Cost Reduction, Informational Efficiency, and Prices of Options

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Abstract

This paper documents four findings in the option market based on two stages of decimalization where switching control and treatment stocks is possible. First, uninformed traders are more cost sensitive than informed traders. Second, the paper proves and verifies that when uninformed traders are more cost sensitive, trading cost reduction causes slower response of price to information. Those findings are contrary to the evidences in the stock market. Third, decimalization narrows bid ask spread, increases volume, and deepens depth, especially for options requiring frequent hedging re-balancing in the stock market. Finally, option prices become more expensive after decimalization.

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1 Introduction

In the option market, the average quoted bid ask spread is on the order of 15%. High frequency strategies based on small price movements are difficult to implement. Harvey and Whaley (1992) point out that although statistical models deliver precise forecasts for volatility, trading costs make one-day abnormal returns on S&P100 options impossible. Studies also show that option volume and prices generate little incremental intra-day information. (Please see Stephan and Whaley (1990), Chan, Chung, and Fong (2002), and Muravyev, Pearson, and Broussard (2013).)

Informed traders in the option market are motivated by informational events[1], stock characteristics, or volatility timing[2] that are likely to drive large variations in prices beyond the intra-day horizon. Contrary to the evidence on intra-day frequency, the literature unanimously conclude that option trading and prices contain information covering longer-term horizons. (For example, Pan and Poteshman (2006), Ni, Pan, and Poteshman (2008), An, Ang, Bali, and Cakici (2014).)

Constantinides (1986) argues that investors accommodate large transaction costs by drastically reducing their frequency of trading. Informed traders tend to trade naked positions to take advantage of leverage in the options (Ge, Lin, and Pearson (2016)). They wait and expect to receive profits more than the trading costs when their information is realized in the public.[3]. In contrast, the expected returns of risk neutral hedgers are close to the risk free rate. Figure 1 plots that with a daily 3% decrease in the stock price or a 5% increase in the volatility, a naked OTM put return will be more than 50%, whereas a protective put return will be below 0.1%. In addition, the relative cost of a protective put with stock is far less than a naked put.

[1]The events include earnings announcements (Amin and Lee (1997), Atilgan (2010), Johannes and Dubinsky (2005), and Ni, Pan, and Poteshman (2008)), analyst recommendations (Kim (2008) and Lin, Lu, and Driessen (2015)), mergers and acquisitions (Jayaraman, Frye, and Sabherwal (2001) and Cao, Chen, Griffin, et al. (2005)), and other scheduled or unscheduled corporate events (Cremers, Fodor, and Weinbaum (2014) and Chesney, Crameri, and Mancini (2015)).

[2]Ofek, Richardson, and Whitelaw (2004) and Johnson and So (2012) find that investors use options to overcome short sale constraints. Aragon and Martin (2012) show that hedge fund positions reflect significant volatility timing and stock selectivity skills.

[3]Amin and Lee (1997) and Ni, Pan, and Poteshman (2008) find that the option market trading activity starts to increase one week before the earnings announcement.

These different returns and cost structures may result in a pattern that uninformed traders are more cost sensitive than informed traders in the option market. When trading costs are reduced, uninformed traders trade more to hedge, speculate, or liquidate. Conversely, informed traders are less responsive because the chance of an informational event or the characteristics of the stock do not vary with exogenous changes in trading costs. This is in sharp contrast to the trend of informed trading in the stock market, where small bid ask spreads allow informed traders to use high frequency strategies to exploit temporary price movements. The market becomes more efficient after trading cost reductions over time because more informed traders enter. (Please see Chordia, Roll, and Subrahmanyam (2011), Brogaard, Hendershott, and Riordan (2014) and others.)

Financial markets have two important functions: liquidity and price discovery for incorporating information in trading (O'Hara (2003)). One question I aim to answer is how a reduction in trading costs, i.e, an increase in liquidity, influences informational efficiency if uninformed traders and informed traders differ in their sensitivities to trading costs. I use the model in Diamond and Verrecchia (1987), where informed traders observe private information and uninformed traders observe only public information. They apply the model to short sales where not all traders face the same costs. I use the model in option trading where traders differ in their sensitivities to the exogenous costs. In applying the model, I consider volatility as the asset in the option market. This treatment is justified in that the market makers can delta hedge the risk associated with the directional move, but collectively they must bear the volatility risk. Jameson and Wilhelm (1992) document that uncertainty over volatility accounts for a significant proportion of the option market-making costs.

The model shows that if uninformed traders are more cost sensitive, a reduction in costs will slow the speed of price adjusting information. On the contrary, if informed traders are equally or more cost sensitive, price will impound information more quickly following an exogenous cost reduction. The latter prediction is consistent with the evidence in the stock market that reduction in trading costs attracts more informed traders using high frequency strategies, and the market becomes more informational efficient.

The endogeneity between transaction costs and informational trading makes it difficult to test how costs influence informational efficiency. To overcome this difficulty, I take advantage of decimalization in 2001. Bessembinder (2003) and others show decimalization brings positive liquidity shocks to the stock market. Two stages of decimalization occur simultaneously in the stock and the option markets. They provide two perfect natural experiments such that the treatment stocks and the control stocks can be switched. In the first experiment in January, the treatment group consists of the 1,104 optionable stocks decimalized on January 29, and the control group consists of the 1,098 optionable stocks not decimalized until April 6. In the second experiment in April, the treatment and the control groups are switched. This unique setting guarantees that the difference in difference (DID) results represent the effects of the exogenous shocks on transaction costs due to decimalization, but not the effects of the cross sectional differences between the treatment and the control groups.

There are two channels through which transaction costs can be reduced in the option market. The first channel is decimalization in the option market itself. Harris (1994) points out that the minimum tick size limits the minimum bid ask spread that can be quoted. This constraint is especially strong for securities with low prices. The median option price is only \$4.7. The reduction in the trading costs from decimalization would, therefore, be obvious in the option market.

The second channel is that decimalization in the stock market facilitates option market maker dynamic hedging inventory. Jameson and Wilhelm (1992) provide evidence that the option market makers bear risks associated with the inability to continuously hedge their inventory. Cetin, Jarrow, Protter, and Warachka (2006) model that liquidity costs of hedging in stock market are a significant component of an option price. Muravyev (2016) shows that inventory risks faced by market-makers have a first-order effect on intra-day option prices. Given a reduced transaction cost in the stock market after decimalization, the option market makers may charge narrower bid ask spreads and reduce the price impact of trading. This reduction in the option transaction costs will be stronger for short-term options because they require much more frequent hedge re-balancing in the stock market than long-term options.[4]

The result suggests that decimalization does improve the option market quality. The effect is especially strong for options with short maturities. The bid ask spread narrows, volume increases, and market depth deepens for one-month options[5]. The DID in dollar spread of one-month options is \$-0.03 (\$-0.08) in the first (second) experiment, equivalent to a 9% (17%) reduction. For longer-term options, the DID in dollar spread is less negative. The one-month option volume increases by 12% (15%) after the first (second) stage of decimalization. The longer-term option volume increases at a lower rate or decreases.

Market depth is measured as the λ in Kyle (1985), which captures the daily impact of order imbalance on volatility. The DID(λ) of one-month options is negative for both stages of decimalization, whereas the DID(λ) of longer-term options is either positive or not statistically different from zero. This result indicates that the depth deepens for one-month options, but not for longer-term options. The reduction in the trading costs being more obvious in short-term options implies that there is a reduced cost of hedge re-balancing in the stock market after decimalization, which plays an important role in improving the quality of the option market as suggested by Cetin, Jarrow, Protter, and Warachka (2006).

Contrary to the evidence in the stock market, a reduction in trading costs in the option market attracts more uninformed traders than informed traders. Both the absolute and the relative option volumes of uninformed traders increase after decimalization, especially for one-month options that have the highest reduction in trading costs. The trading volume from uninformed traders increases by 18% and 26% for one-month options in the two experiments, and by less than 11% for longer-term options. The relative volume of uninformed traders increases at least by 3% to 5% for one-month options; the increase for longer-term options is less obvious.

To estimate whether a reduction in trading costs slow the speed of price incorporating information, I first examine the predictive power of order imbalance for daily and weekly

[4]One month options Gamma, a measure of how frequently hedge re-balancing should be done, is on average more than 50% higher than the two month Gamma.

[5]One-month options are options expiring within next month.

straddle returns. Predictability is an inverse indicator of efficiency. If the speed of price adjusting information slows after decimalization, the order imbalance will be more powerful in forecasting straddle returns. Indeed, the predictive power of the one-month option order imbalances increases, but that of the long-term options does not.

In another method of testing the slowed response to information, I examine whether the autocorrelations of implied volatility change become less negative after decimalization. Harvey and Whaley (1991) implies that if informed trading alters the implied volatility but not the stock price, a negative autocorrelation of implied volatility change will occur once information becomes public and revises the option and the stock prices. The negative autocorrelations can also arise from mean reversion of volatility. If option prices are slow in responding information and trading related to volatility timing, the autocorrelations of the daily implied volatility change will become less negative. Indeed, the result shows that the DID in autocorrelations are all positive and statistically significant, especially for short-term options. More liquid calls have larger increases in autocorrelations than less liquid puts, suggesting the variations in the bid ask bounces is not an alternative explanation. Overall the results confirm the theoretical prediction that when uninformed traders are more cost sensitive, cost reduction causes price to be slower in adjusting information in trading.

In the analyses, I also examine how liquidity shocks brought about by decimalization affect option prices. As suggested by Amihud, Mendelson, and Pedersen (2006), liquidity increases prices of stocks and bonds, but the effect of liquidity on exchange traded options with zero net demand is unclear. Cetin, Jarrow, Protter, and Warachka (2006) first attempt to consider the impact of illiquidity in the underlying asset market on option pricing. Their model shows that liquidity costs are a significant component of an option price, and increase with the imbalance in the number of short or long positions being hedged. Stock options order imbalances are negative on average, their model suggests that option prices will be more expensive after positive liquidity shock in the stock market. To measure option expensiveness, I use excess volatility computed as the difference between ATM implied volatility and various measures of physical volatility. The DID result indicates that option prices become more expensive after decimalization.

The empirical evidence on how liquidity affects price of exchange traded options is very limited.[6] The only study is done by Christoffersen, Goyenko, Jacobs, and Karoui (2015), who show that the combination of selling pressure and liquidity generates that more liquid stock calls are more expensive. The difference between this study and theirs is that this study is based on the natural experiments with simultaneous liquidity shocks to the option and the stock markets, whereas their result is based on the cross sectional return differences among calls with different liquidity.

In summary, this paper contributes to the literature in four respects. First, it demonstrates that uninformed traders in the option market are more sensitive to the reduction in trading costs. This is the opposite of what is documented in the stock market literature, where a reduction in costs attracts more informed traders using high frequency strategies.

Second, this paper proves and verifies empirically that, when uninformed traders are more cost sensitive, a reduction in trading cost causes a slower response of prices to information. This is contrary to Chordia, Roll, and Subrahmanyam (2008), who document that tick size reduction removes the predictability of order imbalance in the stock market. This paper points out that for a cost reduction to increase informational efficiency, it requires the participation of informed traders who are equally or more sensitive to the trading costs. This paper, however, is silent on other aspects of efficiency in the option market after a cost reduction, for example, variance ratios based on high-frequency data.

Third, this paper documents how decimalization reduces trading costs in the option market. Although there are extensive analyses on how tick size reduction affects the stock market, the option market deserves its own page on this question. Option prices are smaller than stock prices. The simultaneous decimalization in the option and the stock markets not only reduces the tick size in the option market, but also eases the hedging of option market maker in the stock market. These two factors result in that the trading cost

[6] Brenner, Eldor, and Hauser (2001) show that prices of bank issued non-negotiable options are lower than those exchange traded options in Isreal. Li and Zhang (2011) find there are price premiums for more liquid warrants relative to more illiquid options on the Hang Seng index. Retail investors, however, cannot short warrants.

reduction in the option market is more obvious than in the stock market, and that the options requiring more frequent hedging re-balancing benefit more from decimalization. Finally, this paper provides evidence that option prices become more expensive after positive liquidity shocks brought about by decimalization.

This paper is related to papers that study the impact of asymmetric information on asset prices. A large literature, starting from the seminal papers by Grossman and Stiglitz (1980), Glosten and Milgrom (1985) and Kyle (1985) show that informed trading increases price impact and bid ask spreads. More recently, Collin-Dufresne and Fos (2015) and Collin-Dufresne and Fos (2016) model and provide evidence that informed traders select times of high liquidity when they trade. They discover that around 13D filings, high informed trading periods are associated with low bid ask spreads and price impact. This paper also suggests informed trading increases after cost reduction, and focuses on the different sensitivities of informed and uninformed traders to cost reduction.

This study relates to the literature examining information in the option market. Easley, O'hara, and Srinivas (1998) model informational role of volume in the option market. Studies using intra-day data show that option market has little predictability for stock prices. For example, Stephan and Whaley (1990) document that stock prices lead option prices at least fifteen minute;. Chan, Chung, and Fong (2002) find that stock net trade volume has predictability for stock and option quote revisions, but option net trade volume has no predictive ability; Muravyev, Pearson, and Broussard (2013) show that when option implied stock price is inconsistent with the actual stock price, option market quotes adjust to eliminate the disagreement, while the stock market quotes behave normally. Finally, Chan, Chung, and Johnson (1993) argue that due to infrequent trading of options, intra-day stock prices leading option prices is spurious.

The literature suggests that option market has information of stock return and volatility over longer horizon. Ni, Pan, and Poteshman (2008) and Muravyev (2016) explain predictability of order imbalance for volatility over weekly and daily horizons. Pan and Poteshman (2006), Cremers and Weinbaum (2010), Johnson and So (2012), and An, Ang, Bali, and Cakici (2014) document stock return predictability over weekly or monthly horizons. Recently, Chen, Joslin, and Ni (2016) find that S&P500 OTM put net volume predicts market returns and volatility up to three months. Finally, Hu (2014) shows that stock order imbalance due to options trading has a higher predictability for one-day stock returns than for half hour returns.

