IMPLICATIONS OF TRADE AUTOMATION
FOR SMALL-SIZE STOCKS

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ABSTRACT

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Using a comprehensive set of liquidity measures, this study examines the impact of the NYSE Hybrid Market on various stock characteristics. In addition, we test the conjecture that trade automation results in more pronounced liquidity improvements for small stocks. The resulting change in the relationship between size and liquidity is also examined, as well as the change in the explanatory power of the SMB factor. We find evidence that the general state of liquidity improved subsequent to migration to Hybrid. However, results for the size-conditioned test are mixed and inconsistent across liquidity measures. While liquidity improvements in terms of amortized spreads are concentrated in small stocks, the pattern is less obvious when other liquidity measures are considered. Also, while the test involves a NYSE event, changes also exist in NASDAQ, probably due to a competitive spill-over effect. We find that the relationship between size and liquidity characteristics has changed post-Hybrid, particularly on NYSE, and that the SMB factor has less effect on asset pricing when the entire CRSP sample is tested but not for the NYSE and NASDAQ subsamples individually. Nevertheless, firm size seems to play an important role in differentiating the impact of changes in market design.

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1. INTRODUCTION

Stock exchanges around the World have undergone remarkable changes in their business models, such as automating trading systems and facilitating the trading process through new regulations. In academia, one of the earliest calls for trade automation appeared in 1971 in a study by Black (Black, 1971) who advocates a fully automated market. In automated markets, real investors share the market making responsibility without the need for intermediaries who inflate the total cost of trading. Recent years have witnessed an intensified pace of developments in stock markets, partly because new technology solutions and communication systems enable exchanges to revolutionize the way trading takes place in markets. For instance, a number of exchanges have either fully or partly transformed from traditional outcry trading floors to automated platforms in the last two decades. These changes in technology have been paralleled by other significant changes in trading regulations that are aimed at simplifying the trading process. Motivated by an increasing need for stock exchanges to keep their competitive advantage, owners of these exchanges are now convinced that an efficient and competitive market design is essential to attract traders in a dynamic market with an abundance of alternative trading venues and low barriers to entry (Jain, 2006).

This study examines the effect of technological changes in financial market design on different stock characteristics. The study also tests whether the impact of such changes has been the same for all stocks regardless of their individual characteristics. Examining the effect of technological and regulatory changes on asset pricing, and stock and market characteristics preoccupies a significant part of the finance literature. Nevertheless, this area of research is still characterized by the lack of consensus, as different schools compete with opposing views on this issue.[1] One possible reason behind this ongoing controversy is that most of these studies assume that changes in market design affect all stocks equally. The novelty of this study is that it does not assume that technological changes have an across-the-board effect, but rather considers that stocks might have been affected differently based on their size, measured by market capitalization.

This thesis also investigates the relationship between the size and liquidity characteristics of stocks by testing the hypothesis that changes in market design decrease the level of association between a stock's size and its state of liquidity. Specifically, we conjecture that, if small stocks experience more pronounced improvements in liquidity after a change event, then these events might help to redefine the determinants of stock liquidity and change the relationship between these two characteristics. 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". Finally, asset pricing implications of such change events are also studied. If changes in market design help to disentangle size and liquidity effects, it is important to know how these events affect the explanatory power of these two factors in the context of a traditional capital asset pricing model.

[1] Examples of studies that support the move to trade automation include: Jain (2006), Stoll (2006) and Gutierrez and Tse (2009). In contrast, Venkataraman (2001) and Hendershott and Moulton (2011) document various disadvantages associated with trade automation. A more detailed description for these two lines of research is presented in the literature review section of this thesis.

This study uses the implementation of the Hybrid system on New York Stock Exchange (NYSE) as the test event. The Hybrid system gives traders the option to process trades and match orders automatically for up to one million shares per trade. The big magnitude of this event and its relative recentness (end of 2006) make it one of the most suitable events for the purpose of this study.[2] In addition, studying the state of the market before and after an event means that the investigation is confined to a *single* market. Some studies (e.g., Venkataraman, 2001) compare characteristics in two different markets, although it is very challenging to either identify or account for all the material differences across different trading venues.

A comprehensive set of liquidity measures are used to examine changes in different aspects of liquidity. These liquidity measures are: quoted spreads, effective spreads, amortized spreads, Amihud's price impact measure, and Zeros measure. Results for the entire CRSP sample are generally supportive of the hypotheses. However, while the test is for a NYSE event, the proposed phenomena are present in not only the NYSE sub-sample but also in the NASDAQ (National Association of Securities Dealers Automated Quotations) sub-sample, probably due to competitive spill-over effects. In addition, the results are not consistent across all liquidity measures. For instance, while some liquidity measures show that liquidity has improved on the NYSE and NASDAQ subsequent to migration to Hybrid, results for other measures show that liquidity has deteriorated. Similarly, firm size appears to be an important factor in explaining liquidity changes, but this finding cannot be confirmed across all liquidity measures. There is also evidence that the relationship between size and liquidity changed post-Hybrid, and that

[2] This is available at: http://www.nyse.com/about/history/timeline_technology.html.

the small-minus-big (*SMB*) factor has lost part of its explanatory power in an asset pricing context.

The remainder of the thesis is organized as follows. Section 2 describes some of the major changes in financial market design on the NYSE and NASDAQ. Section 3 provides a review of the related literature. Section 4 outlines data sources and measures. Both the general and the size-conditioned tests of the automation impact on liquidity are presented in Section 5. The interaction between size and liquidity, and the asset pricing implications are examined in Sections 6 and 7, respectively. Finally, Section 8 concludes.

2. CHANGES IN FINANCIAL MARKET DESIGN

Trading floors around the world witnessed significant modernizations that have reshaped the way trading takes place in these venues. This section briefly reviews recent *technological* and *regulatory* changes in the two most prominent stock markets in the United States; namely, NASDAQ and NYSE. Our focus is the NYSE, since it is the primary exchange of interest in this study. NYSE is one of the oldest and most established financial markets in the world, and by far the largest stock exchange in terms of market capitalization. The most recent annual report of the World Federation of Exchanges (WFE) reports that the market capitalization of NYSE-listed stocks totalled USD 11.796 trillion at the end of 2011, about triple the market capitalization value of USD 3.845 trillion of the World's second largest market, NASDAQ.[3]

Since its launch in 1971, NASDAQ has operated as a purely electronic system, although the system was originally used for information dissemination purposes only.

[3] This is available at: http://www.world-exchanges.org/files/file/stats%20and%20charts/2011%20WFE%20Market%20Highlights.pdf.

NASDAQ was established later as a formal exchange; starting to offer stock listing and a full range of trading services.[4] Unlike NASDAQ, NYSE is known for its open outcry trading floor. Since its inception in 1792 when 24 brokers met under a buttonwood tree, the NYSE has depended on a face-to-face mechanism for trading.[5] Nevertheless, NYSE has experienced a fast pace of development and implementation of the latest technologies despite maintaining the central role of its specialists in trade intermediation. For instance, NYSE is connected to European markets since 1866 through a trans-Atlantic cable that provides near instant communication. Starting in 1878, telephones were installed in the trading floors to communicate trading orders. Dealers at NYSE adopted a fully-centralized clearing system since 1920 (Jain and Johnson, 2006).

This trend towards automation on the NYSE has further intensified in recent decades. In 1976, the automated Designated Order Turnaround (DOT) system was launched to electronically route smaller orders to specialist posts where orders get executed at the end of the trading process. This system later was upgraded to what is known as the Super Dot, enabling more orders to be routed electronically. Traditionally, orders were routed to the market where traded stocks were listed. In 1978, NYSE was connected to other competing exchanges in the U.S., enabling dealers to access quotes offered in other markets for cross-listed stocks and to route their orders to any market that offers the best quote. During the 1990s, the market witnessed major expansions in network bandwidth to handle larger trading capacity, and also to accommodate modern sophisticated systems and the then-newly-introduced communication devices (Jain and Johnson, 2006).

[4] This is available at: http://www.nasdaqomx.com/whoweare/quickfacts/#.
[5] This is available at: http://corporate.nyx.com/en/who-we-are/history/new-york.

Despite introducing such advanced technological solutions, NYSE has preserved the full discretion that specialists have over trading,[6] and therefore cannot be considered as being a fully-automated market. While most of the trading process takes place electronically, trade execution is still dependent on human intervention. Trading is considered automated only when the actual matching of orders happens automatically through the trading systems. The turning point in NYSE happened in 2000, when it introduced its Direct+ system which could immediately execute limit orders of up to 1,099 shares. This feature was further augmented by the launch of the Hybrid Market system in 2006, which is capable of automatically executing orders of up to one million shares. The implementation of Hybrid was facilitated by the merger of NYSE with the giant electronic communication network (ECN) Archipelago earlier in 2006.[7]

There are a number of possible reasons why the NYSE is enriching its automatic execution options to market participants. Fast order execution by ECNs, along with competition from regional exchanges such as Boston, Chicago, and Cincinnati, pressured NYSE to adapt to new technologies (Freund and Pagano, 2000; Stoll, 2006). ECNs have changed the trading process dramatically as they have the ability to mediate trades between two *natural* investors whose orders can be paired off at minimal or zero spreads against a flat fee. This is in contrast to dealers who have an incentive to interfere with order matching and to engage themselves on one side of each trade. This may generate extra fees and unnecessarily widen spreads, which can adversely affect prices and execution speed.

[6] NYSE assigns only one specialist to each stock to handle all market-making activities for that stock. On the other hand, NASDAQ requires at least two dealers to make the market for each stock, with the number of dealers per stock ranging from 2 to 50 (Christie and Schultz, 1994).
[7] This is available at: http://www.nyse.com/about/history/timeline_events.html.

