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ARE SMALL STOCKS ILLIQUID? AN EXAMINATION OF LIQUIDITY-IMPROVING EVENTS

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Abstract

I study the introduction of decimalization in U.S. stock markets and the implementation of the Hybrid system on NYSE, and I examine the impact of these two events on liquidity, conditionally on firm size. I argue that such liquidity-improving events offer more pronounced benefits to the typically-illiquid small stocks. The basis of this conjecture lies in the notion of diminishing marginal utility. That is, the benefit from improvement in liquidity is more pronounced at stages where illiquidity is higher. Consistent with my conjecture, I find that the improvement in liquidity post decimalization and Hybrid is an inverse function of firm size. I also find that the documented positive association between size and liquidity is rendered weaker after these two events. It seems that such liquidity-improving events reduce the overlap between size and liquidity, and help make them two distinct features. The framework of this paper can be utilized in the pursuit to explain the variation of the size effect over time, by examining whether recent market changes has "cleaned" the small-size premium from the illiquidity component.

Keywords: Decimalization, Trade Automation, Liquidity, Size Effect.
JEL Codes: G12, G14.

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1. Introduction

Trading floors around the world witnessed significant modernizations that have reshaped and facilitated the way trading takes place in these venues. This modernization process has coincided with various regulatory changes that also aimed at improving the trading quality[1]. Several academic studies examined the impact of the implementation of such events on various market quality aspects, such as efficiency of pricing and liquidity of trading, with mixed evidence[2]. One potential reason for this disagreement of evidence is ignoring the differential effect that these market events could have on securities, based on their characteristics. In this paper, I also examine the impact of such events on liquidity, but conditional on firm size. One objective of this analysis is to shed light on the interaction between the size and liquidity attributes of stocks.

In this study, I examine the impact of two equity market events in the U.S. that are expected to have implications for liquidity: Decimalization—the reduction of the minimum tick size to one penny in 2000; as an example of a regulatory change event, and the implementation of the Hybrid system on New York Stock Exchange (NYSE) in 2006; as an example of a technological change event[3]. The Hybrid system allows traders the option to automatically process trades of up to one million shares per trade. I study the impact of these two events on market liquidity, generally and conditionally on firm size, where size is measured by market capitalization.

Liquidity, an important determinant of stock returns (e.g. Liu, 2006) and trading costs (e.g. Amihud and Mendelson, 1986), is related to size, which is in turn another return determinant. Banz (1981) documents the so-called size effect, in which small stocks earn a higher risk-adjusted return than large stocks do, on average. Banz (1981) states that it is unknown "whether market value per se matters or whether it is only a proxy for unknown true additional factors correlated with market value." Later studies confirm Banz's doubts and suggest that a relationship exists between the size and liquidity characteristics of stocks, and that the small-size premium is partially a compensation for the illiquidity of such stocks. Pastor and Stambaugh (2003) find in their liquidity-augmented pricing model that portfolios of small size have the highest loadings on the liquidity factor. Amihud (2002) finds that illiquidity, measured by price impact, along with illiquidity premium, are negatively related to size, concluding that size "may be a proxy for liquidity." The last two findings suggest that the size effect can partly be subsumed by liquidity risk and liquidity level, respectively.

Given the above interaction between size and liquidity, one might argue that liquidity-changing events have some implications for the size-liquidity relation and for the size effect. I conjecture that liquidity-changing events have affected stocks differently based on their size, and that the liquidity of small stocks has enjoyed a more pronounced

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[1] Next section reviews major recent regulatory and technological changes in U.S. equity markets.
[2] For instance, a number of studies examined the effect of trade automation without reaching a consensus. Examples of studies that support the move for trade automation include Jain and Johnson (2006), Stoll (2006) and Gutierrez and Tse (2009). In contrast, Venkataraman (2001) and Hendershott and Moulton (2011) document various disadvantages associated with trade automation..
[3] In the robustness checks discussed below, I explain that qualitatively similar results are obtained when other market events are considered.

improvement than that of large stocks. There is a basis to believe that the trading cost and trading volume aspects of liquidity, at least, would exhibit the conjectured pattern[4].

At the front of trading cost, many regulatory and technological events are expected to benefit small stocks in a more pronounced way. This cost reduction argument is obvious -and somewhat mechanical- in the case of the decimalization event. The pre-decimalization minimum tick sizes of sixteenths (6.25¢) may have imposed an artificially wider spreads for small stocks whose prices are relatively low[5], translating into a sizeable proportional trading costs. This suggests that proportional spreads of small stocks; which represent the cost aspect of liquidity, would respond to the decimalization with the highest decrease.

Similar arguments can be made about cost-saving that technology-related events bring. With technology, trading costs are reduced sharply. Modern exchanges function very efficiently at a low profit margin in a way that resembles utility firms. Technology-adopting exchanges can handle a large trading capacity for a relatively fixed running cost, which translates into a lower per-trade cost. Trading cost discount relative to the dollar volume traded is also expected to be the highest for small stocks.

The lower trading volume aspect of the illiquidity of small stocks is partly due to their unpopularity among investors. However, I argue that investors would have a smaller incentive to avoid small stocks after certain modernization events. Small firms might be disregarded by investors due to the large extent of information asymmetry adherent to them (Merton, 1987). Technology alleviates this problem for small stocks through improved information dissemination. Although improved information dissemination is a privilege that stocks of all sizes enjoy, I argue that the benefit is more effective for small stocks, because they depend heavily on these modern mechanisms. In the absence of such mechanisms, one would expect such small firms to be in oblivion. Technology and automated trading platforms help make markets a more level playing field for stocks of all sizes. They allow small stocks to enjoy the privileges that are reserved for large stocks, and to some extent for medium-sized stocks, in a traditional setting.

Recent regulations and trade automation also help liquidity provision, by delegating market-making to a broader base, which is also expected to help small stocks in a particular way. If the relatively lower trading volume of small stocks is related to investor behavior (e.g. Gompers and Metrick, 2001) where investors shy away from small stocks due to their risk of liquidation, then recent regulations and market changes, such as consolidating cross-market orders; automated trading; and granting foreign investors direct access to trade against local investors, could have come to the rescue of small stocks. Again, although all stocks enjoy such benefits from liquidity-improving events, but small stocks have a relatively small trading activity, and the rule of diminishing marginal utility helps us imagine that the benefit of improvement is expected to be the highest for small stocks.

There are analogies that can be made with findings in other fields, such as administrative sciences, marketing, and economics. In essence, small stocks can be considered as the counterparts of small retailers that started recently to have a significant presence in the

[4] My argument is about the direct impact that some market events might have on trading volume. Trading volume can also be indirectly affected by events through their impact on trading cost.
[5] In my sample, the correlation coefficient between firm's size and stock price is about 0.5.

market through technology companies such as Amazon. Amazon and similar companies help all retailers; small to large ones. However, the benefits that such technology solutions offer to small retailers are detrimental compared to the extent of benefits realized by large and well-established companies. A number of studies in the marketing and management information systems fields (e.g., Hsieh and Lin, 1998) find that electronic commerce and automated business applications offer a competitive advantage to small businesses in particular by removing barriers faced by small firms that cannot effectively compete against "big fishes" in a traditional brick-and-mortar market. In economics, researchers observe a "catch-up" or "convergence" effect in which less developed economies grow at a rate faster than that in more developed economies (Abramovitz, 1986). Economists argue that small economies start to enjoy advanced technologies and start to share the use of common platforms and resources at some point in time.