This study relates to the literature examining how tick size reduction affects the stock market. Harris (1994), Ahn, Cao, and Choe (1996), Boellen and Whaley (1998) ant others document narrowed bid ask spreads. Ahn, Cao, and Choe (1996), Bacidore (1997) and Ahn, Cai, Chan, and Hamao (2007) find no increase in trading volume. Boellen and Whaley (1998), Goldstein and Kavajecz (2000) and Ronen and Weaver (2001) show reduced depth in quoted spread. Finally, Bessembinder (2003) and Furfine (2003) document improved market quality.

This paper also relates to studies on the option bid ask spreads. Vijh (1990) shows that options have large bid ask spreads and deep depth, and that the spread due to information is small. George and Longstaff (1993) find that differences in bid-ask spreads are related to differences in market-making costs and trading activity. Mayhew (2002), De Fontnouvelle, Fishe, and Harris (2003) and Battalio, Hatch, and Jennings (2004) document that bid ask spreads decrease and market quality improves after multiple listings. Muravyev and Pearson (2015) show that options bid ask spreads are smaller than they appear to be.

Because straddle returns are examined, this study also relates to the literature on the option returns. Ni (2008) reports that stock call returns decrease in strike prices, and that OTM call returns are negative. She attributes this finding to idiosyncratic skewnees seeking. Boyer and Vorkink (2014) confirm her results. Goyal and Saretto (2009) document a profitable strategy based on long (short) options with low (high) excess volatility. Bakshi, Madan, and Panayotov (2010) point out that index OTM call returns will be negative under a U-shaped pricing kernel. Constantinides, Jackwerth, and Savov (2013) find that delta-hedged option returns decrease with the idiosyncratic volatility of the underlying stock.

The rest of the paper is organized as follows. Section 2 presents the theoretical prediction on informational efficiency when traders have different sensitivities to costs.

Section 3 explains data, variables, experiment set-up based on two stages of decimalization. Section 4 reports the empirical results. Section 5 concludes.

2 Different cost sensitivities, information efficiency

In this section, I present a theoretical model similar to that in Diamond and Verrecchia (1987). In the model, the effect of cost reduction on information efficiency depends on how it alters the relative volume of uninformed to informed traders. If after cost reduction, the relative volume of uninformed traders increases, i.e. uninformed traders are more cost sensitive, prices will be slower in incorporating information in trading. If the proportion of uninformed and informed traders remains the same, or the relative volume of informed traders increases, prices will incorporate information more quickly.

2.1 Uninformed traders are more cost sensitive

The structure of the model is similar to Diamond and Verrecchia (1987). The difference is that they examine trading stocks with short sale restrictions and bans, whereas I examine trading options without short sale constraints. The market makers can delta hedge the risk associated with the directional move, but collectively they must bear the volatility risk. Accordingly, the price of risky asset in this set-up is the implied volatility of the options. Market makers are risk-neutral and earn zero expected profits. Traders are also risk-neutral. Informed traders know the true liquidating value of the risky asset, while uninformed traders make inferences about its value based on all public information. The prior distribution of the risky asset value is Bernoulli: its liquidation value is one with probability one-half, and zero with probability one-half. The liquidation value is paid in the distant future. An informed trader buys the asset if it is underpriced relative to the bid price and sells if it is overpriced relative to the ask price.

Although the price considered here is implied volatility, it is not necessary for an informed trader to trade volatility only. A stock directional trader can be considered as having volatility information in the eyes of the delta hedged market maker. Uninformed trading occurs for reasons exogenous to the model. Their trades can be made for reasons of hedging, speculating or liquidating. A trader is allowed to buy an option, sell an option, or do nothing. A trader's willingness to trade is influenced by the transaction cost.

I consider uninformed traders more cost sensitive if (1) they require lower cost to trade, (2) they trade more than informed traders in terms of percentage increase in trading volume after further cost reduction. The costs fall into one of three categories: low-cost, medium-cost and high-cost. Under low cost, both informed and uninformed traders will trade. Under medium cost, only informed traders will trade. Under high cost, nobody will trade. Following Diamond and Verrecchia (1987), I represent the fraction of the population that encounters low cost by c_1, and the fraction that faces medium and high costs by c_2, and c_3, respectively. All traders, independent of whether they are informed or uninformed, fall into one of these three categories, i.e., $c_1 + c_2 + c_3 = 1$ at all times. The trading decisions of uninformed and informed traders conditional on costs are illustrated in Table 1 Panel A.

The economy operates as follows (please refer to Figure 2 for illustration of its operation, and Table 2 for a summary of the notation). Before trade begins, nature moves to choose either 0 or 1 as the value of the risky asset. After nature moves, time is divided into T discrete intervals. At each interval, there is a probability g that a single trader potentially wants to trade (depending on the costs of trading) and $1 - g$ that no trade is observed. A trader who potentially wants to trade is either an informed trader with probability a or an uninformed trader with probability $1 - a$. If an informed trader private information is good news (i.e., $v = 1$), then he buys one security.[7] If an informed trader private information is bad news (i.e., $v = 0$), he sells one security.[8]

An uninformed trader participates in the market if he has experienced an uninformed shock. Independent of the true state-of-nature, a randomly selected uninformed trader wants to buy (with a probability of one-half) or sell (with a probability of one-half) a security when the cost is low. When the cost is above low, he chooses not to trade when faces an uninformed shock because he is more cost sensitive than an informed trader.

[7] it can be either buy to open a new position or buy to close an existing short position.

[8] It can be either sell to open a new position or sell to close an existing position.

The tree diagram in Figure 2 illustrates the calculation of the probability for each type of observed action, conditional upon the true state-of-nature. The set of actions taken includes buy, sell, and no-trade. The set of actions observed is also buy, sell, and no-trade. Let v represent the true state-of-nature (i.e., v=0 or v=1), and q_v^A represent the probability of observing action A conditional on state v. The conditional probabilities of the possible observable actions are given in Table 3.

At time 1, the bid price P_t^B and the ask price P_t^A are offered by the market maker based on public information. Free entry into market and risk-neutrality imply that market maker expected profit from each trade is zero. The current transaction of either a sell or a buy is informative because of the possibility that the order is placed by an informed trader.

Let P_t denote the probability that the true state-of-nature is v=1, and 1 - P denote the probability that v=0. P_t is the conditional expectation of the asset value at time t given all public information. It is convenient to work with $P_t/(1 - P_t)$, which is analogous to the likelihood ratio of v=1 versus v=0. For any observed action A, the conditional expectation of the value of the asset at time t, P_t is the solution to the expression

$$\frac{P_t}{1 - P_t} = \frac{P_{t-1}}{1 - P_{t-1}} \frac{q_1^A}{q_0^A} \tag{1}$$

where q_1^A (q_0^A) is the probability of observing action A conditional on state $v = 1$ ($v = 0$).

Following Diamond and Verrecchia (1987), I define two prices, P^H and P^L, where P^H is strictly greater than P^L. These serve as benchmarks for how close the trading process comes to reflecting all (private) information. For example, if $P^H = \frac{3}{4}$ and $P^L = \frac{1}{3}$, then, by computing the expected number of periods when the price first exceeds P^H or falls below P^L, I can determine the expected amount of time necessary for the price to reflect (to the uninformed) the three-to-one odds in favor of either a value of 1 or a value 0.

Let the random variable $\tilde{N}$, with realization N, represent the number of time periods that pass until the price first becomes greater than or equal to P^H or less than or equal to P^L. Let $\bar{N}_1$ and $\bar{N}_0$ represent the expected values of the random variable $\tilde{N}$ conditional upon v=1 and v=0, respectively: that is, $\bar{N}_1$=E[$\tilde{N}|v$=1] and $\bar{N}_0$=E[$\tilde{N}|v$=0].

Proposition 1. When $c_3 = 0$, the expected number of periods required for the adjustment of bad and good news, $\bar{N}_1$ and $\bar{N}_0$ are an increasing function of c_1.

For proof, please see the Appendix.

Proposition 1 states when $c_3 = 0$, a decrease in transaction cost is equivalent to an increase in c_1, and more uninformed traders will choose to trade than informed traders. It takes more time for prices to incorporate information after a reduction in transaction cost. The intuition is that the increased participation of uninformed traders impedes the movement of prices in direction indicated by the information in trading.

2.2 Informed traders are equally or more cost sensitive

The condition that uninformed and informed traders are equally cost sensitive can be represented by assuming $c_2 = 0$. In that case, the effect of an exogenous reduction in cost is a decreased c_3, or increased c_1 as $c_1 = 1 - c_3$. (Please see Table 1 Panel B.) Under this set-up, the proportion of informed and uninformed traders choosing to trade remains the same after a reduction in transaction cost.

Proposition 2. When $c_2 = 0$, the expected number of periods required for the adjustment of bad and good news, $\bar{N}_1$ and $\bar{N}_0$ are decreasing function of c_1.

For proof, please see the Appendix.

Proposition 2 states when $c_2 = 0$, it takes less time for the price to incorporate information after a reduction in transaction cost. The intuition is that there are more informed traders than in previous periods when the costs were higher. The increased participation of informed traders speeds up the price movement reflecting information.

The condition that informed traders are more cost sensitive than uninformed traders can be represented by assuming $c_3 = 0$, and that informed traders will not trade until the cost is reduced to c_1, and uninformed traders will start to trade when the cost is c_2. Table 1 panel C illustrates the trading decisions under this situation. The effect of an exogenous reduction in cost is an increased c_1 or a decreased c_2. Under this set-up, the relative proportion of informed traders increases after cost reduction. Based on Proposition 1, the time needed for prices to incorporate information will decrease.

A speedy price adjustment to information helps to explain the empirical evidence documented in Chordia, Roll, and Subrahmanyam (2008) and Chordia, Roll, and Subrahmanyam (2011). The former show that the predictability of order imbalance in the stock market disappears after a reduction in tick size, and the latter show that the stock market becomes more efficient because of the increased participation of informed traders following trading cost reductions.

3 Data, decimalization, variables, and experiment setup

3.1 Data and decimalization

The data used to compute the non-market maker public order imbalance are obtained from the CBOE. The non-market maker public buy and sell volumes are subdivided into three classes of investors: customers of full service brokers, customers of discount brokers, and other public customers. I use this subdivision when separating volume into the volume that could have been initiated by informed traders, and the volume that could have come from uninformed traders.

I obtain end of day option bid ask prices, volume, and implied volatilities from OptionMetrics. End of day stock prices are obtained from the Center for Research in Security Prices (CRSP). Intra-day stock prices are obtained from TAQ.

There were 2,547 optionable stocks during the period from January to April 2001. Among them, 1,104 stocks and their options were decimalized on 29 January, and 1,098 stocks and their options were decimlized on 6 April. The remaining 354 stocks were decimalized before 29 January, in February, or in March 2001. This study focuses on the stocks decimalized on 29 January and 6 April 2001.

Observations with bid price below \$0.125, non-positive bid ask spread, relative bid ask spread larger than 100%, or time to expiration less than 5 trading days are deleted.

Non-market maker public order imbalance is considered available for underlying stock i on day t for maturity M if there are at least five contracts of buy and sell volume made by public investors.

3.2 Variables and summary statistics

I use three measures of the quoted bid ask spread: (1) the dollar spread measured as the difference between the best ask and the best bid prices at market close (BA), (2) the relative spread measured as BA scaled by the mid price (BAM), and (3) the volume weighted relative spread (BAMV), where the weighting is applied within each stock day. The trading volume is measured as the number of daily contracts in logarithm.

The price of options with maturity M on stock i day t is measured as follows:

$$IV_{i,t}^{M} = \frac{1}{2}\left(IV_{i,t}^{C,M} + IV_{i,t}^{P,M}\right), \tag{2}$$

where $IV_{i,t}^{C,M}$ and $IV_{i,t}^{C,M}$ are the average implied volatilities of call and put options with time to expiration M and strike to stock price ratio within 0.90 to 1.10. I use average implied volatility of multiple options for two reasons. First, Ge, Lin, and Pearson (2016) show embedded leverage is the most important reason that option trading has information. OTM options have higher leverage than other moneyness options. Second, averaging implied volatility of multiple options can mitigate the effect of the bid ask bounce on the option prices.

Option trading is measured as the daily order imbalance (OI). I consider OI from the market maker perspective and separate trading volume into non-market maker public buys and sells of call and put options. Both call and put options have positive vega (exposure to volatility), so I treat buy volume as positive OI and sell volume as negative OI for volatility. Because options of varying strike prices have different sensitivities to changes in volatility, I weight the volume for each contract by the return to the option per unit change in volatility.[9] Similar results are obtained with equal weighted order imbalances.

[9] The same weighting scheme is used in Ni, Pan, and Poteshman (2008). Holowczak, Hu, and Wu

For options with maturity M, $OI_{i,t}^{M}$ is measured by

$$OI_{i,t}^{M} \equiv \log\left(\sum_{M}\sum_{K}\frac{\partial \ln C_{i,t}^{K,M}}{\partial \sigma_{i,t}} BuyCall_{i,t}^{K,M} + \sum_{M}\sum_{K}\frac{\partial \ln P_{i,t}^{K,M}}{\partial \sigma_{i,t}} BuyPut_{i,t}^{K,M}\right)$$
$$-\log\left(\sum_{M}\sum_{K}\frac{\partial \ln C_{i,t}^{K,M}}{\partial \sigma_{i,t}} SellCall_{i,t}^{K,M} + \sum_{M}\sum_{K}\frac{\partial \ln P_{i,t}^{K,M}}{\partial \sigma_{i,t}} SellPut_{i,t}^{K,M}\right), \quad (3)$$

where $C_{i,t}^{K,M}$ is the price of the call with strike price K and maturity M; $P_{i,t}^{K,M}$ is the price for the put; $\sigma_{i,t}$ is the volatility of underlying stock; $BuyCall_{i,t}^{K,M}$ is the number of call contracts purchased by non-market makers with strike price K and maturity M; and $SellCall_{i,t}^{K,M}$, $BuyPut_{i,t}^{K,M}$, and $SellPut_{i,t}^{K,M}$ are the analogous quantities for, respectively, the sale of calls and the purchase and sale of puts. The summations in Equation 3 are over all strikes and all maturities in maturity M that are available for underlying stock i on trade day t. I approximate $\partial \ln C_{i,t}^{K,M}/\partial \sigma_{i,t}$ with $(1/C_{i,t}^{K,M})\text{CallVega}_{i,t}^{K,M}$ (and similar for $\partial \ln P_{i,t}^{K,M}/\partial \sigma_{i,t}$), where Vega is computed under Black-Sholes with the volatility of the underlying stock set to the sample volatility from 60 trading days of returns leading up to t. This measure of order imbalance is observable by market makers who can see the buy and sell orders coming into the market, however it is not observable by other option market participants.