The anticipation for increased trading volume has also highlighted the importance of automated trading systems which can handle such operations more efficiently. Another important proposed reason behind the shift to the automated platform is that the Securities and Exchange Commission (SEC) has introduced the "Order Protection Rule" that protects better quotes in different markets only if these quotes are immediately accessible, something that can be guaranteed almost only by automated real-time systems (Hendershott and Moulton, 2011). Therefore, markets started to migrate increasingly to real-time systems to ensure that their quotes are accessible for all traders in other markets.

This revolutionary change in NYSE has possibly supported the position of traders by offering multiple trading venues and options, and simultaneously has limited the powers of specialists. In the presence of an automated system, orders going through specialists need not be executed necessarily at the specialist's discretion. The decreased monopoly power of specialists and floor brokers who trade on behalf of institutional investors is reflected in seat prices that have generally decreased in recent years (Stoll, 2006). Seat ownership represents the right to trade on the market floor. Therefore, falling prices of seats demonstrate the diminishing value of traditional trading methods.

These technological advancements have coincided with other changes in trading regulations and other aspects of market design, which may have further reduced trading costs and enhanced the agility and flexibility of the trading process. Three examples of such changes are discussed next. In 1997, NYSE reduced its minimum tick size to sixteenth instead of eighths, to eventually become one penny in 2000, an event that is commonly referred to as decimalization.[8] The removal of such artificial spread boundaries allows spreads to better adhere to fundamental spread determinants. Therefore, spreads may experience a decline after decimalization if larger tick sizes previously forced them to be unnecessarily wide. A number of studies (e.g., Bessembinder, 2003) find that spreads have significantly declined, and that investors have a higher probability of obtaining price improvements after decimalization.

The second example of regulatory change is the constant reduction of the minimum order size by the SEC. For instance, the minimum order entry size of a Mid-Point Passive Liquidity Order "MPL Order"[9] was reduced from 1000 to 100 shares in 2007, and further to one share in 2011.[10] 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. The reduction might also increase trading volumes, since odd-lot traders (small traders who trade less than 100 stocks) are no longer inhibited from frequently adjusting their holdings as desired.

Finally, while the number of individual specialists is relatively stable over time, the number of specialist firms to which specialists belong has shrunk from 67 in 1975 (Stoll, 2006) to only seven in 2011.[11] The clustering of specialist firms reflects the economies of scale inherent in this business, which may translate into reduced trading costs. This may explain the emergence of discount and deep discount brokerage services that offer

[8] This is available at: http://www.nyse.com/about/history/timeline_trading.html.
[9] 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: http://usequities.nyx.com/markets/nyse-arca-equities/order-types.
[10] This is available at: http://www.sec.gov/rules/sro/nysearca/2011/34-64523.pdf.
[11] This is available at: http://www.nyse.com/pdfs/specialistmagarticle.pdf.

standard trading services at a lower commission fee than that charged by regular brokerage firms.

In contrast to the NYSE, where specialists enjoy monopoly power in handling the order flow of their designated stocks, NASDAQ requires at least two dealers for each stock to handle its trade orders. This market structure is designed to foster competition among dealers, with the hope that this will result in reduced spreads and better services for traders. However, several academic studies (e.g., Christie and Schultz, 1994) show that spreads largely depart from the minimum tick size (one-eighth at that time), and that the inside spread for a large number of stocks is at least $0.25. These studies have uncovered lack of competition among dealers. It seems that NASDAQ dealers were coordinating to keep spreads artificially wide in order to maximize their profits at the expense of investors. This finding led NASDAQ administration to immediately take strict measures to force tighter spreads by urging dealers to stop avoiding odd-eights spreads. On May 24, 1994, NASDAQ officials met with dealers to communicate the new measures. Shortly afterwards, spreads dropped dramatically on the exchange (Christie *et al*., 1994).

This competition increasing action by NASDAQ was further augmented by a series of rules in 1997 that are aimed at increasing inter-dealer competition (Chung and Van Ness, 2001). The order handling rules (OHR), which were phased-in gradually for all NASDAQ stocks during the period from January 20, 1997 to October 13, 1997, intend to make the inter-dealer market more transparent and expose dealers to more competition. The OHR stipulates that market makers should disclose and make accessible limit orders offered by customers, so that any transaction should guarantee the best price available in the limit order book. Even in the case of “preferencing”, the arrangement should satisfy execution at the optimal price. The rule has also banned market makers from directly offering quotes to other dealers or special customers, as any offered quote should first be posted in an ECN, which makes quotes accessible to the public. These essential changes in NASDAQ are an example of important regulatory changes that fostered competition, and possibly increased liquidity.

3. LITERATURE REVIEW

This section presents findings from several studies about the impact of trade automation and other changes in financial market design on liquidity and other aspects of market quality. Although several studies investigate this effect, the evidence on this issue seems to be inconclusive. Two schools of thought can clearly be identified in the literature. One school documents a positive impact of automation on market quality, while the other school finds a negative net benefit from increased automation due to the deterioration in quality and increase in trading costs that have coincided with increased automation.

Domowitz and Steil (1999) construct a benchmark measure of trading costs that accounts for differences in trading characteristics across different U.S. markets. They find that costs are generally lower for trades executed by electronic systems than for those processed through traditional brokers. They also investigate the effect of automation on market structure and find that a number of market quality features have improved in the post-automation era, such as efficiency and contestability. For instance, cross-subsidization of trades, which is a practice of charging a higher price to a subset of investors in order to compensate for discounts offered to another subset of investors, is not as evident in an electronic versus traditional market. The rationale offered is that sustainability of prices in contestable markets impedes exchanges from offering discounted services to institutional investors (large trades) at the expense of retail investors (small trades), resulting in a more efficient pricing for market participants.

Stoll (2006) identifies three major benefits for electronic trading; namely, improved efficiency, increased liquidity, and accuracy of price signals. Although automated systems limit the powers and per trade profits of brokers and market makers, these systems still have the potential to indirectly benefit these intermediaries, because advanced markets attract more firm listings on the supply side and trading volume on the demand side. This increased activity more than offsets the decline in the "per unit" cost of trading. This is evident in the increase of total commissions paid by investors which increased from $4 billion in 1980 to $25 billion in 2011 (Li *et al*., 2007).[12]

Based on an event study using the implementation of Hybrid in NYSE, Gutierrez and Tse (2009) find a significant decrease in inventory control cost for specialists, and changes in effective spreads that range from statistically insignificant differences for trades of certain sizes to a significant average drop of $0.028 for large market orders.

Several studies observe similar effects from trade automation in an international context. For 43 countries including the U.S., Domowitz (2002) finds that electronic trading is associated with lower transaction costs. Frino *et al.* (1998) compare intra-day trading data for the Bund future contracts on both the automated Deutsche Terminborse

[12] This is available at: http://www.nyse.com/press/1330947043600.html.

(DTB) and the then-open-outcry London International Financial Futures Exchange (LIFFE), reporting that spreads are significantly tighter on the DTB. Frino *et al.* also conclude that automated exchanges provide more liquidity than floor-based exchanges, although the performance of automated exchanges deteriorates as volatility increases. Naidu and Rozeff (1994) and Sioud and Hmaied (2003) document a substantial increase in liquidity post-automation for the Singapore and Tunisian Stock Exchanges, respectively.

Jain (2006) finds that 75% of the switches from floor to automated market structures based on a study of 120 exchanges are associated with an improvement in liquidity and that this improvement is more pronounced in emerging than developed markets. The switch to automation reduces the cost of equity for listed firms by up to 0.49% per month. Jain argues that automation increases the popularity of stocks as investment vehicles, and that this increased demand reduces returns. Jain also argues that automated trading reduces the cost of equity due to reduced information asymmetry caused by the increased informativeness that automation conveys to stock markets.

The proliferation of alternative trading venues may also demonstrate the merits of automated trading. Recent years witnessed a significant rise for ECNs, through which trades are directly crossed among investors against a flat fee, avoiding the need for intermediaries (Conrad *et al.*, 2003). In addition to savings in commissions paid to intermediaries, investors enjoy smaller spreads through ECNs and better quote quality (Huang, 2002). The merger of both NYSE and NASDAQ with major ECNs (with Archipelago and Instinet, respectively) shows the increasing popularity of electronic trading in these two major U.S. markets (Stoll, 2006).

A series of studies dealing with the limitations of technology find that trading through electronic systems is more prone to interruptions because of possible technical glitches. Several stock market incidents are linked to technical problems. The "flash crash" on May 6, 2010, in which U.S. markets witnessed the biggest one-day decline, was attributed to programmed traders that blindly followed certain algorithms (Easley *et al.*, 2011). The tepid debut of Facebook's public trading on NASDAQ, which took place on May 18, 2012, is also attributed to a technical glitch that delayed trading to 11:30 am. Delayed trading and accumulation of pending orders allegedly increased uncertainty among investors and contributed to the plunge in share price to less than $35 from its initial price of $38 within the first hours of trading.[13]

Some studies report higher trading costs in automated versus floor-based trade venues. Venkataraman (2001) finds that trading costs on the automated Paris Bourse are higher than those on the traditional NYSE, especially in terms of effective spreads. Venkataraman concludes that the presence of a human interface is essential to enhance liquidity. However, findings from studies where trades are compared across different markets are only indicative, since it is challenging to account for all differences in regulations, insider trading laws, and firm characteristics across different trading venues (Jain, 2006).

Hendershott and Moulton (2011) study the effect of introducing Hybrid to the NYSE where they match NYSE and NASDAQ stocks that have similar characteristics to calculate the differences in spreads for each pair of stocks. The rationale for this methodological approach is to account for market-wide differences, so that such general

[13] This is available at: http://money.cnn.com/2012/05/20/technology/nasdaq-facebook-ipo/index.htm.

changes are not mistakenly taken to be the result of Hybrid. The authors find that spreads have widened on NYSE post-Hybrid due to compensation for increased adverse selection. They speculate that investors interacting through electronic systems have less trust due to the anonymous nature of trades. A possible problem with their approach is that the matching procedure that is intended to exclude seemingly market-wide *unrelated* changes might unwittingly exclude *genuine* Hybrid effects, since inter-market competition could spill-over Hybrid effects from NYSE to other markets, such as NASDAQ.