The first part of this study investigates the overall effect of decimalization and Hybrid events on the state of liquidity. Examining the overall impact of these two events is not novel, but given the lack of consensus in extant literature, it is important to establish the overall effect of these events in the context of my methodology, before the test proceeds to subsequent hypotheses. Liquidity is multidimensional and therefore, it is proxied by multiple measures to incorporate its different facets. Liquidity measures used are trading volume, Amihud's price impact measure, quoted spread, and effective spread. In line with the findings in many studies, my results show that decimalization and Hybrid events are associated with an overall improvement in liquidity[6]. For instance, proportional quoted spreads dropped from 1.21% to 0.91% after decimalization, and from 0.53% to 0.51% after the implementation of the Hybrid system.

My second test is about whether the liquidity improvement associated with the two events is more pronounced for small stocks, as my main hypothesis predicts. Most of my results show that this is the case, indeed. For example, the decrease in quoted spreads following decimalization is by 0.92% for smallest quintile of stocks but by only 0.07% for the largest quintile. Moreover, I find that the percentage of stocks that experience liquidity improvements post-events is often highest for small stocks, and it decreases in stock size.

The third and final aspect of this study examines the implication of this asymmetric liquidity improvement. Given that small stocks have benefited the most from these two liquidity-changing events, then the well-documented association between size and liquidity is expected to be weaker post-events. My results support this conjecture as well. For instance, the correlation between size and liquidity dropped significantly post-events. Moreover, there are fewer stocks that are small *and* illiquid after, than before the events. In addition, the extent of increase in liquidity between neighboring size-ranked portfolios is weaker after the events, that is; the trend of liquidity increase across size-ranked portfolios seems to be weaker and less systematic.

This investigation directly deals with a concern raised in the literature that there is a need to better understand the interaction between the size and liquidity characteristics of individual stocks. For example, in his survey paper about the size effect, van Dijk (2011) states that the way in which "the size effect and liquidity interact is an important area of future research." Moreover, the framework of this paper is probably capable of explaining

[6] Bessembinder (2003) and Jain and Johnson (2006) are examples of studies that offer evidence in favor of decimalization and automation, respectively.

the interaction between stock characteristics, and thereby helps us to better understand the evolution of asset pricing determinants. An extension of this study can examine the asset pricing implications of this weakening relation between size and liquidity that I document in this paper. Such a study would shed light on variations in the size premium and might relate its recent decrease (van Dijk, 2011) to the partial disappearance of the illiquidity component of the size premium as small stocks benefit the most from liquidity-improving events.

The remainder of the paper is organized as follows. Section 2 describes some of the major changes in financial market design on the NYSE and Nasdaq. Section 3 outlines data sources and measures. Hypotheses are tested and test results are presented in Section 4. Section 5 offers concluding remarks.

2. Changes in financial market design

This section briefly reviews recent technological and regulatory changes that are expected to have implications for the liquidity of stocks listed in the two most prominent stock markets in the United States: NYSE and Nasdaq. My focus is on events that are aimed at streamlining the trading process and at reducing the number of trade intermediaries, because those are the types of events that are expected to be associated with improvements in liquidity, through increased trading volume and reduced trading cost. Automation and relaxed regulations help reduce trading cost (Stoll, 2006) and entice more people to trade, including foreign investors who can directly access U.S. markets through automated platforms solely.

My hypotheses are tested using the decimalization event (as an example of a regulatory market change) and the implementation of the Hybrid system (as an example of a technological market change). These two events are chosen because they represent major milestones in the timeline of market changes, as shown in this brief review of the major market changes leading to these two events. For robustness reasons I test two events rather than one only, and the two events are of different nature and have affected different stocks. The Hybrid system was implemented in the NYSE, whereas decimalization affected stocks listed at both the NYSE and Nasdaq markets.

Nasdaq was established in 1971 as a purely electronic system used for information dissemination purposes only. In subsequent years, Nasdaq started to resemble a formal exchange; starting to offer stock listing and a full range of trading services[7]. Unlike Nasdaq, NYSE is known for its open outcry trading floor and its dependence on human intervention and face-to-face mechanism for trading[8].

Despite maintaining the central role of its specialists in trade intermediation, NYSE has experienced significant technological developments, especially in recent decades. In 1976, the automated Designated Order Turnaround (DOT) system was launched to electronically route small orders to specialists. The system was later upgraded to Super DOT, enabling even larger orders to be routed electronically. Traditionally, orders were routed to the market where traded stocks were listed. In 1978, NYSE was equipped with systems to

[7] This is available at: https://www.britannica.com/topic/NASDAQ.
[8] This is available at: https://www.fxcm.com/uk/insights/new-york-stock-exchange-nyse/.

connect to other exchanges in the U.S. to compare if better quotes exist and to route orders to the market with the best quote. During the 1990s, NYSE witnessed significant expansions in network capacity to handle larger trading volume (Jain and Johnson, 2006).

Even after the implementation of multiple technological systems, NYSE was still far from being an automated exchange since trade executions continue to be at the full discretion of the exchange specialists. While most of the trading process takes place electronically, trade execution is still dependent on human intervention. A market is considered automated only when the actual matching of trades takes place automatically. The turning point in the NYSE history took place in 2000, when the market introduced the Direct+ system which can execute relatively small trades involving up to 1,099 shares. This feature was further augmented with the launch of the Hybrid Market System in 2006 which can electronically execute large trades as well; those involving up to one million shares[9]. Both the Direct+ and the Hybrid systems are similar in nature. However, the implementation of the Hybrid system is expected to have a market-wide impact, given its large magnitude, and therefore it is seen as a better candidate for this study.

The NYSE was under pressure to accelerate the pace of technology adoption and to offer automatic execution options to market participants, as explained above. The NYSE competed with alternative trading venues, such as regional exchanges as well as Electronic Communication Networks (ECNs) that were rising at the time (Freund and Pagano, 2000; Stoll, 2006). These technologically-advanced alternatives were a serious threat to a traditional NYSE, because they offer fast automatic trade executions. ECNs played an important competitive role because they allow natural trades to be matched at a minimal cost, threatening the role of specialists or market dealers who interfere in the process of order matching and place themselves on one side of each trade. This traditional role of market-makers slows down trade executions and increases the overall cost of trading through extra fees and wider spreads.

Increasing trading volume has also driven the need for more trade automation, because automated trading systems can handle large loads efficiently. New regulations also played an indirect role in accelerating the trend of automation. For example, the Securities and Exchange Commission (SEC) has introduced the so-called “Order Protection Rule” (OPC), which requires execution at the best quote available across markets, something that is virtually impossible to achieve in absence of automated trading real-time systems (Hendershott and Moulton, 2011). To comply with the OPC regulations, markets shifted increasingly towards automated systems to make quotes visible and accessible by all market participants.

The above describes the important changes that revolutionized trading style in U.S. stock markets, especially the NYSE. Such changes are expected to support the position of traders because they provide them with an abundance of options and venues to execute their trades. In the meantime, those changes are expected to limit the powers of specialists, because with them specialists face more competition and they no longer enjoy a full discretion about trade execution. This decreased power of specialists translated into lower exchange seat prices in recent years (Stoll, 2006). Seat ownership represents the right to

[9] This is available at the NYSE website: http://www.nyse.com.

trade on the market floor. Therefore, falling prices of seats demonstrate the diminishing value of traditional trading methods.