For the period before 2002, the CBOE subdivides the non-market maker public customer data into three classes: customers of discount brokers, customers of full service brokers, and other public customers. For example, clients of E-Trade are discount customers, whereas clients of Merrill Lynch are full-service customers. Hedge funds trade through full-service brokerages. Pan and Poteshman (2006) show that trading by full service customers is informative of the underlying stock prices, but trading by discount customers is not. Aragon and Martin (2012) find that hedge fund option positions predict volatilities and returns of the underlying stocks. By construction, most informed traders are among full service customers. The relative volume of uninformed traders for options with maturity

(2013) show that to forecast volatility, an aggregation method must account for each contracts exposure to volatility.

M, Disc/Full$_{i,t}^M$, is estimated by:

$$\text{Disc/Full}_{i,t}^M = \frac{\text{Disc}_{i,t}^M}{\text{Disc}_{i,t}^M + \text{Full}_{i,t}^M}, \tag{4}$$

where Disc$_{i,t}^M$ is the total volume of discount customers for options with maturity M on underlying stock i and date t, and Full$_{i,t}^M$ is the same variable for full service customers. Because there are also uninformed traders among full service customers, Disc/Full$_{i,t}^M$ captures a lower bound for the relative volume of uninformed traders.

Information is measured by one day and five day ahead straddle returns:

$$StrR_{t\to t+\tau,i}^M = \frac{1}{N^M}\sum_M \left(\frac{C_{t+\tau,i}^M + P_{t+\tau,i}^M}{C_{t,i}^M + P_{t,i}^M} - 1\right), \quad \tau = 1, or\ 5, \tag{5}$$

where N^M is the number of different maturities for options expiring in M, $C_{t,i}^M$ ($P_{t,i}^M$) is the closing mid price of the call (put) expiring in M with strike closest to the stock price on date t, and $C_{t+\tau,i}^M$ or $P_{t+\tau,i}^M$ is the call or put prices with same maturity and strike after τ days.

One measure of option expensiveness, $IV - ERV$, is the difference between implied volatility (IV) of ATM options and expected realized volatility (ERV) computed based on Model 8 in Bekaert and Hoerova (2014):

$$ERV_{i,t}^M = \sqrt{12}\left(3.73 + 0.108\frac{(IV_{i,t}^M)^2}{12} + 0.2V_{i,d}^{(-22)} + 0.33\frac{22}{5}V_{i,t}^{(-5)} + 0.107\cdot 22V_{i,t}^{(-1)}\right)^{\frac{1}{2}} \tag{6}$$

where $IV_{i,t}^M$ is the implied volatility of ATM options expiring in M for stock i at date t, $V_{i,t}^{(-j)}$ is the sum of the daily realized variances from day $t-j+1$ to day t. The daily realized variance sums squared 5-minute stock returns and the squared close-to-open returns. I choose this model because of its simplicity and good performance in predicting physical volatility.

Table 4 contains the mean and the standard deviation of the main variables for stocks decimalized on 29 January and 6 April 2001. The summary statistics are computed from daily cross sectional averages for the period from June 2000 to December 2001. The options decimalized earlier have lower dollar bid ask spreads (BA) and higher relative spreads (BAM and BAMV). The mean BA of the one-month options is $0.33 and $0.42 for options decimalized in January and April, respectively. The average one month relative bid ask spread (BAM) is 17.24% for options decimalized in January, and 18.07% for those decimalized in April. The two groups of stocks have similar options volume for all maturities. Stocks decimalized in January have lower implied volatility, straddle returns, order imbalance and relative volume of discount customers, and higher excess volatility than stocks decimalized in April.

Across options of different maturities, there are not many variations in dollar spreads for options expiring within three months. The relative spreads decrease with time to maturity. Volume weighted relative spreads (BAMV) for the three-month options are around seven percentage points lower than the one-month options. One-month options have a larger trading volume than longer-term options. As the option maturity increases, smaller excess volatility, less negative straddle returns, lower order imbalance, and comparable option prices and relative volume of uninformed traders are observed.

3.3 Experiment Set-up

To investigate how decimalization affects the option market, I use the difference in difference (DID) approach and consider the two stages of decimalization in January and April two natural experiments. In the first experiment, the treatment group consists of the stocks decimalized on January 29th, and the control group consists of the stocks not decimalized until April 6th. In the second experiment, the treatment (control) group is the control (treatment) group from the first experiment. This set-up guarantees that a consistent DID result arises from the exogenous shocks brought about by decimalization, but not from the cross sectional differences in the treatment and the control groups.

In the first experiment, the period before the experiment runs from January 1st to 28th, and the period after the experiment is the month of March. In the second experiment, the preceding and the succeeding periods are March and May, respectively. I skip about one month after the day when each decimalization begins because the option market participants may need time to adapt to the new pricing system. Bessembinder (2003) shows improvement in liquidity in the stock market starts three weeks after decimalization.

The main focus of the empirical analysis is to examine the DID, i.e., the differences in differences between the treatment stocks going through decimalization and the control stocks remaining in the same pricing system. For a variable X, its DID is computed as:

$$DID(X) = \left(\frac{1}{D_{\text{Aft}}} \sum_{t=1}^{D_{\text{Aft}}} X_t^T - \frac{1}{D_{\text{Aft}}} \sum_{t=1}^{D_{\text{Aft}}} X_t^C \right) - \left(\frac{1}{D_{\text{Bef}}} \sum_{t=1}^{D_{\text{Bef}}} X_t^T - \frac{1}{D_{\text{Bef}}} \sum_{t=1}^{D_{\text{Bef}}} X_t^C \right), \quad (7)$$

where

$$X_t^T = \frac{1}{N_t^T} \sum_{i=1}^{N_t^T} X_{i,t}^T, \quad X_t^C = \frac{1}{N_t^C} \sum_{i=1}^{N_t^C} X_{i,t}^C. \quad (8)$$

In the above equations, D_{Aft} (D_{Bef}) is the number of trading days during the period after (before) decimalization. N_t^T (N_t^C) is the number of stocks on date t in the treatment (control) group. X_t^T (X_t^C) is the average X of the treatment (control) stocks on date t. For some of the variables, X_t^T (X_t^C) is the coefficient estimate of the daily cross sectional regression within the treatment (control) group. The t-statistics of DID(X) are computed based on the standard errors of X_t^T and X_t^C.

4 Empirical results

Section 4.1 illustrates that the bid ask spread narrows, volume increases, and the price impact of order imbalance decreases after decimalization. Section 4.2 shows that uninformed investors are more responsive to the cost reduction induced by decimalization. Section 4.3 presents that slow adjustment of information in price is evidenced by that order imbalance is more powerful in predicting straddle returns and that the autocorrelation of implied volatility change becomes less negative. Section 4.4 reports results of robustness test. Section 4.5 documents that option prices are more expensive after decimalization.

4.1 Transaction Costs and Market Quality

The transaction costs and market quality are measured by the bid ask spread, trading volume, and price effect of the order imbalance computed as the λ in Kyle (1985). Low transaction costs and high market quality are associated with low bid ask spread, high trading volume, and small λ.

4.1.1 Option bid ask spread and volume

In this subsection, I present evidence that decimalization reduces options bid ask spreads and increases option volume. I use three measures of the quoted bid ask spread: (1) the dollar spread measured as the difference between the best ask and the best bid prices at market close (BA), (2) the relative spread measured as BA scaled by the mid price (BAM), and (3) the volume weighted relative spread (BAMV). The trading volume is measured as the number of daily contracts in logarithm. Negative DID(AB), DID(ABM) and DID($ABMV$) and positive DID($Volume$) computed based on Equation 7 and Equation 8 indicate that decimalization narrows bid ask spread and increases volume, respectively.

Table 5 Panel A reports the average bid ask spreads before and after the January 29 decimalization for the treatment stocks (T) experiencing change in the pricing system and the control stocks (C) remaining undecimalized. In this first experiment of decimalization, BA of the treatment stocks remains the same after decimalization, whereas BA of control stocks, on average, widens by three cents for options expiring within the next month. The DID(BA^{1Mon}) is \$-0.03, implying, on average, that the quoted dollar spread of the one-month options declined by around 10% after decimalization. The DID(BA^{2Mon}), DID(BA^{3Mon}), and DID(BA^{6Mon}) are \$-0.01, \$0.02, and \$0.02, respectively, suggesting that the quoted dollar bid ask spread either narrows with a smaller magnitude, or increases after decimalization for options with longer-term maturities.

For the relative spread, larger spread reductions are observed for volume weighted BAMV than for equal weighted BAM. This is consistent with the prediction by Harris (1999) that the largest spread reductions are for heavily traded securities. For one-month options, BAMV decreases by -0.52 and increases by 1.13 for the treatment and the control stocks, respectively. The DID($BAMV^{1Mon}$) amounts to -1.65, equivalent to an almost 8% reduction. DID($BAMV$) for longer term options are all negative, suggesting that the relative spreads narrow after decmalization for options of all maturities.

Panel B of Table 5 displays the result around decimalization on 6 April 2001. In this second experiment, the treatment (control) stocks are the control (treatment) stocks from the first experiment. Similar but stronger results on the reduction in spreads are observed after decimalization. All three measures of bid ask spreads decrease for the treatment options expiring within one month. For the control group, the spreads either decrease by a smaller magnitude, barely change, or increase slightly. The DID of the spreads are all negative and statistically significant for the dollar spreads of short-term options and the relative spreads of all options. For example, the DID(BA^{1Mon}) is -0.08, indicating that the dollar spread declines by more than 20% after the April decimalization.

Table 5 also shows the option volume in the months before and after the decimalization. DID($Volume^{\text{1Mon}}$) and DID($Volume^{\text{2Mon}}$) are positive and statistically significant for both the January and the April decimalization. In the April decimalization, the one-month option volume increases by 12% for the treatment stocks, and decreases by 3% for the control stocks, suggesting that decimalization raises the one-month option volume by 15% in aggregate. The increased trading volume is consistent with the prediction of Harris (1994) that the minimum price variation will affect trading volume if it forces dealers to quote a larger spread than they would otherwise quote. A narrower bid ask spread makes trading less expensive and increases trading volume.

4.1.2 Cost reduction in price effect of trade

The previous subsection demonstrates that option bid ask spread narrows and volume increases after decimalization. I now investigate whether decimalization brings variation in the market depth. The depth is measured by the λ in Kyle (1985), which captures the average price effect of a one-unit change in order imbalance, and is measured in the following cross-sectional regression:

$$(IV_{i,t}^{M} - IV_{i,t-1}^{M})/IV_{i,t}^{M} = \alpha_t^M + \lambda_t^M \cdot OI_{i,t}^{M} + \varepsilon_{i,t}^{M}, \quad (9)$$

where $IV_{i,t}^{M}$ is computed based on Equation 2, and measures the average implied volatility of options with maturity M for stock i on day t, $OI_{i,t}^{M}$ is computed based on Equation 3, and measures the order imbalance of public investors for options with maturity M. I normalize variables in above equation by subtracting the cross sectional mean and dividing by the cross sectional standard deviation. Equation 9 is estimated daily to generate the time series of λ_t^M.

The economic interpretation of λ could be twofold. While market makers adjust option prices to protect themselves from informational asymmetry, in the absence of informational asymmetry, they require a premium (discount) to absorb the positive (negative) order flow. As a result, λ contains two components: one corresponding to informational asymmetry and the other to pure inventory pressure. It is unlikely that decimalization directly changes the level of information asymmetry between market makers and informed traders. A decrease in λ after decimalization can be attributed to the likelihood that decimalization eases the market maker delta hedging in the stock market. As Cetin, Jarrow, Protter, and Warachka (2006) model that liquidity costs of hedging option inventory in stock market are a significant component of an option price, and increase with the imbalance in the number of short or long positions being hedged. Muravyev (2016) shows empirically that inventory pressure has the first order effect on the intra-day variation of option prices.

Table 6 reports the estimated λ based on Equation 9, and the DID(λ) based on Equation 7. Among the 24 estimated values of λ, only three of them are negative, suggesting that implied volatility increases with order imbalance. This is consistent with the finding of Bollen and Whaley (2004) and Garleanu, Pedersen, and Poteshman (2009) that public demand brings pressure to the option price. For options expiring within one month, λ^{1Mon} declines for the treatment stocks and rises for the control stocks in both experiments. For example, after the January decimalization, λ^{1Mon} declines by 1.70 for the treatment stocks. Because all of the variables are normalized in the regression, a 1.70

decrease suggests that the reduced price effect of one standard deviation change in the order imbalance is equivalent to a 1.7 standard deviation of the implied volatility returns. The DID($\lambda^{1\text{Mon}}$) are -2.99 (-3.40) with strong statistical significance for the January (April) decimalization. In contrast, for longer-term options, the DID($\lambda^{2\text{Mon}}$), the DID($\lambda^{3\text{Mon}}$) and the DID($\lambda^{6\text{Mon}}$) are all positive. Those positive values are smaller in magnitude and t-statistics in the second experiment, suggesting that the increased price effect wanes in later periods.