4. DATA AND MEASURES

To determine the impact of trade automation, we analyze the changes in stock characteristics around a major NYSE event. Some previous studies identify the effects of automation trends by tracking market expenditures on Information Technology (IT) (e.g., Freund and Pagano, 2000), but this approach may not result in an accurate identification of automation milestones. One reason why IT expenditures may not be a good measure of automation effects is that numerous changes in financial markets which possibly contributed to improved liquidity and build economies of scale in the trading industry may not be captured by IT investments. Nevertheless, there exist few well identified automation events that can be effectively examined. The reason is that some events have taken place gradually over a long period of time such as the consolidation of specialist firms or the events did not have a market-wide impact, such as regulations affecting only certain types of stocks or transactions.

One of the most important changes on NYSE is the adoption of direct exchange systems, such as Direct+ and Hybrid Market. Each of these two events affected *all* NYSE-listed stocks. However, the larger magnitude of Hybrid, which can handle orders of up to one million shares, makes this event more likely to affect system-wide market operations and is therefore a better candidate for study. NYSE rolled out the Hybrid system gradually between October 6, 2006 and January 24, 2007 (Hendershott and Moulton, 2011). The Hybrid four-month roll-out period is relatively short compared to automation events in other markets such as the implementation of the Computer-Assisted Trading System (CATS) on Toronto Stock Exchange that started in 1977 and continued for two decades before including all stocks.[14] The quick implementation of Hybrid reduces the probability that other exogenous factors contribute to any observed change during this period. Shortly after Hybrid came into effect, NYSE lost more than 60% of the trades from its floor to automated exchanges (Gutierrez and Tse, 2009).

To conduct our analysis our main dataset is obtained from the Center for Research in Security Prices (CRSP). The following daily data items are obtained for all stocks for the period from October 2003 to January 2010: closing price, maximum price, minimum price, trading volume, number of shares outstanding, closing bid and ask, and return. Daily Fama and French small-minus-big (SMB) and high-minus-low (HML), and Momentum (UMD) factors are also downloaded through Wharton Research Data Services (WRDS) for the studied period. Market volatility is proxied by the Volatility Index (VIX), whose daily closing values are obtained from the Chicago Board Options Exchange (CBOE) Website.

[14] This is available at: http://www.economywatch.com/stockexchanges/canadian.html.

Stock-day observations are deleted if the number of shares outstanding is unavailable, less than, or equal to zero; trading volume is unavailable or less than zero; minimum price is greater than maximum price; bid is greater than ask; minimum price, maximum price, bid, or ask are unavailable; price is less than $5; and quoted or effective spreads are greater than 30% of price. The latter rule is a common exclusion in the literature [e.g. Chalmers and Kadlec, 1998 (20%) and Zhang, 2010 (30%)] as these observations are extreme outliers. The elimination of "penny stock" observations is also a common practice, in order to ensure that results are not affected by very small stocks or bid-ask bounce of illiquid stocks (Fang and Peress, 2009). We also conducted the analysis with penny-stocks and wide-spread stocks included, but as there are no qualitative differences with the results presented herein they have been omitted in the interest of brevity.

Firm size (*SIZE*) is measured by the natural log of market capitalization value for each stock i at day t as: $SIZE_{i,t} = Log(PRC_{i,t} * number\ of\ shares\ outstanding_{i,t})$, where *PRC* is the closing price of a stock. We exclude observations with *SIZE* values of less than $10 million and larger than $100 billion. This rule resulted in excluding less than 1% of stock-day observations. Stocks are classified each day into deciles based on their *SIZE* values, where deciles 1 and 10 contain the smallest and largest stocks, respectively.

Liquidity is multidimensional in that it reflects trading quantity, trading speed, trading cost, and price impact (Liu, 2006). Since standard liquidity measures usually cover only one or two of these four dimensions, the choice of measure(s) depends on what is being studied**.** While depth (quantity of shares that are available for trade at a certain price), volume, and turnover measure liquidity from a trading quantity perspective, bid-ask spread (as the cost of immediate transactions) is frequently used when the cost side of liquidity is the focus of the investigation. Furthermore, measures based on microstructure data are generally more accurate than measures constructed from daily or monthly data. However, researchers frequently face a trade-off between the simplicity of a measure and the added benefits of using a more accurate one (Amihud, 2002). This tradeoff becomes particularly important when a study involves a long time horizon or if data are not readily available.

A comprehensive set of liquidity measures are used. Bid-ask spreads are one of the relevant liquidity measures for the purpose of this study. The hypothesized role of technology in reducing inventory control risk and order clearance costs is expected to be reflected in spreads if monopoly rents and the asymmetric component of the spread remain unchanged. Quoted, effective, and amortized spreads are used. Quoted Spread for stock *i* at day *t* ($QSPD_{i,t}$) is equal to $\left(ASK_{i,t} - BID_{i,t}\right)/MID_{i,t}$, where $ASK_{i,t}$ and $BID_{i,t}$are closing ask and bid quotes, respectively, for stock *i* at day *t*, and the stock midpoint ($MID_{i,t}$) is $\left(ASK_{i,t} + BID_{i,t}\right)/2$.

Effective spreads are also considered since they represent the *actual* cost incurred by traders. Chalmers and Kadlec (1998) mention that effective spreads are almost 50-70% of quoted spreads, and that the average correlation between them is 31%. Effective spreads are estimated using both the Gibbs estimator (*EGIB*) of Hasbrouck (2009)[15] and Corwin and Schultz (2011) approach (*ECOR*). These two estimation methods are argued

[15] Hasbrouck's approach is a Bayesian estimation of the Roll model (Roll, 1984) and produces estimations on annual frequency. The author argues that using monthly or weekly frequency results in unreliable estimations. I thank Joel Hasbrouck for offering the estimations for all CRSP stocks on his website.

to be very accurate and outperform other approaches. Corwin and Schultz method uses high-low price ratios, assuming that high (low) prices usually correspond to buy (sell) orders. The ratio represents both the bid-ask spread as well as the volatility of a stock. The volatility component of the ratio is proportionate to the interval of the ratio, while the bid-ask spread is constant regardless of the interval. Using these assumptions allows the authors to estimate effective spreads from ratios of one- and two-day intervals. Specifically, the estimation method proceeds as follows:

$$ECOR_{i,t} = \frac{2\,(e^{\alpha_{i,t}}-1)}{1+e^{\alpha_{i,t}}},$$

Where $$\alpha_{i,t} = \frac{\sqrt{2\beta_{i,t}} - \sqrt{\beta_{i,t}}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma_{i,t}}{3-2\sqrt{2}}};$$

$$\gamma_{i,t} = [\ln(\frac{MAX_{i,(t\rightarrow t+1)}}{MIN_{i,(t\rightarrow t+1)}})]^2;$$

$$\beta_{i,t} = [\ln(\frac{MAX_{i,t}}{MIN_{i,t}})]^2 + [\ln(\frac{MAX_{i,t+1}}{MIN_{i,t+1}})]^2;$$

MAX (MIN) is the maximum (minimum) price;

and *t* and *t+1* refer to the day index.

While effective spreads are found for specific transactions with investors having different horizons, amortized spreads incorporate the stock holding period to represent the cost for a *typical* investor. Chalmers and Kadlec (1998) show that a stock's amortized spread is approximately equal to its effective spread multiplied by annual turnover. Price impact measure ($Amihud$) is considered (Amihud, 2002), where $Amihud_{i,t}$ equals to $\frac{Trading\ Volume_{i,t}}{|Return_{i,t}|}$. The original price impact measure is inversed to represent liquidity rather than illiquidity. Lesmond *et al*. (1999) construct a simple liquidity measure (*Zeros*) that is also used in this study. The measure is obtained by dividing the number of zero-return days in a month by the number of trading days in that month. This measure is designed to estimate transaction costs, based on an assumption that investors are deterred from trading when transaction costs are higher than expected return resulting in zero return for that day.

A number of daily firm-level and market-level controls are used in testing the impact of the event on liquidity. Firm-level controls include *SIZE*; turnover (*TO*), which is the daily number of shares traded, divided by the number of shares outstanding; and *PRC*. In their test for the Hybrid effect, Hendershott and Moulton (2011) include daily differences for a number of stock-level data items. The inclusion of these differences accounts for any effect that daily shocks might have on the liquidity level for stocks. In this study, daily differences for price (*PRCDIF*) and turnover (*TODIF*) are considered for each stock *i* at day *t*. Specifically:

$$PRCDIF_{i,t} = \frac{PRC_{i,t} - PRC_{i,t-1}}{PRC_{i,t}}$$

$$TODIF_{i,t} = \frac{TO_{i,t} - TO_{i,t-1}}{TO_{i,t}}$$

Market-level controls include *RETYesterday*, *RETToday*, and *RETTomorrow*, which refer to daily equally-weighted averages of market returns at days *t-1*, *t*, *and t+1*, respectively. Brockman *et al*. (2009) include these three terms in examining changes in liquidity. Finally, market volatility is included in the test specification as a control for market general activity. Volatility is proxied by the closing value of the Volatility Index for the market for each day *t* (*VIX*).

For the purpose of the asset pricing test, we include market excess return (*MKT*), small-minus-big (*SMB*), high-minus-low (*HML*), and momentum (*UMD*) factors, which are all available on a daily frequency. However, no liquidity factor, such as that of Pastor and Stambaugh (2003) or Sadka (2006), is available on a daily basis. Therefore, simple daily liquidity factor (*LIQFAC*) and level liquidity measure (*LIQLEV*) are constructed. The daily *LIQFAC* is constructed in the following manner. First, stocks are sorted into deciles daily based on their *QSPD* values. For each decile, the equally-weighted average market return is calculated for each day. The difference between the averages of deciles 10 and 1 is found, and considered to be the liquidity factor for that day. On the other hand, *LIQLEV*, which is calculated daily for each stock based on one of the liquidity measures at a time, equals the liquidity measure value minus the daily market average of that measure. This construction method is similar to that used by He and Kryzanowski (2006).