Several regulatory and market structure changes accompanied technological changes to further facilitate trading and help reduce its cost. Three regulatory and market structure events are mentioned here as examples. The first example is the two-stage minimum tick reduction that was ordered by the SEC. In 1997, the first stage took place to reduce the minimum tick size to sixteenth from eighth. In the second stage of this event, which took place in 2000, minimum tick was further reduced to one penny, an event that is commonly referred to as decimalization[10]. Bid-ask spreads can never be smaller than the minimum tick size. Therefore, the removal of such artificially-wide spread boundaries allows spreads to better reflect their fundamental determinants. Spreads are expected to decline after this event if previous bigger minimum tick sizes were unnecessarily large for some stocks. Several studies (e.g., Bessembinder, 2003) find that spreads have significantly declined after decimalization.

The second example of regulatory changes is the reduction of the minimum order size by the SEC. The minimum order entry size of a Mid-Point Passive Liquidity Order "MPL Order"[11] was reduced from 1000 to 100 shares in 2007, and further to one share in 2011[12]. Lowering minimum order size enables investors to trade a small number of shares with exchanges directly, without the need to involve intermediaries who profit from unbundling large orders to small individual investors, which results in additional costs for small trades. This reduction might also increase trading volumes, since odd-lot traders (small traders who trade less than 100 stocks) are no longer inhibited from trading with flexibility.

The third and final example is related to changes in the NYSE market structure. While the number of individual specialists is relatively stable over time because it is proportional to the number of listed stocks, the number of specialist firms to which specialists are affiliated has shrunk from 67 in 1975 (Stoll, 2006) to only seven in recent years[13]. The clustering of specialist firms reflects the improving economies of scale in this business, which could also get reflected into lower trading cost. This industry consolidation may explain the emergence of discount brokerage services that charge substantially lower commission fees than those charged by traditional brokerage houses.

While specialists in NYSE enjoy monopoly power in handling the entire market-making activities of their designated stocks, there are at least two dealers per stock to handle order flow for Nasdaq-listed stocks. The Nasdaq market structure is designed to increase competition among dealers, with the hope that this will result in lower cost and better service for traders. Nevertheless, a number of academic studies (e.g., Christie and Schultz, 1994) show that Nasdaq spreads were usually higher than the minimum tick size (one-eighth at that time), and that the inside spread for a large number of stocks was at least $0.25. These results point to a potential coordination between Nasdaq dealers. In fact, this finding led to strict measures to be taken by the Nasdaq administration to reduce spreads.

[10] This is available at the NYSE website: http://www.nyse.com.
[11] NYSE defines an MPL order as "an undisplayed limit order that is priced at the midpoint of the Protected Best Bid and Offer (PBBO)". MPL orders can generally match with any other order regardless of its type. This is available at: https://www.sec.gov/rules/sro/nysearca/2015/34-74415-ex5.pdf.
[12] This is available at: http://www.sec.gov/rules/sro/nysearca/2011/34-64523.pdf.
[13] This is available at the NYSE website: http://www.nyse.com.

Spreads dropped dramatically shortly after those measures came into effect (Christie et al., 1994).

These competition-increasing measures taken by the Nasdaq administration were followed by a series of rules in 1997 that were aimed at fostering inter-dealer competition (Chung and Van Ness, 2001). For example, the order handling rules (OHR) were introduced gradually during the period from January-October 1997; a set of practices that market makers are ordered to follow to ensure that the best order execution is offered to traders.

The above-described trend at the technological and regulatory fronts continues in subsequent years as well. However, I did not consider very recent market events, because a sufficiently large window of time is needed around events used in the tests. For robustness purposes, I conduct my tests on events other than decimalization and the Hybrid. For instance, I examine the impact of the Direct+ and that of the first-stage minimum tick size reduction in 1997. My findings remain unchanged, though the Direct+ results are weaker than those of the Hybrid[14].

3. Data and measures

At the end of 2000 the NYSE began trading stocks in decimal price increments, ending a two-century old tradition of trading in eighths and sixteenths. Decimal pricing has been first implemented on seven stocks only on August 28, 2000. Stocks have been added gradually to the new system afterwards. By January 29, 2001, the system has been fully implemented for all NYSE-listed stocks[15]. On Nasdaq, the pilot phase of the switch to decimalization was launched on March 26, 2001 including 15 stocks, and full conversion took place on April 9, 2001[16].

The Hybrid system was also rolled out gradually on the NYSE between October 6, 2006 and January 24, 2007 (Hendershott and Moulton, 2011). The relatively short four-month period that took the Hybrid system to be fully implemented makes the event suitable as a subject for this study, because changes from before to after the Hybrid are less likely to be attributable to other factors that are unaccounted for. Automation events usually takes a longer period for implementation. For instance, the implementation of the Computer-Assisted Trading System (CATS) on Toronto Stock Exchange started in 1977 continued for two decades before including all stocks[17].

In testing both events, I exclude the roll-out periods. In making comparisons from the pre-event period to post-event period, I use the six-month period prior to the start of the event and the six-month period after the full implementation of the event, excluding the month immediately after the implementation. This exclusion is made in consistence with a common practice in the literature where the thirty-day period immediately following events are excluded, thereby allowing market participants enough time to learn new practices and to develop new trading patterns in accordance with the market change (Chakravarty et al. (2004); Jain (2005); Jiang et al. (2011), etc.)[18]. Therefore, I consider

[14] Those results are unreported, but they are available from the author upon request.
[15] This is available at the NYSE website: http://www.nyse.com.
[16] This is available at: https://money.cnn.com/2001/03/12/markets/nasdaq_decimals.
[17] This is available at: http://www.economywatch.com/stockexchanges/canadian.html.
[18] The effect of this exclusion on the results is only minor.

the trading days in the six-month period from February 28, 2000 to August 27, 2000 prior to decimalization (thereafter, pre-decimalization) and the six-month period from May 10, 2001 to November 9, 2001 subsequent to decimalization (thereafter, post-decimalization). Similarly, the pre-Hybrid period is April 6, 2006 to October 5, 2006; and the post-Hybrid period is February 25, 2007 to August 24, 2007. For the sake of robustness, I vary the length of this six-month test window to three months, one year, and three years. Results based on these robustness windows are not reported, but I comment on their similarities and differences where warranted.

My data set includes common stocks listed on the NYSE and Nasdaq, and can be matched in both the Center for Research in Security Prices (CRSP) and the Trades and Quotes (TAQ) databases. Market volatility is proxied by the Volatility Index (*VIX*), whose daily closing values are obtained from the Chicago Board Options Exchange (CBOE) Website.

I clean my CRSP data set as follows. Stocks with non-continuous observations or with fewer than 50 observations within a six-month window are removed from my data set for that sample[19]. I also exclude observations pertaining to non-ordinary categories of stocks since trading characteristics of these stocks are different than those of ordinary ones[20]. At the stock level, I obtain the following variables at the daily frequency from CRSP: Closing price (*PRC*), return-excluding-dividends (*RET*), trading volume in terms of number of shares (*VOL*), and number of shares outstanding (*SHROUT*).