The result of DID(λ) for options with different maturities is consistent with the hypothesis that a low trading cost in the stock market facilitates the inventory management of the option market makers. Option market makers engage in dynamic hedging to keep their position delta neutral. As delta changes, they need to trade shares to maintain delta-neutral. The frequency of this hedge re-balancing depends on the gamma of the options, which measures the rate of change of the option delta with respect to the price of the underlying stock. If gamma is small, delta changes slowly, and adjustments to keep a portfolio delta neutral need to be made only relatively infrequently. However, if the gamma is highly negative or highly positive, the delta is very sensitive to the price of the underlying asset. It is then quite risky to leave a delta-neutral portfolio unchanged for any length of time. Reduced transaction costs in the stock market are beneficial for options market marker practicing dynamic hedging especially for high gamma options. As shown in Figure 3, the gamma of one-month ATM option is more than 50% higher than it is for the two-month option. Cetin, Jarrow, Protter, and Warachka (2006) suggest that for out-of-the-money options with low initial prices, the impact of illiquidity is very significant despite a small dollar-denominated liquidity cost. So I also scale gamma by option prices. Figure 3 show that the difference between the one-month and the two-month price-scaled gammas is even larger for the ATM and OTM options. Therefore, a reduction in stock trading costs will primarily affect hedge re-balancing of the short-term options. This explains why the DID($\lambda^{1\text{Mon}}$) is negative, whereas the DID(λ) for longer-term options is not. This also explains why the reduction in bid ask spread is more obvious on short-term options than long-term options.

The opposite results of DID(λ) on short-term and long-term options also imply that the variations in the price effect are not from the changes in the level of information asymmetry. If it is information asymmetry that drives the variations in λ, λ of different maturities should move in the same direction, because implied volatilities of different maturities move together on average, so does the order imbalance. A negative DID(λ^{1Mon}) is unique to the options market in the sense that there are two sources of liquidity improvement. One is decimalization in the option market itself. The other is the reduced hedging re-balancing cost in the stock market.

4.2 Trading of uninformed and informed investors

The previous subsections show decimaization reduces transaction costs in the option market, especially for short-term options. In this subsection I present that uninformed traders are more responsive to the reduction in trading costs induced by decimalization. For the period before 2002, the CBOE subdivides the non-market maker public customer data into three classes: customers of discount brokers, customers of full service brokers, and other public customers. The literature shows that trading by full service customers is informative of the underlying stock price and volatility, but trading by discount customers is not.

I use relative volume of discount to full service customers, $\text{Disc/Full}_{i,t}^{M}$, to estimate the relative volume of uninformed traders for options with maturity M. $\text{Disc/Full}_{i,t}^{M}$ is computed based on Equation 4, and captures a lower bound of the relative volume of uninformed traders. A positive DID($\text{Disc/Full}^{\text{M}}$) indicates a lower bound for the increase in the relative volume of uninformed traders after decimalization.

In the option market, informed traders trade naked positions on opportunities associated with corporate events or stock characteristics. Those opportunities do not vary with exogenous trading costs. The volume from informed traders may not increase much after decimalization. In contrast, uninformed traders use options to hedge, speculate, or liquidate. They receive returns close to the risk free rate, and are more cost sensitive than informed traders. I expect the relative volume of uninformed traders will increase after decimalization, especially for short-term options that have large reduction in trading costs.

Table 7 reports the absolute and relative volumes from discount customers. Similar to the DID of the total volume in Table 5, the volume from discount customers in the treatment group increases more than it does in the control group. For example, after the January decimalization, the discount volume in the treatment group increases by 1%, whereas that in the control group it declines by 16%. The DID($Disc^{1\text{Mon}}$) is 0.18 and 0.26 for the experiments in January and April, respectively, suggesting that decimalization raises the discount volume in the treatment group by 18% and 26% in the two experiments.

The relative volume of discount customers increases after decimalizaation for the one-month options in the treatment group, and increases at a smaller magnitude or decreases for those in the control group. DID in the relative volume of one-month options is 0.04 (4%) and 0.05 (5%) in the first and the second experiments, respectively. Those numbers suggest that the relative volume from uninformed traders increases at least by four to five percentage points after decimaization. The increase in the relative volume of discount customers is less obvious for longer term options. For example, in the second experiment, the DID value is 0.02, 0.01, and -0.01 for options expiring in two, three, and at least six months, respectively.

Overall the result in Table 7 shows that uninformed traders are more responsive to the reduction in trading costs than informed traders. The higher cost reduction, the larger increase in the absolute and the relative volume of uninformed traders.

4.3 Slowed speed of impounding information

Previous subsections show that decimalization reduces transaction costs, and uninfomed traders are more responsive to the cost reduction than informed ones. As discussed in Section 2.1, under that situation, reduction in trading costs will slow the speed of price adjusting information. In this subsection I use two methods to show that prices are slower in impounding information after decimalization. The first method is to investigate if predictability of order imbalance increases after decimalization. The second method is to examine whether the first order autocorrelation of implied volatility change becomes less negative after decimalization.

4.3.1 Predictability of order imbalance

If option prices fully adjust information in the trade, order imbalance should show no predictability for price change. If the speed of price adjusting information is slower than it would be in a perfect market, order imbalance will positively predict price change. The predictability I consider here is the predictability for straddle returns because what matters for informed traders are the returns on the options positions. Straddle returns are sensitive to the changes in options prices and are not related to the directional movement of the underlying stock. The one-day and five-day straddle returns ($StrR^{M}_{t \to t+1,i}$ and $StrR^{M}_{t \to t+5,i}$) are computed based on Equation 5.

I use two methods to measure the predictive power of order imbalance for straddle returns. The first is the portfolio approach and the second is the regression approach. In the portfolio approach, stocks are sorted daily into quintiles based on the order imbalance, $OI^{M}_{i,t}$, computed as Equation 3. The predictive power is measured as the straddle return difference between the high (H) and the low (L) OI^{M} quintiles:

$$StrR^{M,H-L}_{t \to t+\tau} = StrR^{M,H}_{t \to t+\tau} - StrR^{M,L}_{t \to t+\tau}, \;\; \tau = 1, or \;\; 5, \tag{10}$$

where $StrR^{M,H}_{t \to t+\tau}$ ($StrR^{M,L}_{t \to t+\tau}$) is the equal weighted average straddle returns in the highest (lowest) OI^{M} quintile. I then calculate DID($StrR^{M,H-L}_{t \to t+\tau}$) to examine the variation in the predictability of order imbalance after decimalization. A positive DID($StrR^{M,H-L}_{t \to t+\tau}$) suggests that the predictability of the order imbalance of options with maturity M increases and the prices of options become less informationally efficient after decimalization. The increased predictive power will be more obvious for short-term options because they have higher cost reductions and attract more uninformed traders.

Table 8 displays the straddle return differences between the high and the low order imbalance quintiles ($StrR^{H-L}_{t \to t+\tau}$) computed from Equation 10 for one-month options. The straddle return differences are positive on average, suggesting that the order imbalance is positively associated with the subsequent one-day and five-day straddle returns. In both experiments, $StrR^{1Mon,H-L}_{t\rightarrow t+\tau}$ of the treatment stocks increases after decimalization, whereas that of control stocks either decreases or increases at a smaller magnitude. For example, after April decimalization, $StrR^{1Mon,H-L}_{t\rightarrow,t+5}$ increases by 3.63% for the treatment stocks, and decreases by 2.23% for the control stocks. DID($StrR^{1Mon,H-L}_{t\rightarrow,t+\tau}$) are all positive and statistically significant. This result indicates that the predictive power of order imbalance increases after decimalization, which is consistent with a slowed speed of price adjusting information after decimalization.

Table 8 shows that DID($StrR^{H-L}_{t\rightarrow t+\tau}$) for options longer than one month is either negative or positive without statistical significance. The only DID value statistically larger than zero is the DID($StrR^{H-L}_{t\rightarrow t+1}$) in the second experiment for options expiring over six months. As reported in Table 6 and Table 7, the cost reduction is smaller and the increase in the volume of uninformed traders is less obvious for long-term options. Consequently, there is no obvious change in the predictive power of order imbalance for those options.

An elevated DID($StrR^{H-L}_{t\rightarrow t+\tau}$) may result from variations in volatility. Large volatility may cause large cross sectional difference in straddle returns. In the second regression approach, I normalize variables by their mean and standard deviation, so the result will not be affected by the volatility of the variables. The predictive power of the order imbalance of options with maturity M is measured by $b^M_{t,\tau}$, the coefficient of $OI^M_{i,t}$ in the daily cross sectional regression :

$$StrR^M_{i,t\rightarrow t+\tau} = a^M_t + b^M_{t,\tau} \cdot OI^M_{i,t} + \epsilon^M_{t\rightarrow t+\tau}, \;\; \tau = 1, or\ 5, \tag{11}$$

The above specification is estimated daily to generate time series of $b^M_{t,\tau}$. A higher b^M_τ indicates that order imbalances have higher predictive power for straddle returns, and the option prices are less informational efficient. A positive DID (b^M_τ) is consistent with the notion that speed of the option price adjusting information slows after decimalization.

Table 9 reports b^M of different maturities based on Equation 11. The predictive power measured in this approach also becomes stronger after decimalization for one-month options. DID($b_{t,\tau}^{\mathrm{1Mon}}$) are all positive and for the most part statistically significant. For the treatment group after the April decimalization, a one standard deviation increase in order imbalance is associated with an 8.59 standard deviation increase of the five-day straddle returns, whereas before the April decimalization, the associated increase is only 4.04. These numbers suggest that for the treatment stocks, the predictive power of order imbalance for one-month options doubles after decimalization.

For options expiring in more than one month, the DID($b_{t,\tau}^{\mathrm{M}}$) is either positive without statistical significance or negative, suggesting that there is no increase in the predictive power of order imbalance for longer-term options.

In summary, Table 8 and Table 9 show that the predictive power of order imbalance increases for one month options. One month options have higher reductions in transaction costs and larger increases in the relative volume of uninformed traders. Those results are consistent the hypothesis in Section 2 that if uninformed traders are more cost sensitive, an exogenous reduction in trading costs will slow the speed of price adjusting informations.

4.3.2 Serial correlation of implied volatility change

In the second method of testing slowed speed of option price adjusting information, I examine whether the autocorrelation of the daily implied volatility change becomes less negative after decimalization. The stock market closes at 3:00 P.M. while the option market closes at 3:15 P.M. When the closing prices are used to estimate implied volatility, Harvey and Whaley (1991) show this timing difference induces negative autocorrelation in the daily implied volatility change. What happens is that, new information enters the market and causes option prices to be revised. When the implied volatility is computed using stock closing prices at 3:00 P.M., the implied volatility from call is higher than it should be when the information is good on stock price, and the implied volatility from put is higher than it should be when the information is bad on stock price. On the following day, the stock price adjusts to the new information, and the implied volatility reverts back to normal level.

Harvey and Whaley (1991) suggests the negative autocorrelation is induced by new information during the interval of 3:00 to 3:15. In fact, their argument implies informed trading in anytime during the day can also cause a negative autocorrelation of daily implied volatility change, as long as (1) informed trading alters the option volatility but not the stock price, and (2) when information becomes public available next day, the stock price changes and the implied volatility reverts back to normal. A typical example is that before the earning announcement, the implied volatilities increase while the stock price remains the same; after the announcement the implied volatilities decrease while the stock price changes according to the earning. If option prices are slower in adjusting information, the autocorrelation of implied volatility change will be less negative.

Another source of the negative autocorrelation of implied volatility change is the mean-reversion of volatility. Aragon and Martin (2012) document hedge fund positions reflect their volatility timing skill. If option prices are slower in adjusting trading related to the mean reversion process of volatility, a higher autocorrelation of volatility change will also be observed.

The bid ask bounce also induces a negative serial correlation of the price change (Roll (1984)). Although the implied volatility is computed from option mid prices, it is still possible for bid ask bounce to play a role. To mitigate this effect, I follow Harvey and Whaley (1991) and use the average implied volatility of a series of options with $0.90 \leq K/S \leq 1.10$. The DID in autocorrelation of daily implied volatility change for options with maturity M, DID(ρ^M), is computed as:

$$DID(\rho^M) = \left(\frac{1}{N^T} \sum_{i}^{N^T} \rho^M_{i,\text{Aft}} - \frac{1}{N^C} \sum_{i}^{N^C} \rho^M_{i,\text{Aft}} \right) - \left(\frac{1}{N^T} \sum_{i}^{N^T} \rho^M_{i,\text{Bef}} - \frac{1}{N^C} \sum_{i}^{N^C} \rho^M_{i,\text{Bef}} \right), \quad (12)$$

where $\rho^M_{i,\text{Bef}}$ ($\rho^M_{i,\text{Aft}}$) is the daily autocorrelation of implied volatility change for options with maturity M on stock i during the periods before (after) the decimalization; N^T (N^C) is the number of the treatment (control) stocks.

If option prices are slower in adjusting information after decimalization due to an increased participation of uninformed traders, a positive DID(ρ^M) will be observed, and

DID(ρ^M) will be larger for short-term options.

Table 10 reports the first order autocorrelations of daily implied volatility change for calls(ρ^{IVC}) and puts (ρ^{IVP}) and their DID before and after the two experiments. There are significant negative autocorrelations of implied volatility changes for both calls and puts. The magnitude of autocorrelation is in the range from -0.33 to -0.23, comparable to that documented in Harvey and Whaley (1991) for S&P100 index options. For one month options, the values of DID are all positive and statistically significant, indicating the autocorrelations become less negative after decimalization. For example, ρ^{IVC} increases from -0.33 to -0.26 for the treatment stocks, while decreases from -0.30 to -0.32 for the control stocks in the first experiment. The reduction in the negative autocorrelations is more obvious for calls than for puts; for one month options, DID(ρ^{IVC}) is 0.09, and DID(ρ^{IVP}) is no larger than 0.05. Calls on individual stocks are more actively traded than puts. Less liquid puts having smaller reduction in the negative autocorrrelation implies that the result is not driven by the variations in the bid ask bounce after decimalization. If it is due to bid ask bounce, less liquid puts should have more reduction in the negative autocorrelation than more liquid calls.