Descriptive statistics and univariate analysis are presented next. Proportions of stocks with declining *QSPD*/*ECOR* in each *SIZE* decile are plotted in Figures 1.A and 1.B for NYSE and NASDAQ sub-samples, respectively. Figure 1.A shows that at least 80% of the stocks in each of the smallest five deciles enjoyed tighter quoted spreads post-Hybrid. The figure is decreasing monotonically in *SIZE* after that. The trend is not as obvious with *ECOR*. Results for NASDAQ stocks in Figure 1.B shows that the number of stocks with declining *QSPD* is less than that on NYSE, but numbers are also smaller for larger deciles. The first four columns of Table 1 present average proportional *QSPD* and

ECOR. Figures show that, by and large, spreads are tighter on NYSE than NASDAQ, especially for small stocks. Large stocks however, enjoy tighter spreads on NASDAQ. The last four columns of the table present mean and median changes in *QSPD* and *ECOR*. Average *QSPD*, *ECOR*, and *SIZE* decile have been found for each stock before and after Hybrid. Averages from the two periods have been matched for each decile. Then changes are calculated based on the difference in spreads in the year following Hybrid implementation from the year preceding that. Results from *QSPD* and *ECOR* are different. Results that are based on *QSPD* show that the amount of reduction is almost monotonically decreasing in *SIZE* deciles, with mean (median) changes for NYSE stocks of -24.58% (-23.84%) and 56.1% (44.87%) in deciles 1 and 10, respectively.

In addition to that, stocks have been sorted into *QSPD*-based deciles on a daily basis, where decile 1 (10) corresponds to the smallest (widest) spread stocks which have the highest (lowest) level of liquidity. The percentage of smallest 30% stocks out of all stocks in each *QSPD* decile has been calculated, for the year preceding the Hybrid and the year subsequent to it, separately. The analysis has been made for the CRSP sample as well as NYSE and NASDAQ sub-samples. Results, which are presented in Table 2, show that the percentage of small stocks that have high levels of liquidity has increased while the percentage of small stocks that have low levels of liquidity has decreased post-Hybrid. This pattern is more apparent in NYSE than in NASDAQ sub-sample. This result gives an indication that the association between size and liquidity of stocks might have decreased in recent years.

5. HYBRID'S IMPACT ON LIQUIDITY: HYPOTHESES AND EMPIRICAL EVIDENCE

5.1 Unconditional Test

As reviewed above, stock trading venues have undergone continual major innovations in technology and regulations. This continuous modernization process, which coincided with an ongoing trend for consolidation in the financial services industry, helped to centralize and facilitate the process of trading and supply of liquidity (Lhabitant *et al.*, 2008). On balance, the evidence on the effect of trade automation on liquidity and other market quality aspects supports positive benefits from trade automation. However, it is important to formally test the following hypothesis about the general impact of automation on liquidity before moving to subsequent tests.

$$H_0^1: Trade\ automation\ has\ no\ direct\ effect\ on\ the\ liquidity\ of\ stocks.$$

$$H_A^1: Trade\ automation\ improves\ the\ liquidity\ of\ stocks.$$

In order to test this hypothesis, we regress liquidity measures on a dummy variable ($Event$) and a set of control variables. Specifically:

$$LIQ_{i,t} = \alpha + \beta\ Event_t +\ \gamma_{VIX} VIX_t + \gamma_{RETYesterday} RETYesterday_t +\ \gamma_{RETToday} RETToday_t + \gamma_{RETTomorrow} RETTomorrow_t + \delta_{SIZE} SIZE_{i,t} + \delta_{PRC} PRC_{i,t} + \delta_{PRCDIF} PRCDIF_{i,t} + \delta_{TO} TO_{i,t} + + \delta_{TODIF} TODIF_{i,t} +\ \sum_{m=1}^{9} \lambda_m\ Dummy\ Interaction_{i,m,t} + \varepsilon_{i,t}, \qquad (1)$$

where $LIQ_{i,t}$ refers to one of the seven liquidity measures presented above of stock i on day t; $Event_t$ is a dummy variable that takes the value of 1 (0) if day t is after (before) the implementation of Hybrid. In addition to $Event$ and control variables, we include $Dummy\ Interaction$ variables which are the interaction of $Event$ with each of the controls in order to capture changes in the explanatory power of these controls subsequent to migration to Hybrid. The test is conducted using observations for two years centered on the event that do not include observations during the event's roll-out period. In October 2006, NYSE started to move stocks to Hybrid. By the end of January 2007, all NYSE stocks had migrated to the new system. Therefore, observations corresponding to this period are excluded. Observations used are for the year preceding the Hybrid (October 2005 to September 2006) and the year subsequent to its implementation (February 2007 to January 2008). The choice of the two years centered on the roll-out period is made partly to avoid the effects that the credit crisis had on equity markets when testing the Hybrid, as the crisis weighed heavily on stock markets during 2008. Qualitatively similar results are obtained when the window is increased to four years. The fixed-effects regressions employ a generalized least squares method where standard errors are adjusted for time- and firm-level clustering as suggested by Peterson (2009). This is based on the Hausman test results which suggest that a fixed effects model produces more efficient estimates than a random effects approach. The Hausman test is conducted for all the variations of Equation 1 and Equation 2 (section 7) with similar results for both models. Equation 1 is estimated for three groups of stocks: CRSP sample, NYSE, and NASDAQ sub-samples. If βs take negative values, then it means that liquidity has improved post-event, hence H_0^1 can be rejected.

Table 3 presents results for estimation of Equation 1. For the CRSP sample results which are presented in Panel A of the table, coefficients of $Event$ dummy (β) have statistically-significant values with conforming sign for all liquidity measures except for $AGIB$, $Amihud$, and $Zeros$. Among spread measures, direct reduction in spreads ranges from 0.18 to 0.8 basis points (BPS) in *EGIB* and *QSPD*, respectively. Examining results for NYSE and NASDAQ sub-samples separately, however, uncovers that the reduction is not confined to NYSE (the event venue) only when some liquidity measures are used. While *QSPD* and *Zeros* shrank for NYSE stocks only, *ECOR* reduction at NASDAQ is double the reduction at NYSE. NASDAQ stocks also experienced a sizeable reduction of almost 5 BPS in *ACOR*.[16]

An alternative testing approach for event studies such as these is to ignore the period immediately following events. This test design is based on the argument that changes might require long periods of time to show effect. Jain (2006) examines the switch from floor trading to electronic trading in 120 countries, he allows a transition period of one year subsequent to changes "for popularity of electronic exchanges". Edwards *et al.* (2007) study the effect of the implementation of the Trade Reporting and Compliance Engine (TRACE) system in the bond market in the U.S.. They also exclude observations during the six months following the implementation of the system in order "to allow market participants time to familiarize themselves with the system". Therefore, Equation 1 is re-estimated using a two-year window as well, but allowing a transitory period following the roll-out period. Observations during this transitory period are excluded from the test and replaced by observations of the year following it. Different transitory periods are used: three months, six months, and one year. Results are untabulated to conserve space, but they are generally in the same direction as those

16 NYSE-NASDAQ dual listing has been allowed in 2004. For robustness, I exclude observations pertaining to dual-listed firms and retest Hypotheses 1 and 2. Results are unaffected by this elimination. Exclusion includes observations of all dual-listed stocks as of November 2006. These stocks are: Apache Corporation, Walgreen Co., American Financial Group, Inc., Chicago Mercantile Exchange Holdings, Ivanhoe Mines Ltd., Harmony Gold Mining Co. Ltd., Nuveen Equity Premium Advantage Fund, Nuveen Equity Premium Income Fund, Nuveen Equity Premium Opportunity Fund, Calamos Strategic Total Return Fund, and First Trust/Aberdeen Emerging Opportunity Fund (Hedge *et al*. 2010).

presented in Table 3 in that improvement in liquidity is not consistent across liquidity measures and that improvement is witnessed for both NYSE and NASDAQ sub-samples.

5.2 Size-conditioned Test

This section investigates whether the obscure evidence from the unconditional test is due to the aggregate nature of the test. Stratifying the sample into *SIZE* deciles might reveal a pattern in liquidity changes. Table 3 shows that some of the *SIZE* interaction terms are associated with significant coefficients especially for NYSE sub-sample, which alludes to the possibility that firm size played a role in explaining the cross-sectional differences of the Hybrid impact.

The basis for this conjecture is made by an analogy with findings in administrative sciences demonstrating that technology through standardization plays an important role in enabling economies of scale in industries (e.g., Douglas and Wind, 1987). Financial markets in competitive economies, such as that of the U.S. and other developed countries, offer transaction services and financial products to traders, who can be considered as consumers (Domowitz and Stein, 1999). Advanced technological solutions are transforming the business model of a traditional stock exchange that offers a bundle of services for each trade. Competition from ECNs and online service providers are forcing exchanges to eliminate their non-essential services and maintain their core business units only (i.e., trade execution, quote and price server, and stock hosting). The exchanges are finding it more efficient to outsource supporting services to specialized firms that can offer such services at lower cost. As a result, modern exchanges resemble utility firms that can operate very efficiently at a low profit margin. Thus, exchanges that adopt modern technologies are able to handle larger trading capacity more efficiently than their less technologically-advanced counterparts. The relatively fixed cost of automated trading platforms makes the direct variable cost "per unit" of trading negligible, as long as automated systems have enough capacity to execute additional trades.