I take the following steps in cleaning the TAQ data set (Holden and Jacobsen, 2014). Trades and quotes outside hours are excluded. I drop trades if the correction indicator shows that they have been revised; that is, I keep trades if the correction indicator equals "00". I also drop trades with non-positive or missing prices. I exclude quotes with abnormal modes, non-positive or missing bid or ask prices, negative spreads on the same exchange, spreads larger than $5, or non-positive or missing depth. Finally, stocks are not included in the post-event window unless they are present in the pre-event window.

Several measures are created using the daily dataset. Firm size is the natural log of market capitalization—price multiplied by the number of shares outstanding. Firm size is denoted by $Size_{it}$, where i and t denote firm and day, respectively. Turnover (TO_{it}) is trading volume divided by the number of shares outstanding. In each month m, stocks are ranked into quintiles based on *Size* as of the last trading day in month $m-1$, where quintile 1 (5) corresponds to smallest (largest) stocks.

Liquidity is multidimensional in that it reflects trading quantity, trading speed, trading cost, and price impact (Liu, 2006). I consider a number of liquidity measures in order to incorporate different facets of liquidity. I consider first both proportional quoted bid-ask spreads (*QSPD*) and proportional effective bid-ask spreads (*ESPD*). The former measures the difference between the best bid and offer quotes, whereas the latter captures the actual cost of a round-trip trade using actual prices at which trades take place. Despite similarities between the two measures, important differences exist between them. For instance, Chalmers and Kadlec (1998) find that effective spreads are almost 50-70% of quoted

[19] This filter targets small and very illiquid stocks whose trading might be of an irregular pattern. This exclusion biases results against my findings.
[20] Non-ordinary categories are as follows: Certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks, and REITs.

spreads, and that the average correlation between them is 31% only. I use the methodology of Holden and Jacobsen (2014) to calculate both spreads for each trade, then I find average quoted and effective spreads for each stock in each day, i.e. $QSPD_{it}$ and $ESPD_{it}$. Holden and Jacobsen (2014) correct for liquidity measurement problems encountered when the regular whole-second TAQ database is used (which applies to my case), where observations' exact times are rounded to the nearest second. This procedure involves the following steps: adjusting for withdrawn quotes rather than deleting them, using the order of quotes in each second to infer the millisecond, and deleting NBBO quotes and trades when the NBBO is "crossed" or "locked."[21] *QSPD* is then calculated as follows:

$$QSPD_{it} = \frac{\sum_{s=1}^{\boldsymbol{S}} \frac{\frac{BestBid_{its} - BestOffer_{its}}{BestBid_{its} + BestOffer_{its}}}{2}}{\boldsymbol{S}}$$

Where *s* refers to the order of the trade of stock *i* at day *t*, and *S* refers to the stock's total number of trades considered during the day. *ESPD* is calculated as follows:

$$ESPD_{it} = \frac{\sum_{s=1}^{\boldsymbol{S}} \frac{\left(\left|PRC_{its} - \frac{BestBid_{its} + BestOffer_{its}}{2}\right|\right) * 2}{\frac{BestBid_{its} + BestOffer_{its}}{2}}}{\boldsymbol{S}}$$

In addition to quoted and effective spreads, I consider TO_{it} to measure the trading quantity aspect of liquidity, and Amihud's measure (Amihud, 2002) to capture price impact. I refer to Amihud's measure by $Amihud_{it}$, and it is calculated for each stock on a daily basis as $\frac{Trading\ Volume_{it}}{|Return_{it}|}$. Note that the original price impact measure of Amihud is inversed to represent liquidity rather than illiquidity. My final data set includes 6,621 (6,494) stocks in the pre-decimalization (post-decimalization) window, and 2,616 (2,528) stocks in the pre-Hybrid (post-Hybrid) window.

4. Tests and results

This section contains three parts. In subsection 4.1, I examine the general impact of decimalization and the Hybrid system on liquidity. In subsection 4.2, the impact of these two events on liquidity is examined, conditionally on firm size. Finally, the interaction between the size and liquidity attributes of stocks are discussed in subsection 4.3.

4.1 General impact on liquidity

As presented thus far, financial markets have undergone continual changes in regulations and technology in recent years. This continuous modernization process, which coincided with an ongoing trend for centralization and consolidation in the financial services industry, facilitated trading and liquidity provision (Lhabitant *et al.*, 2008).

On balance, the evidence in extant literature supports a positive relationship between decimalization and trade automation on one hand, and trading liquidity and quality on the other hand (e.g., Bessembinder (2003) and Jain and Johnson (2006)). However, it is important to formally test the relationship between these events and liquidity within the

[21] An observation is considered "crossed" ("locked") if the bid quote exceeds (equals) the ask quote.

context of my methodology and data, because the overall impact established in this subsection is the basis for the analysis in the size-conditioned test in the following subsections. As explained above, my conjecture is that these two events are accompanied by an overall improvement in liquidity.

Table 1 contains univariate analysis of changes in liquidity measures around the two events by making a comparison between the pre-event and post-event windows, including tests for the significance of pre-post differences. Each of the four daily liquidity measures are averaged at the stock level within each window, then cross-sectional averages are presented in Table 1. Panel A of the table presents results related to the decimalization event for NYSE and Nasdaq stocks, whereas Panel B presents results related to the implementation of the Hybrid system for stocks listed on NYSE; where the Hybrid system got implemented.

Most of the results in Table 1 are in favor of my conjecture that liquidity generally improved post events. The first row of each panel presents average liquidity measures before and after each event for the whole sample. We can quickly see that both quoted and effective spreads dropped after both events, indicating that liquidity (in terms of transaction costs) has improved post these two events. However, the magnitude of decrease in spreads is substantially higher in the case of decimalization than in the case of the Hybrid system. In terms of quoted spreads, the drop is by 0.30%; from 1.21% to 0.91%, compared to a drop of only 0.02% following the implementation of the Hybrid system; from 0.53% to 0.51%. A similar trend is observed when effective spreads are considered. On average, they dropped by 0.24% after decimalization, but only by 0.03% after the Hybrid system. One reason behind this difference between the two events is that the decimalization event is directly related to spreads, and therefore it is expected that it exerts a more pronounced effect on them.

Amihud's price impact measure increased after both events as well, but given that the Amihud's measure used is inversed, this increase indicates a lower price impact, and therefore, improved liquidity. More trading means higher liquidity, thus higher turnover means higher liquidity as well. The extent of decrease in price impact is also slightly higher with decimalization than in the case of the Hybrid system. In the case of decimalization, the inversed Amihud's measure increased by about 25%; from 324 to 404. The increase in the case of the Hybrid system is by about 10% only; from 276 to 303. When measured using the one-year window around events, the improvement in Amihud's measure is about 16% (28%) in the case of the Hybrid system (decimalization)[22]. The reduced gap in improvement obtained with the one-year window indicates that the Hybrid system might be different from decimalization in the period needed before its full impact on liquidity is materialized.

Turnover results are mixed; they show that it increased after the implantation of the Hybrid system (7.98 to 8.45), but contrary to my conjecture, it decreased after decimalization (7.81 to 6.91). One reason behind this decrease can be the timing of the post-event window (May 10 – November 9, 2001) which encompasses two months of the period following the 9/11 attacks; a time of a potentially irregular trading activity. The robustness checks that use three-month windows (and thereby avoid the post-9/11 period) do not indicate

[22] Results from robustness checks using three-month and one-year windows are omitted in the interest of brevity, but they are available from the author upon request.

this decrease in turnover after decimalization. Other results from the three-month and one-year windows are in the same direction with the presented results.