Table 10 also shows the shorter the maturity, the more positive DID(ρ) is observed, except for DID(ρ^{IVP}) in the first experiment. Overall the result is consistent with the theoretical prediction that increased participation of uninformed traders following cost reduction slows the speed of option price impounding information.

4.4 Robustness test: different comparing periods

In the previous empirical test discussed from Section 4.1 to Section 4.3, the periods preceding and succeeding the first experiment are January and March 2001, respectively. The periods preceding and succeeding the second experiment are March and May, respectively. It is possible that the results may be driven by increased attention of investors around decimalization that fades away over longer period of time. The preceding period in the first experiment is January, a special month, where anomalies on stock returns have been found. To exclude the possibility that the results only present for months right before or after decimalization, I adjust the period preceding the first experiment from June to December 2000, and adjust the period succeeding the second experiment from June to December 2001.

Figure 4 plots the point estimates of the DID for the different periods preceding and succeeding the experiments. For the estimates before April 2001, the DID is based on the values from March 2001 relative to the values in a month between June 2000 and January 2001. For the estimates after April 2001, the DID is computed from the values in a month between May and December 2001 relative to the values in March. To make figures clear to read, I only report the DID results for options expiring within the next month (1 Mon) and options expiring in the next three months (3 Month). The results of the two and six-months options are similar to the three month options.

Figure 4 displays that the DID values mostly remain similar if I use different months to compute them. The results reported in the previous sections are not due to a special trading pattern in January, or to temporarily elevated attention right after decimalization. Overall the one-month options experience declines in the dollar bid ask spreads and deepened depth after decimalization. The reductions in trading costs increase the total and the relative volumes of uninformed traders. Consequently, the predictability of the order imbalance for straddle returns increases, and the autocorrelations of implied volatility change become less negative. In contrast, the three-month options do not show an obvious decrease in the dollar spread, deepened depth, or increased volume. As a result, the predictability of the order imbalance remains the same, and the increase in the autocorrelation of the implied volatility change is small after decimalization. Those results are consistent with the theoretical prediction in Section 2.1 that if uninformed traders are more cost sensitive, the speed of price adjusting private information slows after an exogenous reduction in trading costs.

4.5 Volatility, excess volatility and price precision

Positive liquidity shock brought about by decimalization may alter volatility, expensiveness or precision of options prices. In this section I show that after decimalization, volatility decreases, excess volatility increases, and absolute value of excess volatility dose not change.

I use implied volatility of ATM[10] options and realized volatility of stock intra-day returns to measure volatility. Porter and Weaver (1997) find that volatilities display an initial increase but a decline over the longer-term for a sample of NYSE-listed stocks trading in decimals. Ronen and Weaver (2001) and Bessembinder (2003) find that volatilities of stocks decline after a tick size reduction in 1997 and decimalization in 2001, respectively. Similar to their findings Figure 5 shows that implied and realized volatilities on average decrease after decimalization. The DID of volatilities are mostly negative except for those with preceding periods being a few months before January 2001

Option expensiveness is computed as the difference between the implied volatility of the ATM options and the physical volatility. I use three measures of physical volatility. The first is the forward looking realized volatility (FRV) over the remaining life of the options. The second is the historical volatility(HRV) based on intra-day realized volatility (RV) from day $t-21$ to t.[11] The third is the expected realized volatility (ERV) computed based on Equation 6.

The effect of liquidity on option prices is unclear. The buyer and the seller may each demand a liquidity premium, but since the option value sums to zero between two parties, it is unclear that the equilibrium price would reflect any liquidity premium. However, if the seller of the option does not demand a liquidity premium, the equilibrium price may reflect the liquidity premium by the buyer. Brenner, Eldor, and Hauser (2001) show that prices of bank issued non-negotiable options are lower than those exchange traded options in Isreal, suggesting the banks who sell the options do not demand a liquidity premium.

The existing evidence on how liquidity affects exchange traded options with zero net demand is very limited. When market makers net long options, i.e. public net short, market makers may be willing to pay higher prices for options with higher liquidity for easier

[10]The ATM options are options with $0.95 < K/S < 1.05$.

[11]The daily RV for stock i on day t is computed as:

$$RV_{i,t} = \left(252^*(r^2_{i,t,close\to open} + r^2_{i,t,1} + r^2_{i,t,2} + ... + r^2_{i,t,K})\right)^{\frac{1}{2}}, \tag{13}$$

where $r_{i,t,close\to open}$ is the stock return from the previous close to open, $r^2_{i,t,1}$, $r^2_{i,t,2}$ and $r^2_{i,t,K}$ are the first, the second, and the last five minute return on day t, respectively.

inventory management. Christoffersen, Goyenko, Jacobs, and Karoui (2015) document that selling pressure from the public causes liquid calls to be more expensive than illiquid ones. If the prices of stock options increase after a liquidity shock brought about by decimalization, the DID of the excess volatilities will be positive.

Indeed, Figure 5 shows that the DID of excess volatility measured as DID($IV - FRV$), DID($IV - HRV$), and DID($IV - ERV$) are mostly positive, especially in the second experiment, implying that option prices become more expensive following positive liquidity shocks brought about by decimalization.

Finally, decimalization may cause an enhanced precision of option prices. The option price precision is measured as the absolute difference between the implied volatility of ATM options and the expected realized volatility ($|IV - ERV|$). Figure 5 indicates that there is no improvement in the price precision after decimalization. The values of DID($|IV - ERV|$) are not consistently negative.

It is possible that the increased predictive power for straddle returns may be due to volatility, excess volatility, or the precision of volatility. If this is case, those measures must present variations across options with different maturities. Figure 5 show that the DID values of volatility, excess volatility, or the absolute value of excess volatility do not vary with options maturity. This result suggests that the factors related to those variables cannot account for the increased predictive power of order imbalance for short-term options.

5 Conclusion

I model and test the proposition that informational inefficiency will occur after a reduction in trading costs if uninformed traders are more cost sensitive than informed traders. I use the option market as the testing ground because large bid ask spreads impede extensive use of high frequent strategies by informed traders. Informed traders in the option market mainly trade on private information associated with corporate events, stock characteristics, or the timing of volatility. The trading opportunities associated with this private information do not vary with exogenous reduction in trading costs. As a result, uninformed traders using options to hedge, speculate, or liquidate, are more cost sensitive than informed traders.

Applying a model designed by Diamond and Verrecchia (1987), I prove that if uninformed traders are more cost sensitive, an exogenous reduction in trading cost slows the speed of price adjusting information. Alternatively, if informed traders are equally or more cost sensitive, reduction in trading cost expedites the process of price impounding information.

In conducting the empirical test, I take advantage of two stages of decimalization in 2001 that occur at the same time in the stock and the option markets. The two stages of decimalization provide two perfect natural experiments such that the treatment stocks and the control stocks can be switched in the two experiments. A consistent DID result must arise from the effects brought about by decimalization but not from the cross sectional differences between the treatment and the control stocks. The DID results show that decimalization narrows bid ask spreads, increases volume, and reduces the price effect of order imbalance. Those reductions in trading costs are more obvious for options with short-term maturities, whose delta hedging requires frequent re-balancing and benefits most from enhanced liquidity in the stock market.

As expected, uninformed traders in the option market are more responsive to the cost reduction induced by decimalization. The relative trading volume of investors that are likely to be uninformed traders increases after decimalization, especially for short-term options where the reduction in trading cost is most obvious. Consequently, the order imbalances of short-term options become more powerful in predicting straddle returns, and the autocorrelations of daily implied volatility changes are less negative after decimalization. Those results are consistent with the prediction that when uninformed traders are more cost sensitive, a reduction in trading costs makes the market less informationally efficient.

Finally, this study provides evidence that the prices of stock options increase following the exogenous liquidity shocks brought about by decimalization. The analysis also suggests that the results are not due to a unique trading behavior in a particular month or an elevated attention during periods around decimalization.

Appendix

The proof follows Diamond and Verrecchia (1987). First, I compute the expected number of periods until the price of the asset is within some range of being totally informative. The time series property of the log of the posterior likelihood ratio, i.e., $\log(P_t/(1-P_t))$, is similar to a Wald sequential likelihood ratio test of the hypothesis v=0 versus v=1. Let Ψ=$P^H/(1-P^H)$ and Φ=$P^L/(1-P^L)$: logΨ and logΦ are possible values of the posterior log likelihood ratio. That is, the expressions logΨ and logΦ provide boundaries such that when either $\log(P_t/(l-P_t))$ exceeds logΨ, or falls below logΦ, then the price is within an acceptable range of fully informing an uninformed trader that the true state-of-nature is either 1 or 0.

Let Ω represent the set of observable actions: buy, sell and no-trade, and let A represent some member of Ω (i.e., A is some observable action). Define the following relations:

$$\Lambda_N = \frac{P_N}{1-P_N}, \quad Z^A = \log(\frac{q_1^A}{q_0^A}), \tag{14}$$

where q_v^A, $A \in \Omega$ and $v = 0$ or $v = 1$, is defined in Table 2. Let $\tilde{Z}$ represent the random variable whose realization is Z^A, $A \in \Omega$. Let the random variable $\tilde{N}$ represent the number of time periods until the posterior log likelihood ratio of prices first reaches the boundary of log Ψ, or the boundary of logΦ. Wald's Lemma states that

$$\mathrm{E}[\tilde{N}] = \frac{\mathrm{E}[\log(\tilde{\Lambda}_N)]}{\mathrm{E}[\tilde{Z}]}, \tag{15}$$

which can be computed approximately. That is, the random variable log$\tilde{\Lambda}_N$ is approximately a Bernoulli variable, with the value logΨ, if the decision is to reject v=0, and the value logΦ, if the decision is to accept v=0. (In each case the approximation arises because of the possibility of passing a boundary.) Note that Ψ and Φ are arbitrary fixed parameters. I choose Ψ and Φ such that $\bar{N}_0$ equals $\bar{N}_1$. This requires that $\Psi = \Phi^{-1}$, where $\Psi > 1 > \Phi$. In particular,

$$\mathrm{E}\left[\log(\tilde{\Lambda}_N)|v=0\right] \cong \frac{1-\Phi}{\Psi-\Phi}\log\Psi + \frac{\Psi-1}{\Psi-\Phi}\log\Phi < 0, \tag{16}$$

$$\mathrm{E}\left[\log(\tilde{\Lambda}_N)|v=1\right] \cong \frac{\Psi(1-\Phi)}{\Psi-\Phi}\log\Psi + \frac{\Phi(\Psi-1)}{\Psi-\Phi}\log\Phi > 0. \tag{17}$$

Furthermore,

$$\mathrm{E}[\tilde{Z}|v=v] = \sum_{A\in\Omega} q_v^A Z^A = \sum_{A\in\Omega} q_v^A \log\left(\frac{q_1^A}{q_0^A}\right). \tag{18}$$

This allows to define $\bar{N}_0$ and $\bar{N}_1$ as follows:

$$\bar{N}_0 = \mathrm{E}[\tilde{N}|v=0] \cong \frac{\frac{1-\Phi}{\Psi-\Phi}\log\Psi + \frac{\Psi-1}{\Psi-\Phi}\log\Phi}{\sum_{A\in\Omega} q_0^A \log\left(\frac{q_1^A}{q_0^A}\right)}, \tag{19}$$

$$\bar{N}_1 = \mathrm{E}[\tilde{N}|v=1] \cong \frac{\frac{\Psi(1-\Phi)}{\Psi-\Phi}\log\Psi + \frac{\Phi(\Psi-1)}{\Psi-\Phi}\log\Phi}{\sum_{A\in\Omega} q_1^A \log\left(\frac{q_1^A}{q_0^A}\right)}. \tag{20}$$

Because the numerators in the definitions of $\bar{N}_0$ and $\bar{N}_1$ are fixed, it is sufficient to consider the effect of changes in c_i, i=1,2,3, on denominators so as to prove Propositions 1 and 2. Let α and β represent $\mathrm{E}[\tilde{Z}|v{=}0]$ and $\mathrm{E}[\tilde{Z} \mid v{=}1]$, respectively. This implies that α and β are defined by

$$\begin{aligned}\alpha &= q_0^B\log\left(\frac{q_1^B}{q_0^B}\right) + q_0^S\log\left(\frac{q_1^S}{q_0^S}\right) + q_0^N\log\left(\frac{q_1^N}{q_0^N}\right), \\ &= x\log\left(\frac{y}{x}\right) + y\log\left(\frac{x}{y}\right),\end{aligned} \tag{21}$$

$$\begin{aligned}\beta &= q_1^B\log\left(\frac{q_1^B}{q_0^B}\right) + q_1^S\log\left(\frac{q_1^S}{q_0^S}\right) + q_1^N\log\left(\frac{q_1^N}{q_0^N}\right), \\ &= y\log\left(\frac{y}{x}\right) + x\log\left(\frac{x}{y}\right).\end{aligned} \tag{22}$$

where

$$
\begin{aligned}
x &= \frac{1}{2}g(1-a)c_1, \\
y &= \frac{1}{2}g(1+a)c_1 + gac_2
\end{aligned}
\tag{23}
$$

Let primes ($'$) denote differentiation with respect to c_1, holding c_3 constant at any fixed value (e.g., not necessarily zero), where c_2=1-c_1. And let asterisks (*) denote differentiation with respect to c_1, holding c_2=0, where c_3=1-c_1.