Reductions in trading costs are expected to be reflected in both explicit and implicit trading costs (Stoll, 2006). Explicit costs include brokerage fees, commissions, and trading loss due to the effective bid-ask spread. The automation of trading platforms along with the disintermediation process due to the reduction in the number of intermediaries through which a trade order passes results in less fees and commissions borne by traders. Electronic trading systems do not require traders to report physically to trading floors. In an electronic market, traders can remotely trade and contribute to the supply of liquidity in a more effective manner than in a traditional floor-trading system. Automated systems also allow foreign investors to enter markets, causing even more competition among suppliers of liquidity. In addition, the automatic execution of orders eases the *monopoly of dealers*, reduces *clearing cost* (particularly in the presence of a consolidated national book of orders), offers higher opportunities to clear outstanding orders, which relieves dealers from part of the *inventory risk*. All of these are important components of the bid-ask spread (Glosten and Harris, 1988). Implicit costs include the cost of delay between order entry and order execution, which is largely alleviated by automated trading.

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 a separate field, economists have formulated what is known as the "catch-up" or "convergence" effect (Abramovitz, 1986). Researchers observe a tendency for less developed economies to grow at a faster rate than more developed economies as they "catch-up". 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.

This hypothesis incorporates the conjecture that recent changes in financial market design offer *different relative benefits to stocks differentiated by their size*. Specifically, the conjecture is that the liquidity of small stocks has benefited most from trade automation systems.

H_0^2: $Trade\ automation\ results\ in\ similar\ liquidity\ improvement\ to\ all\ stocks\ regardless\ of\ their\ size.$

H_A^2: $Trade\ automation\ results\ in\ more\ pronounced\ liquidity\ improvement\ for\ smaller\ versus\ larger\ stocks.$

To test this hypothesis, Equation 1 is estimated for each *SIZE* decile individually rather than for the entire groups of stocks. Coefficients across deciles are compared and statistically-tested for differences among them. This involves testing pairs of coefficients for differences between their values. Computed statistics are based on the asymptotic chi-square distribution of the likelihood ratio statistic. Table 4 contains results for estimating Equation 1 for each *SIZE* decile individually, for CRSP sample (Panel A), NYSE (Panel B) and NASDAQ (Panel C) sub-samples. For brevity, we present results for the coefficient estimates of *Event*, *SIZE*, and *SIZE Interaction* only. Results for the CRSP sample shows that statistically-significant improvements in liquidity are concentrated in smaller stocks, with some exceptions. For instance, *ECOR* (*ACOR*) has reduced for decile 2 (1) only. The reduction in *QSPD* is probably most aligned with our hypothesis, as reduction is almost monotonically decreasing in deciles. Spreads measured by *AGIB* have actually widened for stocks in deciles 4, 6, 7, and 10. In terms of *Amihud*, however, there is evidence that smaller stocks (deciles 1, 3, 4, and 6) have experienced more deterioration in liquidity. In addition, *EGIB* seems to be reduced for decile 9 only.

Results presented in Panel B of Table 4 show that unlike the rest of the stocks, small NYSE stocks (decile 1) have experienced a decline in terms of the two amortized spreads measures; *ACOR* and *AGIB*. The coefficients of effective spreads measures show that large stocks (decile 9) only have experienced the decline which is contradictory to our hypothesis. In addition, results for *Amihud* show that the liquidity of smallest 20% of stocks has deteriorated. Improvement in terms of *QSPD* and *Zeros* is limited to middle size stocks (deciles 3, 5, 6, and 7). Panel C shows a different pattern for NASDAQ stocks. Small (large) stocks experienced liquidity improvement in terms of *ACOR* and *Zeros* (effective spreads).

According to the previous results, H_0^2 can be rejected for the NYSE sub-sample when liquidity is measured by amortized spreads only. The overall evidence underscores the important role that *SIZE* seems to play in differentiating the Hybrid's impact on liquidity, which can be witnessed from statistical differences among βs across deciles in Table 4 and significant values associated with *SIZE Interaction* terms in Table 3.

However, the evidence does not seem to be specifically in favor of our hypothesis regarding the distribution of the relationship across *SIZE* deciles. Also, despite controlling for many possible factors, it is still unclear whether the differences across deciles can be attributed to size per se or to other correlated factors. Nevertheless, we can conclude that Hybrid did not impact all stocks in the same fashion, and this fact might be behind the controversy of the literature examining the impact of automation on market quality.

6. THE RELATIONSHIP BETWEEN SIZE AND LIQUIDITY: HYPOTHESIS AND EMPIRICAL EVIDENCE

Small stocks have realized a higher average return than larger stocks, even after adjusting returns for risk. However, 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" (Banz, 1981). Various theories are proposed to explain the so-called "small size puzzle". One such explanation involves greater liquidity and transaction costs. This line of research finds that the abnormality in small stock returns can be explained at least partially by larger transaction costs due to the relatively illiquid nature of such stocks. In other words, liquidity which is highly correlated with firm size is a partial explanation for the puzzle.

Stoll and Whaley (1983) investigate the small size issue and find that the abnormal return observed for small stocks merely represents the difference of trading costs between small and large stocks. Stoll and Whaley consider returns from the investor perspective net of transaction costs. Assuming that investors incur a round trip cost each quarter, they find that the size effect has disappeared. Amihud and Mendelson (1986) incorporate the holding period and clientele effect in addition to trading costs and conclude that firm size is a proxy for liquidity. In more recent evidence, Pastor and Stambaugh (2003) find that portfolios of small size have the highest loadings on the liquidity factor based on their liquidity-augmented pricing model. This reasoning implies that the interaction between size and liquidity effects has obscured the way through which each of these two factors affect returns.

If the former argument that the size effect partly represents a liquidity premium, then any liquidity-affecting mechanism is expected to have some bearing on the size effect. Observing a reduction in the size effect after an important automation event would lend credence to the liquidity and transaction costs explanations for the size effect in returns. In fact, a number of studies (e.g., Chan *et al*., 2000; Dimson and Marsh, 1999) empirically document a reduction in the size effect in the recent period. Another channel by which technology may reduce the size effect is in the context of market informativeness about stocks. Merton (1987) finds that less well-known (usually small) stocks have higher expected returns. If advanced trading methods help disseminate information about small firms, possibly through available electronic order books, then this may increase both the breadth and depth of investor cognizance about small stocks. In turn, this would result in smaller size premiums. If small stocks have benefitted more from trade automation than larger stocks, then we are interested in whether the liquidity of a stock has become less dependent on its size subsequent to automation. Therefore, the change in relationship between liquidity and size is investigated by this hypothesis.

$$H_0^3: Automation\ did\ not\ affect\ the\ relationship\ between\ liquidity\ and\ size.$$

H_A^3: *Liquidity of stocks has become less dependent on size after automation.*

Figure 2 plots monthly average Pearson correlation values between *SIZE* and both *QSPD* and *ECOR*. The figure clearly shows that the correlation is generally decreasing during and subsequent to Hybrid, specifically for NYSE stocks. In order to formally test Hypothesis 3, we observe the coefficient of the *SIZE* interaction term ($\lambda_{Event*SIZE}$) from Equation 1, which can be interpreted as the change in the contribution of the firms size to the liquidity of their stocks from the pre-Hybrid level, represented by the *SIZE* coefficient (δ_{SIZE}). Panel A of Table 4 presents results for *SIZE* deciles for the CRSP sample. Most of the interaction coefficients lack statistical significance. However, coefficients for decile 1 are associated with significant positive values for quoted spreads, amortized spreads, and zeros measures, which counters the negative relationship between size and liquidity, indicating that these very small stocks are less penalized by illiquidity in the subsequent period. Results are also in the same directions for stocks in decile(s) 2 (3 and 5) for the zeros (quoted spreads) measures. A number of significant negative values are scattered across deciles 2 to 10. Results for the NYSE sub-sample (Panel B) shows that H_0^3 can be rejected for decile 1 stocks when amortized spreads measures are used only. The hypothesis can also be rejected for medium size stocks (deciles 4 to 8) using other liquidity measures. Results for the NASDAQ sample (Panel C) also do not show a discernible pattern.

7. ASSET PRICING IMPLICATIONS: HYPOTHESIS AND EMPIRICAL EVIDENCE

The evidence from the previous section indicates a changing relation between size and liquidity. This is interpreted as indirect evidence that trade automation has succeeded, to some extent, in disentangling the liquidity and size attributes of stocks. We further extend the investigation to examine the impact from an asset pricing perspective by assessing any effect automation could have on the different parameters that the asset pricing literature finds relevant in explaining stock returns. To put this in a more precise way; if automation has "purified" the size effect, does the size effect continue to have the same impact on stock pricing? Or it has lost a portion of its effect that corresponds to the dislinked liquidity component? The hypothesis is as follows:

H_0^4: $Automation\ did\ not\ change\ the\ explanatory\ power\ of\ the\ size\ factor$

$on\ asset\ pricing.$

H_A^4: $Automation\ reduced\ the\ explanatory\ power\ of\ the\ size\ factor\ on$

$asset\ pricing.$

If market changes succeed in decreasing the relationship between liquidity and size effects, then the latter as represented by the SMB factor is expected to have less explanatory power for returns. This assumes that the size effect captures part of the liquidity premium. To test this conjecture, the four-factor model of Carhart (1997) is employed, augmented by $LIQFAC$ and $LIQLEV$ in order to examine factor and level effects of liquidity. According to He and Kryzanowski (2006) and Luo and Sadka (2011), liquidity has two channels through which it affects equity returns; level effect and sensitivity effect. On a priori basis, the level effect is expected to be more relevant for this test, since it directly captures changes in the infrastructure costs of trading attributable to automation events. Nevertheless, it is important to account for the sensitivity component. Hence, both measures are included in the model. The model also includes six *Dummy Interaction* terms, which are the interaction of *Event* with each of the independent variables. The used model has the following form:

$$RET_{i,t} = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \beta_{LIQFAC}LIQFAC_t + \beta_{LIQLEV}LIQLEV_{i,t} + \sum_{m=1}^{6} \lambda_m \, Dummy\ Interaction_{i,m,t} + \varepsilon_{i,t} \qquad (2)$$

Equation 2 is estimated for the CRSP sample as well as the NYSE and NASDAQ sub-samples. In addition, the equation is estimated for each *SIZE* decile individually in each of the three samples. Coefficients are estimated using the generalized least squares method where standard errors are adjusted for time- and firm-level clustering as suggested by Peterson (2009). The coefficients of $SIZE_{i,t}$, $LIQFAC_t$, and $LIQLEV_{i,t}$ are compared across deciles. As mentioned above, Pastor and Stambaugh (2003) have observed that small stocks tend to have the highest loadings on the liquidity factor. We examine whether this phenomenon continues to be the same post-event or not. For the sake of robustness, this test is conducted a number of times using different horizons around events, as any impact on pricing explanatory factors might require long periods of time to materialize.