To formally test the conjecture of overall liquidity improvement post-events, I estimate the following regression model:

$$LIQ_{i,t} = \alpha + \beta\ Event_t + \gamma_{VIX} VIX_t + \gamma_t RM_t + \delta_{SIZE} SIZE_{i,t} + \varepsilon_{i,t} \qquad (1)$$

The dependent variable in Equation (1) is $LIQ_{i,t}$, which refers to one of the four liquidity measures used, for stock *i* at day *t*: quoted spreads (*QSPD*), effective spreads (*ESPD*), inversed Amihud's price impact measure (*Amihud*), or turnover (*TO*). The main variable on the right-hand side of the equation is *Event*; a dummy variable that takes the value of 1 (0) after (before) decimalization or the implementation of Hybrid system. The remaining right-hand side variables are included as controls, and they include: daily closing volatility index value (*VIX*), equally-weighted average market return (*RM*), and the natural log of market capitalization value (*SIZE*).

For each event, I estimate Equation (1) at the stock-level first, then cross-sectional average coefficients are provided along with the t-stat of the average. I estimate this regression equation, as well as the rest of the regression equations in this study, using this method. A number of similar studies also report cross-sectional statistics about coefficients obtained from time-series regressions. For instance, Chan and Fong (2000) and Chordia and Subrahmanyam (2004) report the cross-sectional average coefficients obtained from time-series regressions. In addition to mean coefficients, I also consider but do not report median coefficients, the proportion of coefficients that are statistically significant, and the proportions of significant coefficients that are positive/negative. I find that these additional statistics are predominantly in the same direction of average coefficients that I report.

Panel A of Table 2 presents the results of estimating Equation (1) for the decimalization event, whereas Panel B of Table 2 presents results related to the implementation of the Hybrid system. The variable of interest is *Event*, and its average coefficients indicate that spreads have dropped after decimalization (-0.032 for quoted spreads and -0.026 for effective spreads) and post-Hybrid (-0.0009 for quoted spreads and -0.001 for effective spreads), though the extent of decrease in the case of Hybrid is significantly smaller than that in the case of decimalization. Smaller price impact is also found after both events. This is evident in the statistically- and economically-significant average coefficients of 13.69 in the case of decimalization and 18.56 in the case of the Hybrid. Finally, average turnover coefficient is statistically-insignificant in the case of decimalization, and marginally significant in the case of Hybrid, indicating a slight increase in turnover (average coefficient is 0.008). In sum, the univariate analysis in Table 1 and regression results in Table 2 point to a significant improvement in liquidity following both the decimalization and the implementation of the Hybrid system events.

4.2 Size-conditioned impact on liquidity

This subsection examines whether recent changes in financial markets, specifically decimalization and the implementation of the Hybrid system events, offered different relative liquidity benefits to stocks based on their market capitalizations. My conjecture is that the liquidity of small stocks has benefited the most from such events. Preliminary evidence in support of this conjecture can also be found in Table 1, which also presents average liquidity measures before and after decimalization (Panel A) and Hybrid (Panel

B) for each size quintile. As explained in the data section, stocks are ranked into size quintiles in each month *m* based on the market capitalization as of the last trading day in month *m-1*.

Size-based results in Table 1 show that stocks across all size quintiles have benefitted from both events, with an exception in the case of turnover after decimalization. However, the extent of liquidity benefit for small stocks seem to be bigger, and in many cases it decreases in size. For instance, average quoted spreads fall after decimalization by 0.92% (from 2.31% to 1.39%) in size quintile 1, whereas they fall only by 0.07% (from 0.39 to 0.32) in size quintile 5. Even proportionally, quoted spreads fall by about 40% for size quintile 1 and by about 18% for size quintile 5. Even in the case of turnover after decimalization, while turnover generally falls slightly after decimalization and in size quintiles 2-5, the change in turnover for size quintile 1 is statistically-insignificantly different from zero (it changes from 1.75 to 1.76).

Results related to the Hybrid system (Panel B) depict a similar picture, though the magnitude of the effect is significantly smaller than that in the case of decimalization. For instance, quoted and effective spreads fall each by 0.07% in size quintile 1, but the change is neither statistically- nor economically-significant for size quintile 5. Size quintile 5 is the only quintile where effective spreads remain unaffected at 0.22%.

Another piece of preliminary evidence can be found in Figure 1, where the percentage of stocks that experience liquidity improvement are plotted for each size quintile. Decimalization results are presented in Figure 1.A and the Hybrid results are presented in Figure 1.B. Size quintile membership are generally defined monthly. But in this test, I consider only the stocks that do not change size quintile within the six-month pre-event window. I then track these stocks after each event and calculate the percentage of those that experience improvement in liquidity in the post-event six-month window. In many instances, we can find that this percentage decreases in size quintile, which means that the number of small stocks that benefited from the two events in terms of liquidity is higher than that of large stocks. The percentage decrease is monotonic in the case of Amihud's measure in Figure 1.B, and near monotonic in the case of turnover (Figures 1.A and 1.B) and spreads (Figure 1.A).

Formally, the hypothesis to be tested in this subsection is as follows (Hypothesis 1):

H_0^1: *Decimalization and Hybrid events result in similar liquidity improvements for all stocks regardless of their size.*

H_A^1: *Decimalization and Hybrid events result in a more pronounced liquidity improvement for smaller than for larger stocks.*

To test the above hypothesis, I estimate a regression equation similar to Equation (1) but augmented by the interaction of *Event* and *Small*—another dummy variable that takes the value of 1 for stocks in the smallest quintile or 0 otherwise. Specifically, the equation is as follows:

$$LIQ_{i,t} = \alpha + \beta\, Event_t + \lambda\, Event_t * Small_{i,t} + \gamma_{VIX} VIX_t + \gamma_t RM_t + \delta_{SIZE} SIZE_{i,t} + \varepsilon_{i,t} \qquad (2)$$

The interaction term is designed to identify the incremental effect of liquidity-changing events for smallest stocks, and therefore it is our variable of interest. Panel A of Table 3 presents the results of estimating Equation (2) for the decimalization event, whereas Panel B of Table 3 presents results related to the implementation of the Hybrid system. All average coefficients for this interaction term come with a sign that is consistent with my hypothesis. Nevertheless, statistical significance is lacked in the case of turnover in Panel A (significance is only marginal in Panel B), and quoted spreads in Panel B. We can also notice that the introduction of the interaction term to the equation does not take away the significance from average coefficients of *Event*; β. To summarize, results in Table 3 show that decimalization and the Hybrid system benefited all stocks in terms of liquidity (except for decimalization when liquidity is measured by turnover), but the benefit in most cases is more pronounced for small stocks.

4.3 Changes in the size-liquidity relationship

A number of studies relate the size and liquidity characteristics of stocks. For instance, some studies have explained abnormal returns of small stocks by their relative illiquidity. A paper by Stoll and Whaley (1983) is an example of this line of research. The authors find that small stocks experience higher returns due to their difficulty of trading and their higher trading costs. Similarly, Pastor and Stambaugh (2003) find that small stocks have the highest loadings on the liquidity factor that the authors construct. A study by Amihud and Mendelson (1986) goes further by stating that the firm size is a proxy for liquidity.