$$
\alpha' = g(1-a)\frac{(x-y)^2}{2xy} > 0, \quad \text{hence,} \quad \frac{\partial \bar{N}_0}{\partial c_1} > 0 \text{ if } c_2 = 1 - c_1. \tag{24}
$$

$$
\beta' = -g(1-a)\frac{(x-y)^2}{2xy} < 0, \quad \text{hence,} \quad \frac{\partial \bar{N}_1}{\partial c_1} > 0 \text{ if } c_2 = 1 - c_1. \tag{25}
$$

$$
\alpha^* = -ga\log\frac{1+a}{1-a} < 0, \quad \text{hence,} \quad \frac{\partial \bar{N}_0}{\partial c_1} < 0 \text{ if } c_2 = 0. \tag{26}
$$

$$
\beta^* = ga\left(1 + \log\frac{1+a}{1-a}\right) > 0, \quad \text{hence,} \quad \frac{\partial \bar{N}_1}{\partial c_1} < 0 \text{ if } c_2 = 0. \tag{27}
$$

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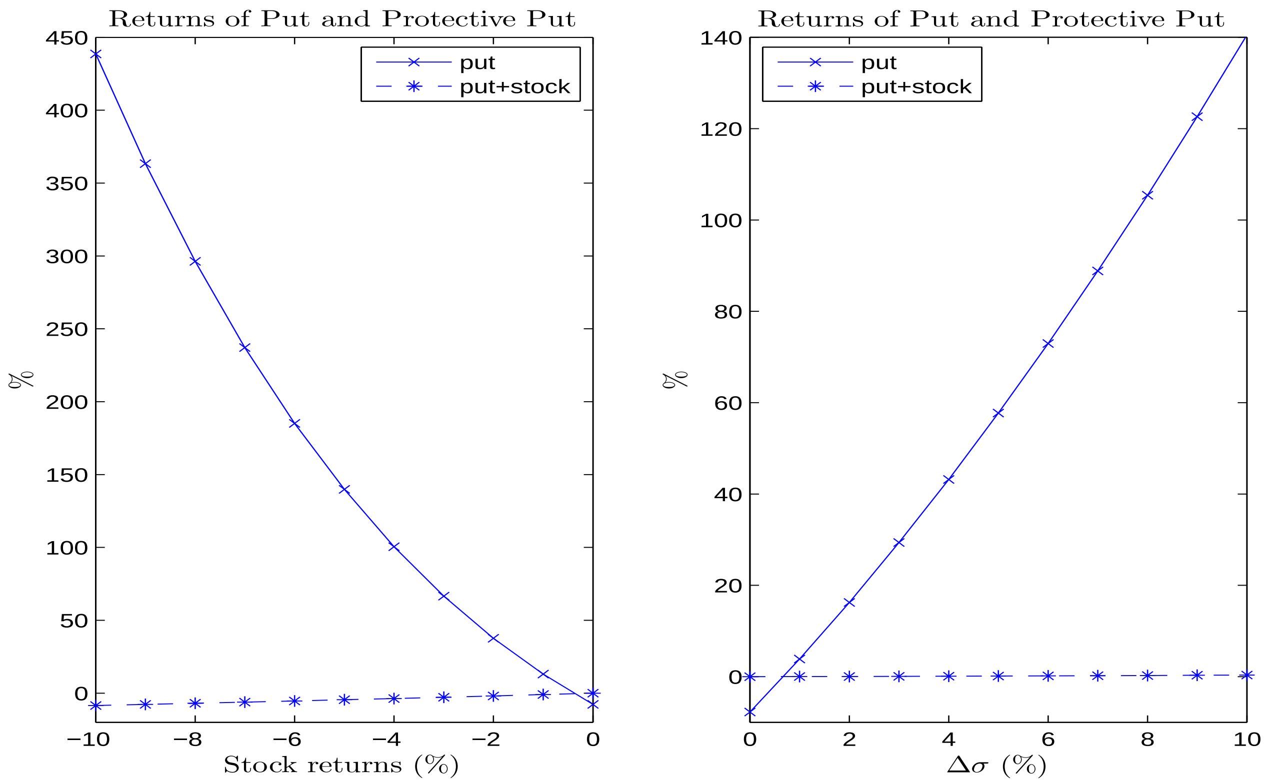

Figure 1: **Returns of put and protective put after stock price or volatility changes.** One-day returns of put and protective put (put and stock) with stock price 30, strike price 25, volatility 40%, and 30 calendar days of maturity. Stock returns are the stock returns over one day. $\Delta\sigma$ is the change of volatility over one day. Put prices are computed based on the Black-Scholes model.

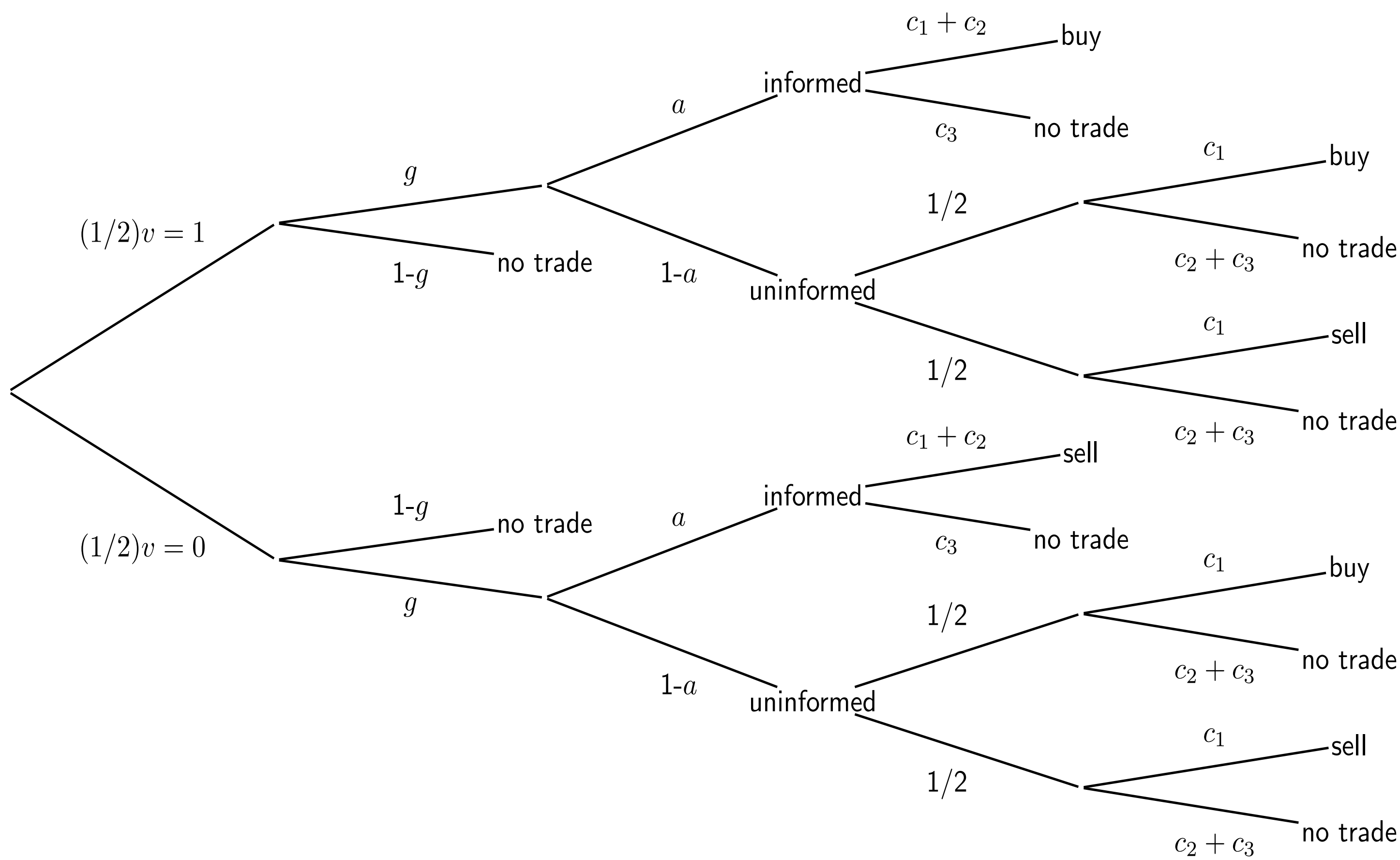

Figure 1: Tree diagram

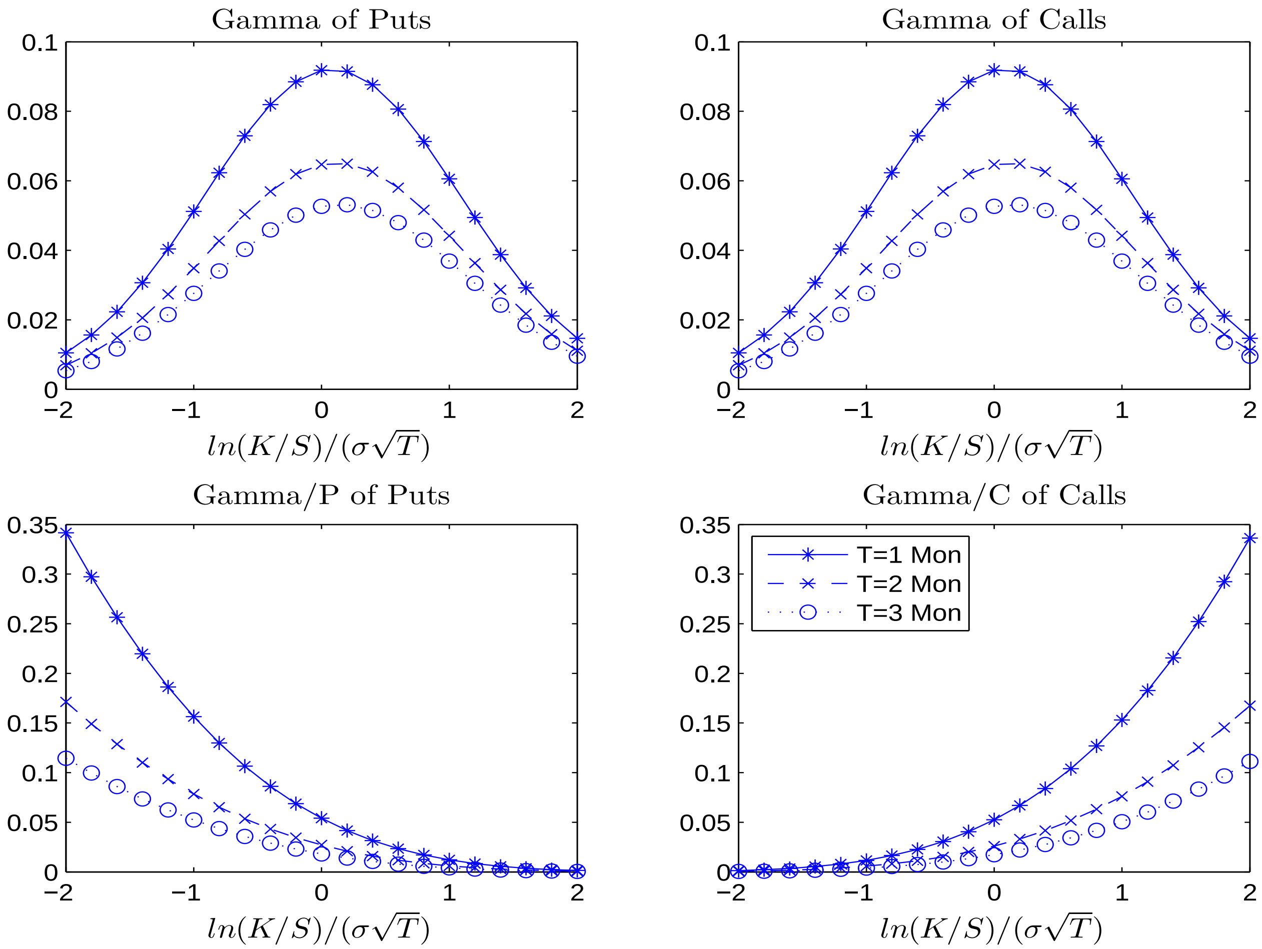

Figure 3: **Gamma of Options with Various Maturity.** Gamma is computed based on Black-Scholes with stock price \$30, and volatility 50%. C and P are calls and puts prices, respectively.