Panel A of Table 5 presents results for estimating Equation 2 for the CRSP sample. Consistent with Hypothesis 4, *SMB interaction* terms across all liquidity measures are associated with significant negative loadings, indicating that the SMB factor lost part of its explanatory power. This allows us to reject H_0^4 with 99% confidence level. Results for the NYSE sub-sample (Panel B) show that changes in the SMB factor loadings remain negative but they lose their statistical significance. NASDAQ sub-sample results (Panel C) are also insignificant but mixed on signals. Results are similar when the window is reduced to two years, which indicates that the results for the four-year window are not materially affected by the credit crisis in 2008. When the window is increased to six years, the NYSE sub-sample results show reductions in the SMB factor loadings that are significant at the 10% level, whereas changes remain insignificant for the NASDAQ sub-sample. Extended results for individual $SIZE$ deciles of the CRSP sample are presented in Panel A of Table 6. The reduction in the SMB factor power is isolated in the smallest 2 and largest 3 deciles, with the most pronounced reduction for smallest stocks in decile 1. Findings are similar for the NYSE and NASDAQ sub-samples, whose results are presented in Panels B and C, respectively.

To extend the Pastor and Stambaugh (2003) analysis about the association of small size stocks with high loadings on the liquidity factor, we observe changes in liquidity factor loadings in Equation 2. Aggregate sample results in Table 5 show that the $LIQFAC\ interaction$ terms are associated with significant positive values, indicating that liquidity risk exposure has generally increased after Hybrid. The increase is even more pronounced for the NYSE sub-sample. NASDAQ sub-sample results, however, show that liquidity risk has in fact decreased. In untabulated results, changes in $LIQFAC$ coefficients show that increases are more concentrated in smaller stocks in NYSE, whereas the decreases are scattered across most of the deciles in NASDAQ.

8. CONCLUSION

The purpose of this study is to examine the effect of trade automation and other recent changes in financial market design on stock characteristics. The study also investigates whether trade automation has offered similar advantages to stocks regardless of their size, a factor that seems to be overlooked by most of studies that have examined the effect of trade automation. The conjecture tested is that small-size stocks have benefited the most and that liquidity improvement is a negative function of size. This result implies that liquidity is becoming less dependent on size and that technology, along with other changes in market design, are disentangling these two factors that used to be more closely related in a traditional market setup. This paper has asset pricing implications as automation has a differential impact on liquidity for firms of different sizes.

The impact of trade automation on stocks listed on NYSE is tested by examining the impact of the implementation of the Hybrid system on various liquidity aspects. Orders containing up to one million shares can be executed electronically through Hybrid. The system has been gradually activated between October 2006 and January 2007. Tests have also been applied to NASDAQ stocks as a control group for robustness purposes. The relatively short implementation period of Hybrid and the use of control variables in the test specifications reduce the probability that exogenous factors contributed to the observed effect. This possibility however is not eliminated, and findings are attributed to automation based on the assumption that no other factor has a significant contribution to changes.

Findings can be summarized as follows. Liquidity has generally improved after the implementation of the Hybrid, and this improvement is more pronounced for smaller stocks for some liquidity measures only. The relation between size and liquidity changed post-Hybrid, especially for NYSE stocks. The size effect in asset pricing significantly decreased post-Hybrid for the CRSP sample, but we do not find evidence on that when the NYSE and NASDAQ sub-samples are tested individually. Also, there is evidence that NYSE small stocks are recently becoming more prone to liquidity risk.

While the test involves a NYSE event, hypothesized phenomena are also present in NASDAQ to varying extents. Competitive spill-over effects can be one possible reason for that. Other markets, such as NASDAQ, might be forced by competition to react to such an event in a similar way to that of NYSE. But the magnitude of the similarity of results between NYSE and NASDAQ might point at other possible explanations. In addition, the findings are not consistent across all liquidity measures. Finally, despite the use of multiple controls, we are not completely certain that the observed changes are a direct result of Hybrid, and not a consequence of some other factor(s).

The study could be further improved by using transaction-level data. This would allow for the development of finer liquidity measures and for the decomposition of spreads into their basic components. This can help, for instance, to exclude the information asymmetry component of spreads, which is thought to be adversely reacting to automation (Hendershott and Moulton, 2011). Transaction-level data would also allow focusing on specific transactions that are more affected by changes than others. For example, the Direct+ system processes small orders of less than 1,099 shares. One can examine transactions involving only such orders. Also, examining ECN transactions could also add further insight into this investigation. Finally, obtaining access to the transaction history of a brokerage house can possibly reveal actual behavior of brokers towards small stocks after such automation events. Nevertheless, we argue that this study has an important contribution to the literature. Studies in this area tend to assume that changes in market design are like a rising tide that lifts all boats. This study identifies an important issue that needs to be considered; namely, stocks are affected differently by market changes based on their *individual characteristics*, such as size.

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Table 1: Univariate analysis for changes in spreads

Univariate analysis for changes in both quoted spreads (*QSPD*) and effective spreads based on Corwin and Schultz (2011) estimation method (*ECOR*), after the implementation of the Hybrid system on the NYSE, for the entire CRSP sample as well as NYSE and NASDAQ sub-samples. Statistics are also presented for each size decile individually for NYSE and NASDAQ sub-samples, where decile 1 (10) contains smallest (largest) stocks. Stocks are assigned to their size deciles based on their pre-Hybrid average size decile. The first four columns contain average *QSPD* and *ECOR* both before and after Hybrid. In the next four columns, percentage change in spreads are presented, defined as the average spread of the post-Hybrid year minus the average spread of the pre-Hybrid year, divided by the pre-Hybrid average, and multiplied by 100 to obtain percentages. Observations during the Hybrid roll-out period (October 2006 to January 2007) are excluded. Significance levels are indicated by *, **, and *** which denote significance at 10%, 5%, and 1% levels, respectively.

Market		Average proportional spreads in percentages				Percentage change in spreads			
		QSPD		*ECOR*		*QSPD*		*ECOR*	
		Pre-Hybrid	Post-Hybrid	Pre-Hybrid	Post-Hybrid	Mean	Median	Mean	Median
CRSP - 5704 Stocks		0.473	0.492	0.651	0.739	8.51***	0.66	42.98***	18.61***
NYSE - 2543 Stocks		0.249	0.229	0.471	0.613	11.15***	-1.02	85.06***	45.09***
NYSE – By *SIZE* Deciles	**1**	0.662	0.488	0.213	0.275	-24.58***	-23.84***	18.12***	10.33***
	2	0.563	0.428	0.305	0.415	-22.37***	-29.23***	19.98***	7.179***
	3	0.506	0.406	0.411	0.530	-21.8***	-26.22***	16.96***	5.3***
	4	0.394	0.326	0.490	0.646	-22.3***	-26.89***	40.62***	16.18***
	5	0.318	0.286	0.501	0.657	-16.24***	-22.98***	51.77***	25.43***
	6	0.269	0.237	0.540	0.721	-10.3***	-15.67***	59.32***	37.77***
	7	0.194	0.202	0.550	0.711	2.96	-9.02***	80.24***	62.23***
	8	0.144	0.173	0.541	0.670	15.91***	10.88***	76.65***	66.96***
	9	0.108	0.141	0.469	0.593	36.43***	36.43***	104.89***	87.63***
	10	0.075	0.111	0.465	0.583	56.1***	44.87***	176.03***	140.27***

Table 1 – Continued

Market		Average proportional spreads in percentages: *QSPD* Pre-Hybrid	*QSPD* Post-Hybrid	*ECOR* Pre-Hybrid	*ECOR* Post-Hybrid	Percentage change in spreads: *QSPD* Mean	*QSPD* Median	*ECOR* Mean	*ECOR* Median
NASDAQ - 2547 Stocks		0.647	0.702	0.873	0.941	6.52%***	1.81%**	5.87%	3.5%***
NASDAQ – By *SIZE* Deciles	**1**	1.84	2.25	0.878	0.825	17 ***	8.52**	-13.58***	0.24
	2	1.15	1.19	0.833	0.974	0.56	-10.76***	-4.8	1
	3	0.63	0.74	0.955	0.974	1.57	-2.51	23.95	2.48
	4	0.36	0.42	1.009	1.108	-4.52**	-7.82***	28***	26.9***
	5	0.27	0.31	0.932	1.102	-4.11**	-7.36***	28.89***	33.34***
	6	0.20	0.23	0.866	0.979	0.62	0.14	20.16*	14.34
	7	0.15	0.16	0.794	0.842	5.28**	7.46**	-19.11	3.24
	8	0.10	0.14	0.741	0.761	12.15***	11.31***	-21.63	-15.3
	9	0.09	0.12	0.682	0.684	34.81***	33.68***	-47.19*	-22.13
	10	0.04	0.07	0.622	0.672	70.15***	72.31***	28.80	37.54

Table 2: Percentage of small stocks across quoted spread deciles

Percentage of small stocks across quoted spread (*QSPD*) deciles. Stocks have been sorted into *QSPD* deciles on a daily basis, where decile 1 (10) corresponds to the smallest (widest) spread stocks. The percentage of smallest 30% stocks in each decile has been calculated for the year preceding Hybrid (Pre-event: October 2005 to September 2006) and the year subsequent to it (Post-event: February 2007 to January 2008), separately. The analysis has been made for the CRSP sample as well as NYSE and NASDAQ sub-samples.

