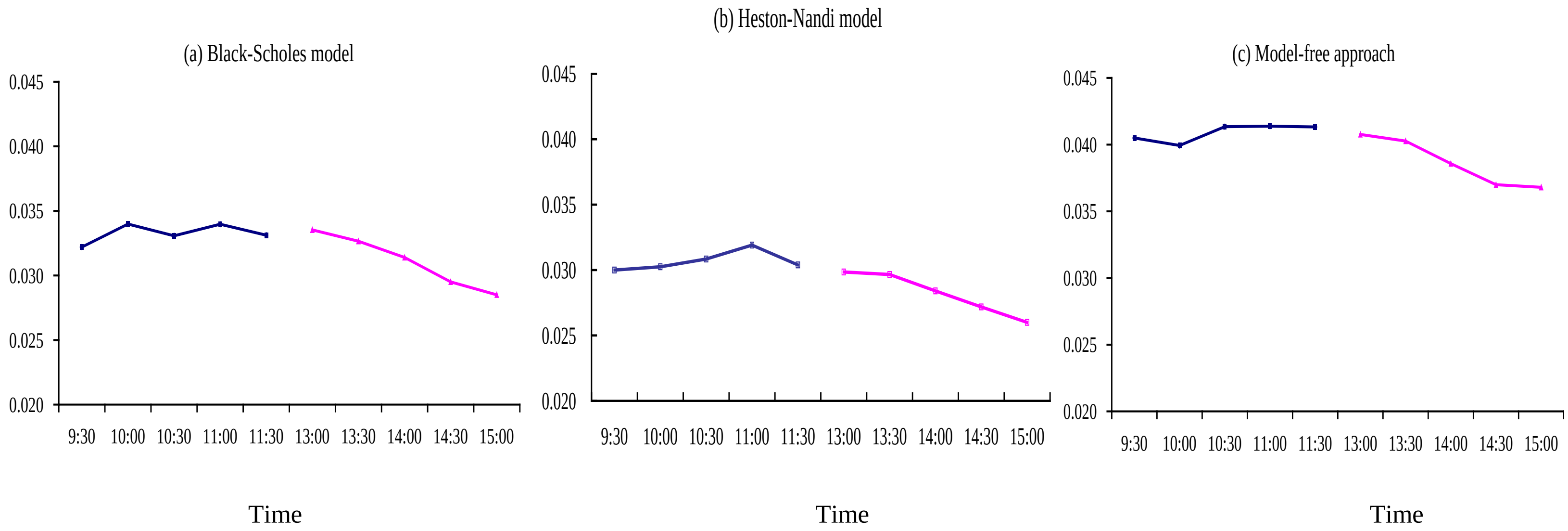

Figure 2
Market Depth during a Trading Day

This figure presents the medians of the market depth for each 30-minute interval during a trading day. We define market depth as the average of the sum of the five best bid prices multiplied by the corresponding bid volumes and the sum of the five best ask prices multiplied by the corresponding ask volumes. The market depth is expressed in terms of million yuan. Every 30 minutes, we take the time weighted average of all the market depths during that 30-minute period to obtain the market depth for that time interval. The solid line represents the median market depth of stocks and the dashed line is the median market depth of warrants. In this figure, we observe that in the stock market the market depth increases during the trading day from the market open to market close. However, the market depth in the warrant market stays roughly constant during a trading day.