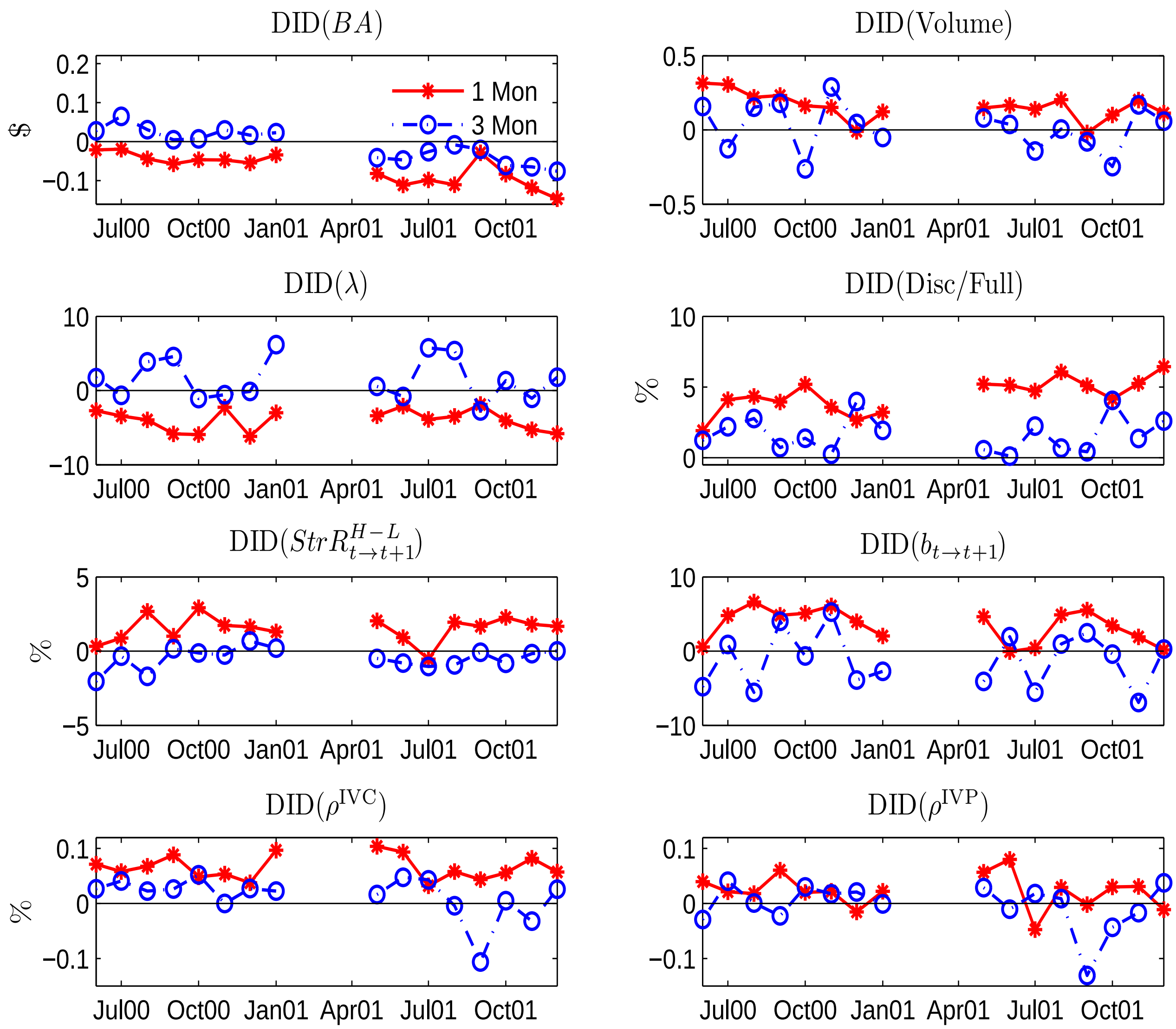

Figure 4: **DID with different comparing months.** BA is the bid ask spread in dollars. Volume is the number of daily average contracts in logarithm. λ is Kyle (1985)'s λ of price effect of order imbalance measured in $(IV^i_t - IV^i_{t-1})/IV^i_{t-1} = \alpha + \lambda\ \text{OI}^i_t + \epsilon_t$, where IV is the average implied volatilities. Disc/Full is the volume from discount investors relative to the sum of discount and full service investors. $StrR^{H-L}_{t\to t+1}$ is the one day ahead straddle return difference between the high and the low order imbalance quintiles. $b_{t\to t+1}$ is the coefficient on order imbalance in the predictive regression: $StrR^i_{t\to t+1} = a + b_{t\to t+1}\ \text{OI}^i_t + \epsilon^i_{t\to t+1}$. ρ^{IVC} (ρ^{IVP}) is the daily first order autocorrelation of call (put) implied volatility change. 1 Mon (3 Mon) indicates that variables are computed from options expiring within one month (in three months). Before Apr 01, DID is based on Mar 01 relative to a month from Jun 00 to Jan 01 between treatment stocks decimalized on 29 Jan 01 and control stocks not decimalized until 6 Apr 01. After Apr 01, the treatment and control groups are switched. DID is based on a month from May to Dec 01 relative to Mar 01.

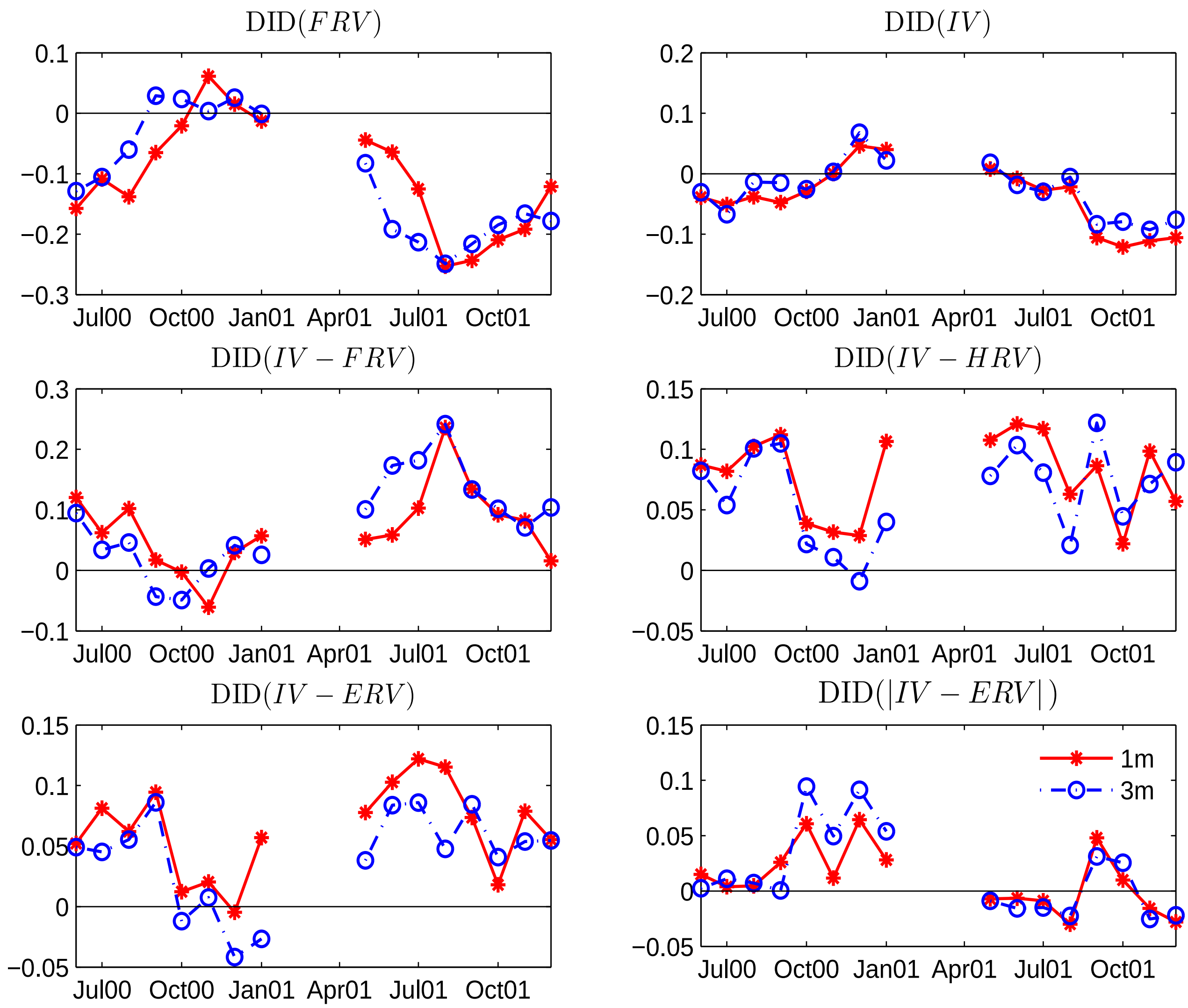

Figure 5: **The DID with difference comparing months.** FRV is the forward looking realized volatility during the remaining life of the options. IV is the implied volatility of the ATM options. HRV is the historical realized volatility from trade day t-22 to t. ERV is the expected realized volatility. All of the volatility measures are in logrithm. 1 Mon (3 Mon) indicates that variables are computed from options expiring within the next month (in three months). Before Apr 01, DID is based on Mar 01 relative to a month from Jun 00 to Jan 01 between treatment stocks decimalized on 29 Jan 01 and control stocks not decimalized until 6 Apr 01. After Apr 01, the treatment and control groups are switched. DID is based on a month from May to Dec 01 relative to Mar 01.

Table 1: **A summary of the types traders who trade**

	Informed traders	Uninformed traders
Panel A: uninformed traders are more cost sensitive: $c_3 = 0$		
c_1: low cost	yes	yes
c_2: medium cost	yes	no
c_3: high cost	no	no
Panel B: uninformed and informed traders are equally cost sensitive: $c_2 = 0$		
c_1: low cost	yes	yes
c_2: medium cost	yes	yes
c_3: high cost	no	no
Panel C: informed traders are more cost sensitive: $c_3 = 0$		
c_1: low cost	yes	yes
c_2: medium cost	no	yes
c_3: high cost	no	no

Table 2: **A summary of notations used in the tree figure and the model**

Variable	Definition
v	Value of the asset: either one or zero.
g	Probability that one trader potentially wants to trade (for either uninformed or information based motives).
a	Probability that a given trader is informed. This also represents the fraction of traders who are informed among those who actively participate in the market.
c_i	Probability that a trader faces cost i of short-selling. This also represents the fraction of traders who face this cost independent of whether they are informed or uninformed.
q_v^A	The probability of observing action A when the value of the asset is v.
P_t^A	The price or conditional expectation associated with an action A at t.
P^H (P^H)	Threshold price that good (bad) news are public available

Table 3: **Conditional probabilities of actions directly observed,** where g is the probability that some traders potentially wants to grade, a is the probability that a trader is informed, and c_i is the probability that a trader faces cost i of trading.

Actions directly observed	Conditional probabilities when state-of-nature is $v = 1(q_1^A)$	Conditional probabilities when state-of-nature is $v = 0(q_0^A)$
Buy	$q_1^B = \frac{1}{2}g(1+a)c_1 + gac_2$	$q_0^B = \frac{1}{2}g(1-a)c_1$
Sell	$q_1^S = \frac{1}{2}g(1-a)c_1$	$q_0^S = \frac{1}{2}g(1+a)c_1 + gac_2$
No-trade	$q_1^N = (1-g) + gac_3 + g(1-a)(c_2+c_3)$	$q_0^N = (1-g) + gac_3 + g(1-a)(c_2+c_3)$

Table 4: **Summary Statistics**

BA is the ask price minus the bid price. BAM is the BA scaled by the mid price. BAMV is volume weighted BAM. Volume is the number of daily contracts in logarithm. Price is options price. IV is the aveage implied volatility. IV-ERV is ATM implied volatility minus expected realized volatility. $\text{StrR}_{t\to t+1}$ and $\text{StrR}_{t\to t+5}$ are one-day and five-day straddle returns, respectively. OI is vega weighted order imbalance. Disc is the option volume of investors using discount brokerages in logarithm. Full is the option volume of investors using full service brokerages. Disc/Full is the discount volume scaled by the sum of discount and full volumes. The statistics are computed based on daily cross sectional averages from Jun 2000 to Dec 2001. 1 Mon, 2 Mon, 3 Mon, and 6 Mon indicates that the samples are options with expiration days within the next month, in two months, in three months, and at least in six months, respectively.

	A: Decimalized on 29 January 2001							
	$T \leq 1$ Mon		$T = 2$ Mon		$T = 3$ Mon		$T \geq 6$ Mon	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
BA ($)	0.33	0.03	0.33	0.05	0.38	0.03	0.49	0.03
BAM (%)	17.24	1.18	12.11	1.40	11.07	1.28	7.53	1.18
BAMV(%)	23.02	1.59	17.94	1.94	11.22	1.74	11.37	1.73
Volume (ln)	4.44	0.20	3.76	0.25	3.74	0.33	3.39	0.31
Price ($)	4.72	0.48	4.80	0.85	5.17	0.82	5.03	0.80
IV (%)	48.72	5.25	47.32	4.43	46.88	4.26	45.58	4.06
IV-ERV (%)	1.76	3.81	0.15	3.25	-0.28	3.08	-1.56	3.07
$\text{StrR}_{t\to t+1}$ (%)	-0.12	1.81	-0.03	1.35	-0.05	1.13	-0.02	0.95
$\text{StrR}_{t\to t+5}$ (%)	-0.41	6.44	-0.10	4.75	-0.15	4.04	-0.07	2.97
OI	-0.88	0.59	-1.21	0.72	-1.44	0.60	-1.83	0.62
Disc	2.39	0.25	1.42	0.22	1.55	0.26	1.28	0.24
Disc/Full	0.20	0.02	0.21	0.04	0.21	0.04	0.21	0.04
	B: Decimalized on 6 April 2001							
	$T \leq 1$ Month		$T = 2$ Month		$T = 3$ Month		$T \geq 6$ Month	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
BA ($)	0.42	0.07	0.40	0.07	0.41	0.07	0.46	0.06
BAM (%)	18.07	1.55	12.34	1.60	9.66	1.41	7.59	1.21
BAMV(%)	23.37	2.45	18.24	2.76	11.67	1.92	11.08	2.13
Volume(ln)	4.42	0.21	3.63	0.20	3.63	0.23	3.32	0.21
Price($)	6.61	1.30	6.75	1.82	7.16	1.79	6.42	1.66
IV (%)	80.58	10.32	78.79	8.69	77.64	8.21	74.69	8.16
IV-ERV(%)	-2.99	8.09	-5.22	7.50	-6.02	7.00	-8.82	7.15
$\text{StrR}_{t\to t+1}$ (%)	-0.03	2.39	0.04	1.84	0.01	1.72	-0.02	1.55
$\text{StrR}_{t\to t+5}$ (%)	-0.24	6.23	-0.12	4.40	-0.06	3.95	-0.15	3.41
OI	-0.53	0.54	-0.53	0.73	-0.65	0.66	-0.97	0.61
Disc	2.70	0.28	1.56	0.23	1.44	0.25	1.20	0.22
Disc/Full	0.22	0.02	0.23	0.04	0.23	0.05	0.24	0.05

Table 5: **Option Bid Ask Spread and Volume**

BA is the ask price minus the bid price. BAM is the BA scaled by mid price. BAMV is the volume weighted BAM. Volume is the daily number of contracts traded in logarithm. DID is the difference in difference between treatment (T) stocks going through decimalization and control (C) stocks not experiencing changes in the pricing system. Panel A treatment stocks are stocks decimalized on 29 Jan 01, control stocks are stocks not decimalized until 6 Apr. The Panel B treatment (control) stocks are the control (treatment) stocks in panel A. The periods before and after the experiment are Jan 1st-28th and Mar 01 for Panel A, and Mar and May 01 for Panel B. The parentheses contain t-statistics computed from standard errors of daily cross sectional averages.