QSPD	**CRSP sample**		**NYSE sub-sample**		**NASDAQ sub-sample**	
decile	**Pre-Hybrid**	**Post-Hybrid**	**Pre-Hybrid**	**Post-Hybrid**	**Pre-Hybrid**	**Post-Hybrid**
1	2.20%	3.62%	0.90%	2.00%	3.51%	3.00%
2	2.70%	7.25%	1.50%	4.55%	2.45%	5.17%
3	7.98%	10.83%	5.01%	6.70%	6.91%	8.26%
4	11.52%	14.41%	7.21%	8.79%	10.80%	10.90%
5	17.97%	17.94%	12.47%	11.67%	16.00%	13.84%
6	22.71%	21.54%	16.51%	15.69%	19.94%	16.98%
7	30.57%	29.39%	23.84%	22.72%	30.00%	26.15%
8	47.06%	45.41%	36.30%	34.84%	50.44%	45.87%
9	69.62%	65.88%	54.21%	47.20%	74.19%	70.60%
10	87.63%	83.70%	61.42%	47.64%	93.03%	90.06%

Table 3: Estimation of equation 1

Results for estimating Equation 1:

$$LIQ_{i,t} = \alpha + \beta\, Event_t + \gamma_{VIX}VIX_t + \gamma_{RETYesterday}RETYesterday_t + \gamma_{RETToday}RETToday_t + \gamma_{RETTomorrow}RETTomorrow_t + \delta_{SIZE}SIZE_{i,t} + \delta_{PRC}PRC_{i,t} + \delta_{PRCDIF}PRCDIF_{i,t} + \delta_{TO}TO_{i,t} + \delta_{TODIF}TODIF_{i,t} + \sum_{m=1}^{9} \lambda_m\, Dummy\ Interaction_{i,m,t} + \varepsilon_{i,t}$$

Where $LIQ_{i,t}$ refers to one of the seven liquidity measures used, for each stock *i* at day *t*: quoted spreads (*QSPD*), effective spreads based on both Corwin and Schultz (2011) estimation method (*ECOR*) and the Gibbs estimator (*EGIB*) of Hasbrouck (2009), amortized spreads (*ACOR* and *AGIB*) based on the two estimations of effective spreads, Amihud's price impact measure (*Amihud*), and the Zeros measure (*Zeros*) of Lesmond *et al*. (1999). Each of these liquidity measures are regressed on *Event*; a dummy variable that takes the value of 1 (0) after (before) the implementation of Hybrid, and a set of nine control variables. Control variables are: daily closing volatility index value *VIX*; *RETYesterday*, *RETToday*, and *RETTomorrow* which refer to equally-weighted average market returns at days *t-1*, *t*, and *t+1*, respectively; natural log of market capitalization value (*SIZE*); closing price (*PRC*); turnover (*TO*); and daily differences of closing price and turnover (*PRCDIF* and *TODIF*, respectively). In addition, interaction terms of *Event* with each of the controls are also included in the specification (*Dummy Interaction*). Hybrid was phased-in gradually between October 6, 2006 and January 24, 2007. Observations pertaining to this period are excluded. Observations used are of the year preceding Hybrid (October 2005 to September 2006) and the year subsequent to its implementation (February 2007 to January 2008). Coefficients are estimated using generalized least squares method with adjustment for time and firm effects. Significance levels are indicated by *, **, and *** which denote significance at 10%, 5%, and 1% levels, respectively. Panel A presents results for the CRSP sample, whereas Panels B and C present results for NYSE and NASDAQ sub-samples, respectively. Panels B and C include estimates of *Event* and *Dummy Interaction* variables only.

Panel A *- CRSP sample: 2,802,436 stock-day observations*

Independent Variables	***Liquidity Measures***						
	QSPD	***ECOR***	***EGIB***	***ACOR***	***AGIB***	***Amihud***	***Zeros***
α	0.0427673***	0.0061166***	0.0145215***	0.0010435	0.0078565	-3.35E+09***	0.2239418***
β	-0.0080011**	-0.0062092***	-0.0017959**	-0.0305891**	-0.0053699	-1.02E+09***	-0.0359528
γ_{VIX}	-0.0000091***	0.0001803***	-0.0000149***	0.0003737***	-0.0000466***	-21337224***	-0.0006227***
$\lambda_{Event*VIX}$	0.0001776***	0.00014***	0.0000725***	0.0005599	0.0001368	5170793	-0.0001043
$\gamma_{RETYesterday}$	-0.0022466	-0.0045991	-0.0008975***	-0.0328798***	-0.0036104**	-1.14E+09**	-0.0060612
$\lambda_{Event*RETXYesterday}$	0.0031549	0.0075467	-0.0006119	0.0814056*	0.0142689***	1.92E+09***	-0.0265606
$\gamma_{RETToday}$	-0.0024338**	0.0167567***	-0.0013158***	0.0526624***	0.0017481	1874820524	-0.0342329***
$\lambda_{Event*RETXToday}$	0.0121137***	-0.0360568***	0.0029774**	-0.1235867***	0.0121856***	-4.35E+09	-0.0184926
$\gamma_{RETXTomorrow}$	0.001949**	-0.0129354	-0.0000746	-0.0372563	-0.0032626***	-3.62E+09**	0.0361536
$\lambda_{Event*RETXTomorrow}$	-0.0050095***	0.007503	-0.0034643	0.025444	-0.0052119	-1.09E+09	-0.0001245
δ_{SIZE}	-0.0019192***	-0.0001102***	-0.0005595***	0.0001691	-0.0001724	184500850***	-0.0091226***
$\lambda_{Event*SIZE}$	0.0002398	0.0001775***	0.0000399***	0.000953**	0.0002312	53420956**	0.0018251
δ_{PRC}	0.0000034***	-0.000009***	-0.0000011***	-0.0000118***	-0.0000007***	-9.54E+05***	-0.0000347***
$\lambda_{Event*PRC}$	-0.0000018***	0.0000013***	0.0000002***	0.0000071***	0.0000038***	110187	-0.0000015***
δ_{PRCDIF}	0.0008341***	0.0003655	0.0000292***	-0.0165441***	-0.0056769***	-3.25E+09	0.0015403**
$\lambda_{Event*PRCDIF}$	-0.0005726	0.0011315**	0.0001259***	-0.0002477	0.0020216	2.83E+09	-0.0011666
δ_{TO}	-0.0141803***	0.0147782***	-0.0006933**	0.5501931***	0.2208689***	1.59E+10***	-0.1016239***
$\lambda_{Event*TO}$	0.0058448***	-0.0081274	-0.000609	0.302895	-0.0202422	-3.93E+09	0.0472095***
δ_{TODIF}	0.0000071***	-0.0000003***	0.000002***	-0.0000784***	-0.000026***	-2436745***	0.0000559***
$\lambda_{Event*TODIF}$	-0.0000067***	0.0000007***	-0.0000019***	0.0000637***	0.0000223***	2230619***	-0.0000528***

Panel B *- NYSE sub-sample: 1,279,145 stock-day observations*

Independent Variables	***Liquidity Measures***						
	QSPD	***ECOR***	***EGIB***	***ACOR***	***AGIB***	***Amihud***	***Zeros***
β	-0.0089626***	-0.0016462*	0.0006875	-0.0105047	0.0058217	-693811759	-0.0367611***
$\lambda_{Event*VIX}$	0.0000703***	0.000162***	0.0000447***	0.0004716	0.000087	-1979882	-0.0001436
$\lambda_{Event*RETXYesterday}$	0.00111	0.0070998*	0.0002151	0.022529**	0.0135375***	-499689340**	-0.0277756
$\lambda_{Event*RETXToday}$	0.0037574***	-0.0320872***	0.0027968***	-0.0644632***	0.0252305***	1342763212***	-0.0210377
$\lambda_{Event*RETXTomorrow}$	-0.0006035	0.0080926	-0.0023868	0.0083229	-0.0086388	505652633	0.0055078
$\lambda_{Event*SIZE}$	0.0003534***	-0.0000513***	-0.0000625***	0.0000927	-0.0003995***	37039871	0.0018061
$\lambda_{Event*PRC}$	0.0000003***	0***	0.0000003***	-0.0000037***	0.0000001***	-50173	0.0000109***
$\lambda_{Event*PRCDIF}$	0.0003958***	0.0004377	-0.0004925***	-0.0237239***	-0.0129243***	-95041017	0.0003886
$\lambda_{Event*TO}$	0.0082266***	0.0111016***	0.0170578***	0.4218992***	0.3325738***	684819184	0.0483081
$\lambda_{Event*TODIF}$	-0.0000058***	0.0000037***	-0.0000003***	0.000045***	0.0000119***	74144	-0.0000559***

Panel C - *NASDAQ sub-sample: 1,199,959 stock-day observations*

Independent Variables	***Liquidity Measures***						
	QSPD	***ECOR***	***EGIB***	***ACOR***	***AGIB***	***Amihud***	***Zeros***
β	-0.0072877	-0.0033177***	-0.0021019	-0.0487579*	-0.018807	-614194278	-0.038602
$\lambda_{Event*VIX}$	0.0002919***	0.0001404***	0.0001041***	0.0002933**	0.0001388***	5320960	0.0000762***
$\lambda_{Event*RETXYesterday}$	0.0014613	0.0110905	0.0002269	0.0866035***	0.0175225***	4.99E+09**	-0.0165639
$\lambda_{Event*RETXToday}$	0.0202284**	-0.0394943***	0.0048515***	-0.1013217***	0.0174034***	-3.10E+09	-0.0081007
$\lambda_{Event*RETXTomorrow}$	-0.0125619***	0.0025434	-0.0048032	0.0068721	0.0005935	-2.65E+09	-0.0069141
$\lambda_{Event*SIZE}$	0.0001404	-0.0000141***	0.000026	0.00212	0.0008566	27177272	0.0019335
$\lambda_{Event*PRC}$	-0.000013***	0.0000231***	0.0000022***	0.0000517***	0.0000184***	-1953200	-0.0000206***
$\lambda_{Event*PRCDIF}$	-0.0006243	0.0024207	0.0002394	0.0031797	-0.0015138	-2.97E+09	-0.0001998
$\lambda_{Event*TO}$	0.009275***	-0.0120631***	0.0004383	-0.0376835	-0.0090862	1.62E+10	0.0743565***
$\lambda_{Event*TODIF}$	-0.0000132***	0.0000039***	-0.0000037***	0.0001519***	0.0000512***	9244859***	-0.0000955***