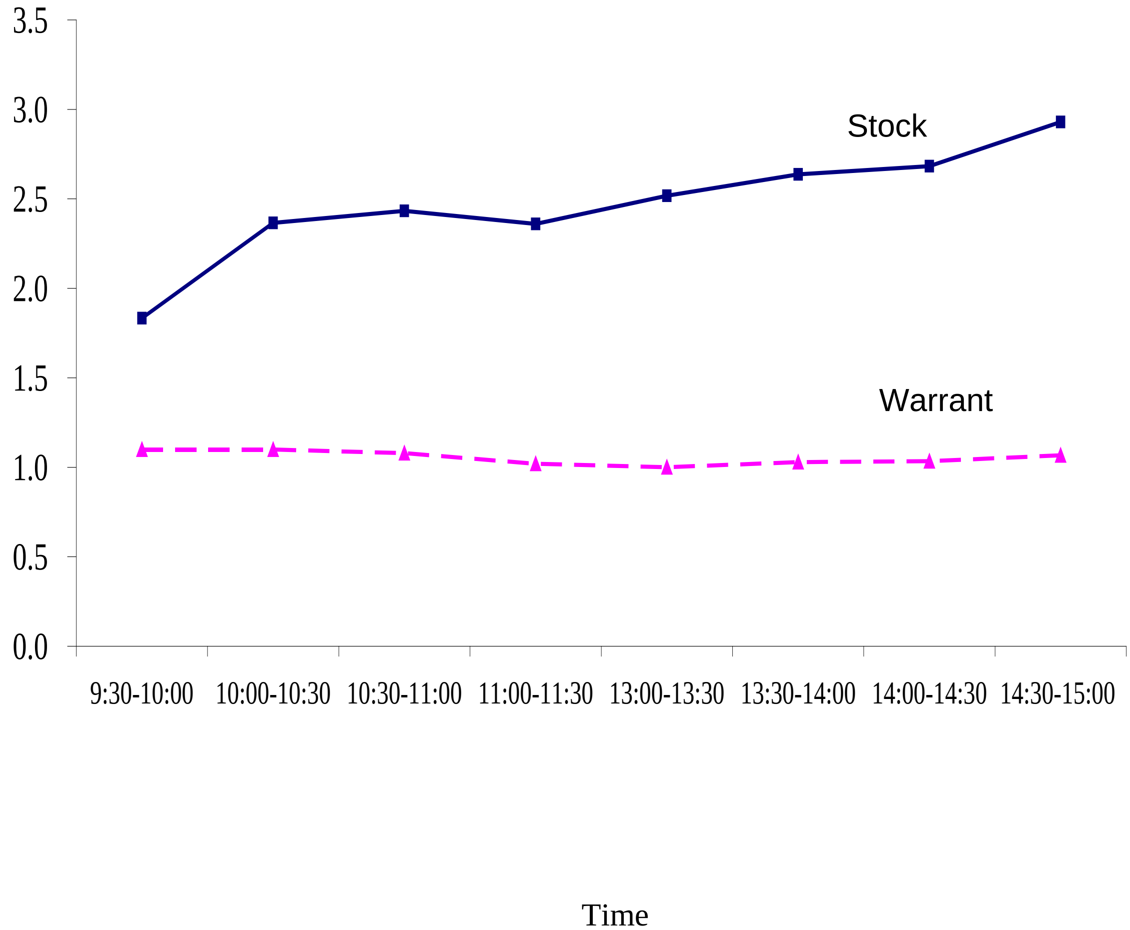

Figure 3
Trade Imbalance during a Trading Day

This figure presents the median of the share volume imbalance, yuan volume imbalance, and trade number imbalance for every 30-minute interval during the course of a trading day. The share volume imbalance is the difference between the share volume of buy trades and the share volume of sell trades during the 30-minute interval divided by the total share volume in the day. The yuan volume imbalance is the difference between the yuan volume of buy trades and the yuan volume of sell trades during the 30-minute interval divided by the total yuan volume in the day. The trade number imbalance is the difference between the number of buy trades and the number of sell trades during the 30-minute interval divided by the total number of trades in the day. The solid line is the median measure for stocks and the dashed line is the median measure for warrants. The graphs indicate that in the stock market, trading imbalance increases towards the market close, suggesting that there are more buying activities towards the market close when the marketability constraint is the weakest. In the warrant market, we do not observe the same pattern.

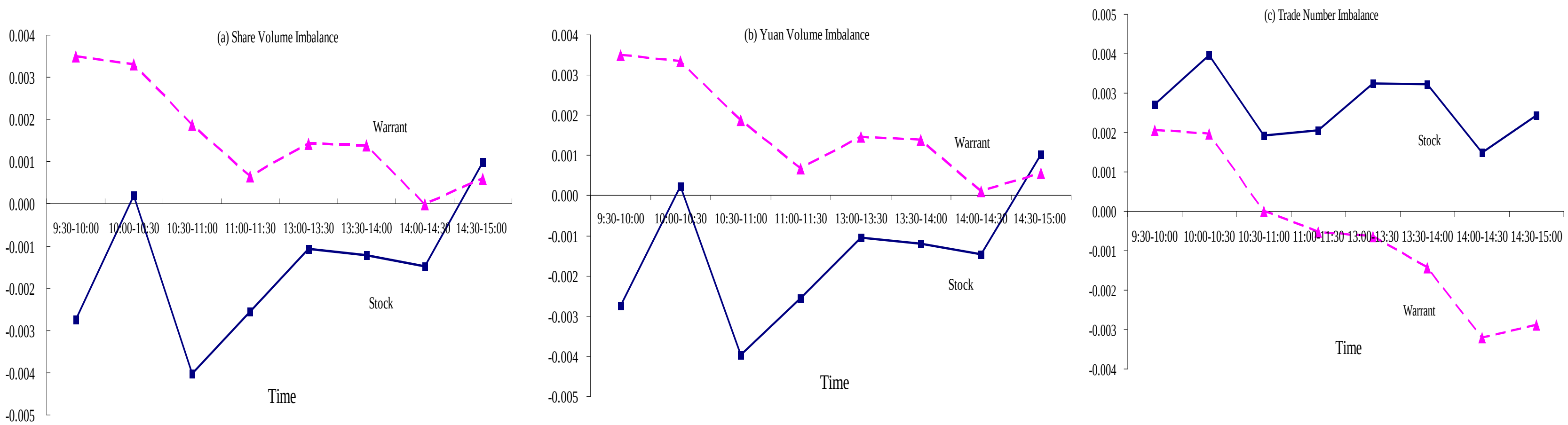

Figure 4
Yuan Volume Imbalance for Large and Small Trades during a Trading Day

This figure presents the median of the yuan volume imbalance of large and small trades for every 30-minute interval during the course of a trading day. The yuan volume imbalance is the difference between the yuan volume of buy trades and the yuan volume of sell trades during the 30-minute interval divided by the total yuan volume in the day. The solid line represents the median for stocks and the dashed line is the median for warrants. We find that large traders actively participate in buying activities in the stock market towards the market close. However, small traders do not appear to systematically do so. Warrant traders do not show a significant increase in buying activities around the market close. The results suggest that large traders may take advantage of the reduced adverse impact of non-marketability near the market close and strategically time their buy trades towards the market close.