A: before and after JAN decimalization, controls are non-decimalized.								
	BA ($)		BAM (%)		BAMV(%)		Volume (ln)	
	T	C	T	C	T	C	T	C
Aft	0.33	0.46	16.91	18.32	21.77	23.82	4.46	4.33
Bef	0.34	0.44	17.03	18.02	22.29	22.69	4.45	4.44
Aft-Bef	-0.01	0.02	-0.12	0.30	-0.52	1.13	0.01	-0.11
	(-2.33)	(6.46)	(-1.99)	(2.67)	(-3.42)	(4.29)	(1.93)	(-4.99)
DID 1 Mon	-0.03		-0.41		-1.65		0.12	
	(-9.17)		(-4.35)		(-8.54)		(7.73)	
DID 2 Mon	-0.01		-0.45		-1.67		0.07	
	(-2.61)		(-5.27)		(-14.46)		(5.40)	
DID 3 Mon	0.02		-1.00		-1.74		-0.05	
	(6.91)		(-8.30)		(-9.46)		(-3.13)	
DID 6 Mon	0.02		-1.07		-1.78		-0.13	
	(8.52)		(-17.15)		(-17.03)		(-8.85)	
B: before and after APR decimalization, controls are decimalized.								
	BA ($)		BAM (%)		BAMV(%)		Volume (ln)	
	T	C	T	C	T	C	T	C
Aft	0.36	0.31	17.60	16.93	23.02	22.13	4.45	4.43
Bef	0.46	0.33	18.32	16.91	23.82	21.77	4.33	4.46
Aft-Bef	-0.10	-0.02	-0.72	0.02	-0.80	0.36	0.12	-0.03
	(-16.14)	(-8.67)	(-4.24)	(0.25)	(-3.79)	(2.41)	(6.69)	(-1.42)
DID 1 Mon	-0.08		-0.74		-1.77		0.15	
	(-19.30)		(-6.40)		(-7.82)		(11.41)	
DID 2 Mon	-0.03		-0.78		-1.22		0.03	
	(-9.47)		(-8.50)		(-8.35)		(1.87)	
DID 3 Mon	-0.04		-1.66		-2.46		0.08	
	(0.38)		(8.57)		(13.29)		(3.37)	
DID 6 Mon	0.03		-1.40		-2.59		-0.00	
	(12.22)		(-17.05)		(-19.84)		(-0.13)	

Table 6: **Price Effect of Order Imbalance**

Reported are the λ in Kyle (1985) measured as the coefficient of order imbalance(OI^M) regressed on implied volatility returns:

$$(IV_{i,t}^M - IV_{i,t-1}^M)/IV_{i,t-1}^M = \alpha^M + \lambda^M \cdot \mathrm{OI}_{i,t}^M + \epsilon_t^M.$$

$\lambda^{1\mathrm{Mon}}$ is estimated from options expiring within the next month. $\lambda^{2\mathrm{Mon}}$, $\lambda^{3\mathrm{Mon}}$, and $\lambda^{6\mathrm{Mon}}$ are estimated from options expiring in two months, three months and at least in six months, respectively. λ is computed daily within treatment (T) stocks going through decimalization or within control (C) stocks not experiencing changes in the pricing system. DID is the difference in difference in λ between the treatment stocks and the control stocks. The Panel A treatment stocks are stocks decimalized on 29 Jan 01, the control stocks are stocks not decimalized until 6 Apr 01. The Panel B treatment (control) stocks are the control (treatment) stocks in panel A. The periods before and after the experiment are Jan 1st-28th and Mar 01 for Panel A, and Mar and May 01 for Panel B. The parentheses contain t-statistics computed from standard errors of daily λ.

A: before and after JAN decimalization, controls are non-decimalized.

	$\lambda^{1\mathrm{Mon}}$		$\lambda^{2\mathrm{Mon}}$		$\lambda^{3\mathrm{Mon}}$		$\lambda^{6\mathrm{Mon}}$	
	T	C	T	C	T	C	T	C
Aft	0.30	2.01	3.29	0.53	2.94	1.85	1.43	-0.48
Bef	2.00	0.72	1.39	1.74	-1.25	3.83	2.21	3.29
Aft-Bef	-1.70	1.28	1.90	-1.21	4.19	-1.98	-0.78	-3.76
	(-3.24)	(2.28)	(2.04)	(-1.05)	(3.77)	(-1.71)	(-0.79)	(-2.95)
DID(λ)	-2.99		3.11		6.17		2.99	
	(-8.08)		(4.70)		(7.62)		(4.20)	

B: before and after APR decimalization, controls are decimalized.

	$\lambda^{1\mathrm{Mon}}$		$\lambda^{2\mathrm{Mon}}$		$\lambda^{3\mathrm{Mon}}$		$\lambda^{6\mathrm{Mon}}$	
	T	C	T	C	T	C	T	C
Aft	0.55	2.24	-1.10	0.30	2.21	2.74	0.25	1.04
Bef	2.01	0.30	0.53	3.29	1.85	2.94	-0.48	1.43
Aft-Bef	-1.46	1.94	-1.63	-3.99	0.36	-0.20	0.73	-0.39
	(-3.00)	(3.95)	(-1.71)	(-3.85)	(0.33)	(-0.19)	(0.61)	(-0.36)
DID(λ)	-3.40		2.36		0.56		1.11	
	(-10.16)		(2.76)		(0.73)		(1.43)	

Table 7: **Options Volume of Different Types of Investors**

Disc denotes the log volume from investors using discount brokerages. Full is the volume from investors using full service brokerages. Disc/Full is the discount volume relative to the sum of the discount and full volumes. DID is the difference in difference of volumes between treatment (T) stocks going through decimalization and control (C) stocks not experiencing changes in the pricing system. In Jan decimalization, the treatment stocks are stocks decimalized on 29 Jan, the control stocks are stocks not decimalized until 6 Apr. In Apr decimalization, the treatment and the control stocks are switched. The periods before and after the experiment are Jan 1st-28th and Mar for Jan decimalization, and Mar and May for Apr decimalization. The parentheses contain *t*-statistics computed from standard errors of daily cross sectional average.

	JAN Decimalization				**APR Decimalization**			
	Disc		Disc/Full		Disc		Disc/Full	
	T	C	T	C	T	C	T	C
Aft	2.34	2.31	0.26	0.22	2.49	2.27	0.30	0.27
Bef	2.35	2.50	0.24	0.24	2.31	2.34	0.22	0.26
Aft-Bef	0.01	-0.16	0.02	-0.02	0.18	-0.07	0.07	0.02
	(2.25)	(-6.39)	(5.93)	(-5.25)	(7.46)	(-3.99)	(14.47)	(6.50)
DID 1 Mon	0.18		0.04		0.26		0.05	
	(10.25)		(11.78)		(15.08)		(17.14)	
DID 2 Mon	0.11		0.01		0.17		0.02	
	(6.23)		(4.49)		(7.88)		(8.39)	
DID 3 Mon	0.6		0.04		0.08		0.01	
	(4.37)		(8.42)		(4.73)		(2.04)	
DID 6 Mon	0.03		0.02		0.03		-0.01	
	(1.35)		(2.31)		(2.17)		(-1.74)	

Table 8: **Predictability of Order Imbalance– Portfolio Return Differences**

$StrR^{H-L}_{t\to t+1}$ and $StrR^{H-L}_{t\to t+5}$ are future one day and five day straddle return differences between the high (H) and the low (L) order imbalance quintiles, respectively. DID is the difference in difference in $StrR^{H-L}_{t\to t+\tau}$ between the treatment (T) stocks going through decimalization and the control (C) stocks not experiencing changes in the pricing system. In Jan decimalization, the treatment stocks are stocks decimalized on 29 Jan, the control stocks are stocks not decimalized until 6 Apr. In Apr decimalization, the treatment and the control stocks are switched. The periods before and after the experiment are Jan 1st-28th and Mar for Jan decimalization, and Mar and May for Apr decimalization. The parentheses contain t-statistics computed from standard errors of daily cross sectional average.

	Jan Decimalization				**Apr Decimalization**			
	$StrR^{H-L}_{t\to t+1}$		$StrR^{H-L}_{t\to t+5}$		$StrR^{H-L}_{t\to t+1}$		$StrR^{H-L}_{t\to t+5}$	
	T	C	T	C	T	C	T	C
Aft H-L	1.26	0.48	3.34	2.12	1.18	-0.08	5.75	1.10
	(3.51)	(1.16)	(3.87)	(1.98)	(3.05)	(-0.16)	(4.87)	(1.11)
Bef H-L	0.39	0.90	0.73	0.49	0.48	1.26	2.12	3.34
	(1.13)	(1.93)	(1.06)	(0.48)	(1.16)	(3.51)	(1.50)	(3.87)
A-B H-L	0.88	-0.42	2.61	1.63	0.69	-1.34	3.63	-2.23
	(3.34)	(-1.30)	(4.32)	(1.78)	(2.42)	(-4.11)	(3.82)	(-3.33)
DID 1 Mon	1.30		0.98		2.04		5.87	
	(6.28)		(1.80)		(9.41)		(10.01)	
DID 2 Mon	0.22		0.65		-1.15		-0.12	
	(0.82)		(1.19)		(-5.86)		(-0.27)	
DID 3 Mon	0.20		2.64		-0.49		0.10	
	(0.75)		(5.18)		(-2.22)		(0.17)	
DID 6 Mon	0.55		1.07		0.56		0.83	
	(1.72)		(1.59)		(2.08)		(1.45)	

Table 9: **Predictability of Order Imbalance–Predictive Regression**

Reported are the coefficients on order imbalance (OI) and their DID in the predictive regression for one-day and five-day straddle returns. The predictive regression is

$$StrR^M_{i,t\to t+\tau} = a^M + b^M_\tau \cdot OI^M_{i,t} + \epsilon^M_{t\to t+\tau} \quad \tau = 1, or\, 5.$$

OI is the vega weighted order imbalance. b_τ is estimated daily within the treatment (T) group or within the control group (C). DID is the difference in difference in $b^M_{t\to t+\tau}$ between the treatment stocks going through decimalization and the control stocks not experiencing changes in the pricing system. In Jan decimalization, the treatment stocks are stocks decimalized on 29 Jan, the control stocks are stocks not decimalized until 6 Apr. In Apr decimalization, the treatment and the control stocks are switched. The periods before and after the experiment are Jan 1st-28th and Mar for Jan decimalization, and Mar and May for Apr decimalization. The parentheses contain t-statistics computed from standard errors of daily b_τ.

	Jan Decimalization				**Apr Decimalization**			
	b_1		b_5		b_1		b_5	
	T	C	T	C	T	C	T	C
Aft	3.76	2.91	4.57	4.04	5.79	2.01	8.59	1.87
Bef	2.44	3.62	4.45	4.19	2.91	3.76	4.04	4.57
Aft-Bef	1.32	-0.71	0.12	-0.15	2.88	-1.75	4.54	-2.70
	(2.68)	(-1.66)	(0.18)	(-0.19)	(4.92)	(-2.83)	(7.07)	(-4.12)
DID 1 Mon	2.04		0.27		4.63		7.24	
	(4.20)		(0.54)		(10.61)		(16.20)	
DID 2 Mon	-0.26		-1.63		-2.15		-2.70	
	(-0.33)		(-2.34)		(-2.30)		(-1.92)	
DID 3 Mon	-2.72		-2.34		-1.07		-3.81	
	(-1.45)		(-2.03)		(-1.35)		(-2.43)	
DID 4 Mon	1.44		-4.82		2.70		1.67	
	(1.79)		(-5.44)		(1.55)		(1.31)	

Table 10: **Autocorrelation of the Implied Volatility Change**

Reported are the first order autocorrelations of daily implied volatility (IV) change. ρ^{IVC} is for calls and ρ^{IVP} is for puts. For each stock, the daily IV is the average IV of options with $0.90 \leq K/S \leq 1.1$. DID is the difference in difference of ρ between the treatment stocks and the control stocks. In Jan decimalization, the treatment stocks are stocks decimalized on 29 Jan, the control stocks are stocks not decimalized until 6 Apr. In Apr decimalization, the treatment and the control stocks are switched. The periods before and after the experiment are Jan 1st-28th and Mar for Jan decimalization, and Mar and May for Apr decimalization. The parentheses contain t-statistics computed from standard errors of ρ of all stocks.

	Jan Decimalization				**Apr Decimalization**			
	ρ^{IVC}		ρ^{IVP}		ρ^{IVC}		ρ^{IVP}	
	T	C	T	C	T	C	T	C
Aft	-0.26	-0.32	-0.26	-0.27	-0.25	-0.29	-0.23	-0.27
Bef	-0.33	-0.30	-0.28	-0.27	-0.32	-0.26	-0.27	-0.26
Aft-Bef	0.07	-0.02	0.02	0.00	0.07	-0.03	0.04	-0.01
	(15.29)	(-5.69)	(4.37)	(-1.02)	(17.57)	(-6.70)	(9.57)	(-2.16)
DID 1 Mon	0.09		0.01		0.09		0.05	
	(24.41)		(4.98)		(34.05)		(16.79)	
DID 2 Mon	0.04		-0.01		0.05		0.07	
	(16.29)		(-2.49)		(18.87)		(25.83)	
DID 3 Mon	0.02		-0.00		0.02		0.03	
	(5.49)		(-0.15)		(3.43)		(5.81)	
DID 6 Mon	-0.01		0.01		0.00		0.02	
	(-1.63)		(1.82)		(0.53)		(4.64)	