The analysis presented in the previous subsection shows that small stocks have gained additional liquidity improvement subsequent to decimalization and the implementation of the Hybrid system. Given this disproportionate shift in liquidity and given the association between size and liquidity documented in the literature, one would expect that liquidity-changing events to have implications for this size-liquidity association. In this subsection I test the conjecture that decimalization and the Hybrid events helped disentangling these two characteristics and reduced the overlap between them.

I conduct three tests to that effect. First, I look at the correlation between size and liquidity, before and after the two test events. Size, measured by market capitalization, is paired on a monthly basis at the stock level with each of the four liquidity measures, then Pearson's correlation coefficient is calculated across stock-months within each of the four windows (pre-decimalization, post-decimalization, pre-Hybrid, and post-Hybrid). Panel A of Table 4 presents the results for the pre- and post-decimalization windows, whereas Panel B of the table presents the results for the pre- and post-Hybrid windows.

We first notice that correlation coefficients are generally high; they range between 0.27 and 0.55. This relatively high level of correlations is evident of the association between size and liquidity attributes of stocks, as documented in the literature. Consistent with my conjecture, I find that correlations between size and liquidity have dropped in seven out of the eight cases. The exception is also observed for the turnover measure around decimalization, in which the correlation coefficient increases slightly from 0.41 to 0.42. The most notable decrease in correlations can be seen for spreads around decimalization; correlation between size and quoted (effective) spreads have dropped from 0.55 to 0.42 (0.52 to 0.43). Note that the exception of results for turnover in this test correspond to the exception observed for turnover results in the previous subsection. While the exception, per se, is contrary to my conjecture, the alignment of results assures that the change in correlations documented in this subsection is an implication of the disproportionate pattern of liquidity change, shown in the previous subsection.

In the second test, I look at the number and proportion of stocks that are both small *and* illiquid. Lower association between size and liquidity imply that a smaller percentage of small stocks are expected to remain illiquid after liquidity-changing events, and that illiquid stocks become more scattered across stocks of different sizes. To conduct this test, I rank stocks in each month into size and liquidity quintiles independently. I then consider in each month the percentage of stocks that are present in both size quintile 1 and liquidity quintile 1 (i.e. smallest *and* most illiquid stocks), where liquidity is measured by one of the four measures at a time. Finally, I calculate the average of this percentage over the months within each window.

Panel A of Table 5 presents the results for the pre- and post-decimalization windows, whereas Panel B of the table presents the results for the pre- and post-Hybrid windows. Note that the maximum values for these percentages is 20%, which is obtained if all stocks in size quintile 1 happen to be in liquidity quintile 1. I find that these percentages have dropped in all cases by varying degrees, except in the case of turnover after the Hybrid system, where percentage of small stocks that are also illiquid slightly increased from 8.47% to 8.51%. Therefore, the results in Table 5 indicate that there are generally fewer small stocks that are also illiquid after the two test events.

The third and final test involves observing the extent of increase in liquidity measures between adjacent size quintiles in the pre- and post-event windows. If liquidity-changing events helped reduce the association between the size and liquidity attributes of stocks, it is expected that the differences in liquidity between neighboring size quintiles to get smaller post-events. In other words, we expect to find the variation of liquidity across size quintiles to be moving a step away from being systematically increasing in size quintile, and moving a step towards becoming random and less systematic.

To conduct this test, I rank stocks in each month into size quintiles. Then, I calculate in each month the difference in average liquidity measure between adjacent quintiles (i.e. average liquidity measure in size quintile 2 minus that in quintile 1, quintile 3 minus that in quintile 2, quintile 4 minus that in quintile 3, and quintile 5 minus that in quintile 4). Finally, I average those differences across the four windows (pre-decimalization, post-decimalization, pre-Hybrid, and post-Hybrid).

A positive (negative) figure, when liquidity is measured by *Amihud* or *TO* (*QSPD* or *ESPD*), indicates that liquidity shows improvement when size increases. I find that figures do indicate that liquidity generally improves as we move from smaller to larger quintiles (few exceptions in quintile 5-4 and 4-3). I do find that the improvement in liquidity between neighboring size quintiles slightly attenuates post-events, but the decrease is statistically-insignificant. The overall results in this subsection support the conjecture that the association between size and liquidity attributes of stocks decreased after decimalization and the implementation of the Hybrid system.

5. Conclusion

Recent years have witnessed an intensified pace of developments in financial markets, both in terms of technology and regulation. These changes are designed to expedite and facilitate the trading process. For instance, a number of exchanges have either fully or partially transformed from traditional outcry trading floors to automated platforms in the last two decades. A number of regulatory changes have also been introduced to make the trading experience fairer and more transparent.

In this study, I focus on two such changes in stock markets in the U.S.: Decimalization in 2000; as an example of a regulatory change, and the implementation of the Hybrid System on the NYSE in 2006; as an example of a technological change. In particular, I examine the impact of these two events on market liquidity, where liquidity is measured by quoted spreads, effective spreads, Amihud's price impact measure, and turnover. I find out that these two events are followed by significant overall improvements in liquidity.

I then conduct my analysis conditionally on firm size, where firm size is measured by market capitalization. Even though stocks of all sizes benefit from liquidity-improving events, I argue that these events offer a particular benefit to smaller stocks than it does for larger stocks. The basis of this conjecture lies in the diminishing marginal utility notion. Small stocks, known to be the most illiquid, are expected to benefit in a more pronounced way from such events. For instance, without these advancements in markets, trading costs would be inhibitingly high for small stocks, and small firms would suffer from extreme information asymmetry in absence of modern information dissemination technologies. Recent market changes come to the rescue of small stocks by offering significantly cheaper trading solutions and by disseminating information effectively. I argue that these offerings are dramatically more beneficial for small stocks than they are for large stocks. These changes help make financial markets a more level playing field for all stocks.

Consistent with my conjecture, I find that decimalization and the implementation of the Hybrid system brought more pronounced liquidity improvements for small stocks. I continue this investigation by considering the possible implications of this disproportionate change in liquidity on the well-documented size-liquidity association. I also find that there is less association between these two characteristics after the two test events. In a way, such liquidity-changing events reduce the overlap between size and liquidity, and help make them more distinct features.

The size-liquidity relationship has preoccupied a significant part of the literature. In his survey paper, van Dijk (2011) mention that the way "the size effect and liquidity interact is an important area of future research". I argue that this paper sheds light on this association. It also shows that liquidity-changing events are not always a rising-tide-that-lifts-all-boats, because their effect can be more pronounced for certain subsets of stocks. In fact, implicitly assuming that such events have an across-the-board effect might be the reason why the evidence on these events is still inconclusive in the literature. Another way that this study can be examined, is by conditioning the impact of liquidity-changing events on the level of liquidity itself, rather than on size. If the liquidity improvement is also found to be an increasing function of illiquidity, for instance, then the implication of such finding would be that the variation of liquidity across stocks is diminishing.

Another way that this study can be extended is by examining the asset pricing implications of my findings. Small stocks are known to enjoy higher returns, and one explanation for this phenomenon is that small stocks exhibit this premium due to their illiquidity. In this case, given that the liquidity of small stocks experienced the most significant improvements post liquidity-changing events, then one would expect the size premium to diminish. This is because the component of the size premium that compensates for illiquidity is shrinking after such events. In fact, this could explain the finding in many papers (e.g., Chan *et al*., 2000; Dimson and Marsh, 1999) that the size effect has dropped in the recent decades. Generally, this type of asset pricing tests might prove capable of explaining the patterns of variation that return determinants exhibit over time.

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Table 1: Univariate analysis of liquidity change

Univariate analysis for changes in quoted spreads (*QSPD*), effective spreads (*ESPD*), inversed Amihud's price impact measure (*Amihud*), and turnover (*TO*). Measures are presented separately for the period before and the period after of both the decimalization event (Panel A) and the implementation of the Hybrid system on the NYSE (Panel B). Statistics are presented for the overall sample (NYSE and Nasdaq in the case of decimalization, and NYSE in the case of the Hybrid) as well as for size quintiles, where quintile 1 (5) contains smallest (largest) stocks. Measures are averaged at the stock level in each window, then the cross-sectional averages are presented in the table. The pre-decimalization (post-decimalization) window includes trading days in the period from February 28, 2000 to August 27, 2000 (May 10, 2001 to November 9, 2001). The pre-Hybrid (post-Hybrid) window includes trading days in the period from April 6, 2006 to October 5, 2006 (February 25, 2007 to August 24, 2007). Amihud's measure is multiplied by 10^3 whereas turnover is multiplied by 10^{-5}. Significance of mean differences is tested and significance levels are indicated by *, **, and *** (next to post-event averages), which denote significance at 10%, 5%, and 1% levels, respectively.

Panel A – Decimalization

Sample		*QSPD*		*ESPD*		*Amihud*		*TO*	
		Pre	Post	Pre	Post	Pre	Post	Pre	Post
All (NYSE and Nasdaq)		1.21	0.91***	1.02	0.78***	324	404***	7.81	6.91**
Size Quintiles	1	2.31	1.39***	2.04	1.28***	188	246***	1.75	1.76
	2	1.64	1.15***	1.4	1.01***	216	260***	4.71	4.48*
	3	1.15	0.96***	0.93	0.74***	298	365***	6.88	6.13***
	4	0.86	0.69*	0.59	0.58*	385	429**	9.76	8.35**
	5	0.39	0.32**	0.31	0.28	546	591***	13.93	13.46***

Panel B – The Hybrid system

Sample		*QSPD*		*ESPD*		*Amihud*		*TO*	
		Pre	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**
All (NYSE)		0.53	0.51**	0.46	0.43***	276	303***	7.98	8.45***
Size Quintiles	**1**	0.92	0.85***	0.88	0.81**	167	257***	2.12	2.54***
	2	0.71	0.68***	0.69	0.64***	263	294***	5.22	5.71***
	3	0.52	0.48**	0.51	0.46**	291	311***	8.58	8.74***
	4	0.38	0.38	0.32	0.31	332	378***	9.45	9.71*
	5	0.25	0.24*	0.22	0.22	448	485***	14.87	14.92

Table 2: Estimation of Equation 1

$$LIQ_{i,t} = \alpha + \beta\ Event_t +\ \gamma_{VIX}VIX_t + \gamma_t RM_t + \delta_{SIZE}SIZE_{i,t} + \varepsilon_{i,t}$$

Where $LIQ_{i,t}$ refers to one of the four liquidity measures used, for stock *i* at day *t*: quoted spreads (*QSPD*), effective spreads (*ESPD*), inversed Amihud's price impact measure (*Amihud*), or turnover (*TO*). Each of these liquidity measures are regressed on *Event*; a dummy variable that takes the value of 1 (0) after (before) decimalization or the implementation of Hybrid system, daily closing volatility index value *VIX*, *RM*; which refers to the equally-weighted average market return, and the natural log of market capitalization value (*SIZE*). The above equation is estimated for two events: decimalization (Panel A) and the implementation of the Hybrid system on the NYSE (Panel B). A time-series regression is estimated first for each stock, then cross-sectional average coefficients are presented in the table. The pre-decimalization (post-decimalization) window includes trading days in the period from February 28, 2000 to August 27, 2000 (May 10, 2001 to November 9, 2001). The pre-Hybrid (post-Hybrid) window includes trading days in the period from April 6, 2006 to October 5, 2006 (February 25, 2007 to August 24, 2007). Amihud's measure is multiplied by 10^3 whereas turnover is multiplied by 10^{-5}. The t statistics (t-stat) are those of cross-sectional averages.

	QSPD		*ESPD*		*Amihud*		*TO*	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	0.004	21.69	0.001	14.62	-0.912	-17.78	0.009	8.71
$Event_t$	-0.032	-3.71	-0.026	-4.72	13.69	7.41	0.018	1.14
VIX_t	-0.002	-1.97	0.017	2.92	1.33	2.12	-0.093	-6.54
RM_t	0.017	2.92	0.001	6.76	2.74	0.87	0.167	5.78
$SIZE_{i,t}$	-0.002	-2.77	-0.0001	-1.45	1.48	5.62	0.082	3.71

Panel B – The Hybrid system

	QSPD		*ESPD*		*Amihud*		*TO*	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	-0.002	-34.73	-0.0004	-12.66	0.715	12.56	0.017	7.19
$Event_t$	-0.0009	-9.45	-0.001	-13.48	18.56	9.89	0.008	2.14
VIX_t	0.001	1.41	-0.022	-0.89	0.82	4.97	-0.178	-8.43
RM_t	0.012	3.5	0.008	4.65	3.51	1.41	0.103	6.75
$SIZE_{i,t}$	-0.001	-3.49	-0.0001	-2.11	1.24	6.47	0.053	4.05

Table 3: Estimation of Equation 2

$$LIQ_{i,t} = \alpha + \beta\, Event_t + \lambda\, Event_t * Small_{i,t} + \gamma_{VIX} VIX_t + \gamma_t RM_t + \delta_{SIZE} SIZE_{i,t} + \varepsilon_{i,t}$$

Where $LIQ_{i,t}$ refers to one of the four liquidity measures used, for stock *i* at day *t*: quoted spreads (*QSPD*), effective spreads (*ESPD*), inversed Amihud's price impact measure (*Amihud*), or turnover (*TO*). Each of these liquidity measures are regressed on *Event*; a dummy variable that takes the value of 1 (0) after (before) decimalization or the implementation of Hybrid system, the interaction of *Event* with *Small*; where *Small* is also a dummy variable that takes the value of 1 if stock *i* is in the smallest quintile of stocks or 0 otherwise, daily closing volatility index value *VIX*, *RM*; which refers to the equally-weighted average market return, and the natural log of market capitalization value (*SIZE*). The above equation is estimated for two events: decimalization (Panel A) and the implementation of the Hybrid system on the NYSE (Panel B). A time-series regression is estimated first for each stock, then cross-sectional average coefficients are presented in the table. The pre-decimalization (post-decimalization) window includes trading days in the period from February 28, 2000 to August 27, 2000 (May 10, 2001 to November 9, 2001). The pre-Hybrid (post-Hybrid) window includes trading days in the period from April 6, 2006 to October 5, 2006 (February 25, 2007 to August 24, 2007). Amihud's measure is multiplied by 10^3 whereas turnover is multiplied by 10^{-5}. The t statistics (t-stat) are those of cross-sectional averages.

Panel A – Decimalization

Variable	QSPD Estimate	QSPD t-stat	ESPD Estimate	ESPD t-stat	Amihud Estimate	Amihud t-stat	TO Estimate	TO t-stat
Intercept	0.004	20.56	0.001	14.64	-0.918	-17.07	0.009	8.45
$Event_t$	-0.026	-3.98	-0.023	-3.55	11.56	4.17	0.009	1.56
$Event_t * Small_{i,t}$	-0.021	-2.78	-0.029	-4.78	5.78	6.79	0.012	1.18
VIX_t	-0.002	-1.91	0.018	2.97	1.31	2.32	-0.093	-6.35
RM_t	0.016	2.97	0.001	6.89	2.61	1.02	0.171	4.91
$SIZE_{i,t}$	-0.001	-2.07	-0.0001	-1.38	1.36	3.32	0.071	2.68

Panel B – The Hybrid system

Variable	QSPD Estimate	QSPD t-stat	ESPD Estimate	ESPD t-stat	Amihud Estimate	Amihud t-stat	TO Estimate	TO t-stat
Intercept	-0.003	-31.62	-0.0005	-11.39	0.713	13.51	0.017	7.49
$Event_t$	-0.0012	-7.45	-0.0006	-11.45	15.78	9.11	0.008	1.81
$Event_t * Small_{i,t}$	-0.0004	-1.45	-0.001	-2.56	8.46	6.72	0.003	1.68
VIX_t	0.001	1.4	-0.029	-1.13	0.82	4.95	-0.174	-9.64
RM_t	0.011	3.41	0.007	4.49	3.11	1.62	0.104	5.77
$SIZE_{i,t}$	-0.001	-3.63	-0.0001	-2.38	1.01	4.78	0.031	2.78

Table 4: Correlation between size and liquidity

This table presents the correlation between size, measured by market capitalization, and each of the four liquidity measures: quoted spreads (*QSPD*), effective spreads (*ESPD*), inversed Amihud's price impact measure (*Amihud*), and turnover (*TO*). Panel A presents correlations in the pre- and post-decimalization windows, whereas Panel B presents correlations in the pre- and post-Hybrid windows. The pre-decimalization (post-decimalization) window includes trading days in the period from February 28, 2000 to August 27, 2000 (May 10, 2001 to November 9, 2001). The pre-Hybrid (post-Hybrid) window includes trading days in the period from April 6, 2006 to October 5, 2006 (February 25, 2007 to August 24, 2007). Size and liquidity measures are paired monthly at the stock-level, then Pearson's correlation coefficient is calculated across stock-months within each window.

Panel A – Decimalization

Correlation between market capitalization and:							
QSPD		*ESPD*		*Amihud*		*TO*	
Pre	Post	Pre	Post	Pre	Post	Pre	Post
0.55	0.42	0.52	0.43	0.36	0.33	0.41	0.42

Panel B – The Hybrid system

Correlation between market capitalization and:							
QSPD		*ESPD*		*Amihud*		*TO*	
Pre	Post	Pre	Post	Pre	Post	Pre	Post
0.44	0.42	0.47	0.43	0.28	0.27	0.36	0.33

Table 5: Percentage of small-and-illiquid stocks

This table presents the average percentage of stocks that are small-and-illiquid. In each month, I independently rank stocks into quintiles based on their size, measured by market capitalization, and each of the four liquidity measures: quoted spreads (*QSPD*), effective spreads (*ESPD*), inversed Amihud's price impact measure (*Amihud*), and turnover (*TO*). Then I calculate the percentage of stocks that are in both size quintile 1 (smallest) and liquidity quintile 1 (most illiquid), where liquidity is measured by one of the four liquidity measures at a time. Finally, I average these percentages across the six months in each of the four windows. Panel A presents results for the pre- and post-decimalization windows, whereas Panel B presents results for the pre- and post-Hybrid windows. The pre-decimalization (post-decimalization) window includes trading days in the period from February 28, 2000 to August 27, 2000 (May 10, 2001 to November 9, 2001). The pre-Hybrid (post-Hybrid) window includes trading days in the period from April 6, 2006 to October 5, 2006 (February 25, 2007 to August 24, 2007).

Panel A – Decimalization

Percentage of stocks present in both size quintile 1 and liquidity quintile 1, where liquidity is measured by:							
QSPD		*ESPD*		*Amihud*		*TO*	
Pre	Post	Pre	Post	Pre	Post	Pre	Post
15.60%	13.12%	16.91%	14.61%	12.78%	11.43%	9.56%	9.34%

Panel B – The Hybrid system

Percentage of stocks present in both size quintile 1 and liquidity quintile 1, where liquidity is measured by:							
QSPD		*ESPD*		*Amihud*		*TO*	
Pre	Post	Pre	Post	Pre	Post	Pre	Post
11.18%	10.59%	10.54%	9.73%	10.68%	10.74%	8.47%	8.51%

Figure 1: Percentage of stocks with improving liquidity

Percentage of stocks witnessing improved liquidity (i.e. smaller quoted or effective spreads, higher turnover, or smaller price impact). Figure 1.A (Figure 1.B) presents this percentage in each size quintile by each liquidity measure for the decimalization (the Hybrid) event. Stocks (NYSE and Nasdaq stocks in the case of decimalization event and NYSE stocks in the case of the Hybrid) are classified monthly into size quintiles in the pre-event window. Stocks are included if they do not change quintile from one month to another during the pre-event window. Stocks are then tracked post-event to find the percentage of those showing improvement in liquidity. Quintile 1 (5) includes smallest (largest) stocks.

Figure 1.A - Decimalization

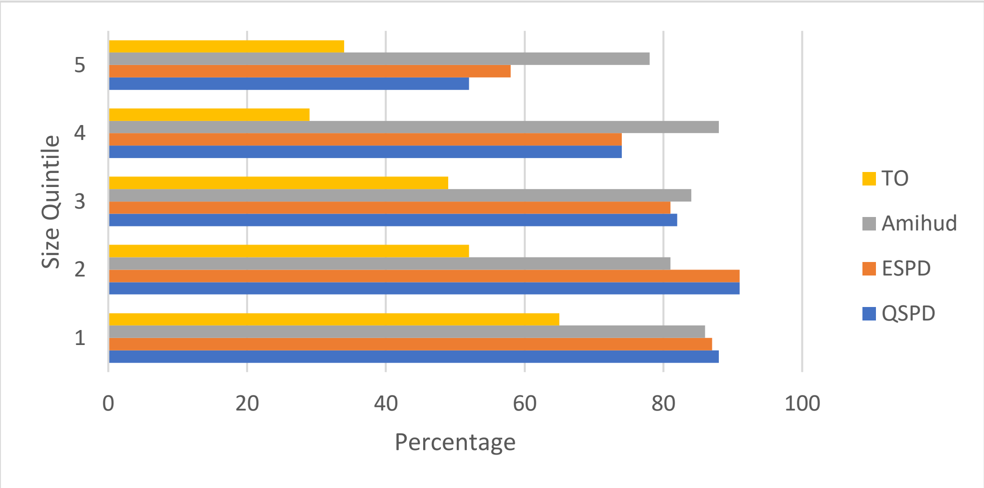

Figure 1.B – The Hybrid system