Table 4: Estimation of equation 1 for size deciles

Results for estimating Equation 1:

$$LIQ_{i,t} = \alpha + \beta\ Event_t + \gamma_{VIX}VIX_t + \gamma_{RETYesterday}RETYesterday_t + \gamma_{RETToday}RETToday_t + \gamma_{RETTomorrow}RETTomorrow_t + \delta_{SIZE}SIZE_{i,t} + \delta_{PRC}PRC_{i,t} + \delta_{PRCDIF}PRCDIF_{i,t} + \delta_{TO}TO_{i,t} + \delta_{TODIF}TODIF_{i,t} + \sum_{m=1}^{9} \lambda_m\ Dummy\ Interaction_{i,m,t} + \varepsilon_{i,t}$$

Where $LIQ_{i,t}$ refers to one of the seven liquidity measures used, for each stock *i* at day *t*: quoted spreads (*QSPD*), effective spreads based on both Corwin and Schultz (2011) estimation method (*ECOR*) and the Gibbs estimator (*EGIB*) of Hasbrouck (2009), amortized spreads (*ACOR* and *AGIB*) based on the two estimations of effective spreads, Amihud's price impact measure (*Amihud*), and the Zeros measure (*Zeros*) of Lesmond *et al*. (1999). Each of these liquidity measures are regressed on *Event*; a dummy variable that takes the value of 1 (0) after (before) the implementation of Hybrid, and a set of nine control variables. Control variables are: daily closing volatility index value *VIX*; *RETYesterday*, *RETToday*, and *RETTomorrow* which refer to equally-weighted average market returns at days *t-1*, *t*, and *t+1*, respectively; natural log of market capitalization value (*SIZE*); closing price (*PRC*); turnover (*TO*); and daily differences of closing price and turnover (*PRCDIF* and *TODIF*, respectively). In addition, interaction terms of *Event* with each of the controls are also included in the specification (*Dummy Interaction*). Hybrid was phased-in gradually between October 6, 2006 and January 24, 2007. Observations pertaining to this period are excluded. Observations used are of the year preceding Hybrid (October, 2005 to September, 2006) and the year subsequent to its implementation (February 2007 to January 2008). Coefficients are estimated using generalized least squares method with adjustment for time and firm effects. Significance levels are indicated by *, **, and *** which denote significance at 10%, 5%, and 1% levels, respectively. Panel A presents results for the CRSP sample, whereas Panels B and C present results for NYSE and NASDAQ sub-samples, respectively. Presented results include estimates of *Event, SIZE,* and *Event*SIZE* variables only. The equation has been estimated for each size decile individually, where decile 1 (10) contains smallest (largest) stocks.

Panel A - *CRSP Sample: 2,802,436 stock-day observations*

SIZE decile	***Independent Variables***	***Liquidity Measures***						
		ACOR	***AGIB***	***Amihud***	***ECOR***	***EGIB***	***QSPD***	***Zeros***
	β	-0.31879***	-0.09648**	-295659795***	-0.007911	-0.00454	-0.04282***	-0.08044**
1	δ_{SIZE}	-0.00915*	-0.00533**	9508702	0.0001769	-0.00163***	-0.00443**	0.006136**
	$\lambda_{Event*SIZE}$	0.016384***	0.005162**	-1567627	0.0002652	0.000126	0.001835**	0.004745**
	β	-0.0203781	-0.0167994	-252262370	-0.002244*	0.0071943	0.0272087	-0.0443361**
2	δ_{SIZE}	-0.001178	-0.0015089	-7580657*	0.0008757**	-0.0020773***	-0.006405***	-0.0173498***
	$\lambda_{Event*SIZE}$	0.0006603	0.0008262	14457697	0.000026	-0.0004662	-0.0017635*	0.0030019**
	β	-0.1134239	-0.0252195*	-132982665***	0.0051617	-0.003861	-0.0235582**	-0.1297822
3	δ_{SIZE}	0.0028515	0.0004067	4932481**	0.0024751***	-0.0007639***	-0.0046833***	-0.0321932***
	$\lambda_{Event*SIZE}$	0.0056547	0.0012604	7270121***	-0.000463***	0.0001604	0.0010728*	0.0076709
	β	0.2334571***	0.0726449***	-790303566***	0.0356555	0.0258158*	-0.0143634	-0.0941009*
4	δ_{SIZE}	0.0075383***	0.0018085***	17666699***	0.001875***	-0.000274	-0.0031929***	-0.0143591***
	$\lambda_{Event*SIZE}$	-0.0123103***	-0.0037246***	40847259***	-0.001964	-0.0013687*	0.0006413	0.0045756*
	β	0.0472216	-0.0078564	-114684263	0.0106125	0.0077283	-0.0194673***	-0.0738771
5	δ_{SIZE}	-0.0007589	-0.0009519	45452073***	-0.000802	-0.0004783***	-0.0018656***	-0.0000828
	$\lambda_{Event*SIZE}$	-0.0027609	0.0003215	5871748	-0.000663	-0.0004317	0.0008743***	0.0035039
	β	0.1012614***	0.0613148*	-592319029***	0.0343633***	0.0212043	-0.0021831	0.2235281
6	δ_{SIZE}	0.0027273	0.0007356	39965355***	0.0000525	-0.0004614***	-0.001056***	-0.0037818
	$\lambda_{Event*SIZE}$	-0.0056131***	-0.0030383*	29680795***	-0.001795***	-0.001079	0.0000211	-0.0111027

SIZE decile	Independent Variables	Liquidity Measures						
		ACOR	AGIB	Amihud	ECOR	EGIB	QSPD	Zeros
7	β	0.1962015***	0.0857695***	-1.11E+09	0.0226446***	0.0075424	-0.0177451***	-0.0533575
	δ_{SIZE}	0.0030543**	0.0008155***	90520711***	-0.00078***	-0.0004332***	-0.0012942***	-0.0068861*
	$\lambda_{Event*SIZE}$	-0.0103939***	-0.0041004***	55545412	-0.00122***	-0.0003871	0.0007905***	0.0025103
8	β	-0.0620819	-0.0013419	141423148	-0.007923	0.0069232	-0.0018915	-0.0018915
	δ_{SIZE}	-0.0064327***	-0.0020007***	124136204***	-0.002361***	-0.0003781***	-0.0004402***	-0.0004402
	$\lambda_{Event*SIZE}$	0.0021439	0.0000145	-3145940	0.0002325	-0.0003581	0.0000397	0.0000397
9	β	-0.0236101	-0.0244138***	-2.88E+09	0.001009	-0.0039765**	-0.0017762	-0.0141734
	δ_{SIZE}	-0.0013119***	-0.0014816***	222090064***	-0.000305***	-0.0003539***	-0.0003951***	-0.0018061*
	$\lambda_{Event*SIZE}$	0.0005472	0.0010688**	129092377	-0.000188***	0.0001459	0.0000519***	0.0004761
10	β	0.0208259	0.0075035**	-592796377	-0.001165	-0.0003859	0.0007004	-0.0141734
	δ_{SIZE}	-0.0019273***	-0.0012228***	1549232616***	-0.000227***	-0.000181***	-0.0001125***	-0.0018061***
	$\lambda_{Event*SIZE}$	-0.0013426	-0.0004308	47861604	-3.22E-05	-0.0000057***	-0.0000453***	0.0004761

Panel B *- NYSE sub-sample: 1,279,145 stock-day observations*

***SIZE* decile**	***Independent Variables***	***Liquidity Measures***						
		ACOR	***AGIB***	***Amihud***	***ECOR***	***EGIB***	***QSPD***	***Zeros***
1	β	-0.0932328***	-0.0753573***	-58536280***	0.0014821**	0.0099178**	-0.0060676	-0.0597502
	δ_{SIZE}	-0.001763**	-0.0040353***	3315832***	0.0003766***	-0.0004233*	-0.0007276	0.0200703***
	$\lambda_{Event*SIZE}$	0.0053638***	0.0041384***	2993438***	-0.0001624	-0.0006593**	0.0000025	0.0029912
2	β	0.0985831***	0.1157443***	-69636895**	0.0111024**	0.0139957***	-0.0050513	-0.0231385
	δ_{SIZE}	0.0018737	0.0009821**	8526700***	0.0011708**	0.0001396	-0.0012836***	-0.016684
	$\lambda_{Event*SIZE}$	-0.0053457***	-0.0063646***	3761238**	-0.0006599**	-0.0007955***	0.0001445	0.0009351
3	β	0.0223018	-0.0216642	-123552589	0.0062216	0.0019949	-0.0326003	-0.1884441**
	δ_{SIZE}	0.00326***	0.0000381	8455244***	0.0020412***	-0.0004674***	-0.0030024***	-0.0156929*
	$\lambda_{Event*SIZE}$	-0.001342	0.0010632	6481350	-0.0004549	-0.0001528	0.0015739	0.0115676**
4	β	0.1363529	0.0460908***	-630246576***	0.0834752	0.0280456***	-0.0216417	-0.0549902
	δ_{SIZE}	0.0042683***	0.0007694***	20767828***	0.0019612***	0.000157	-0.0023509***	0.0020186
	$\lambda_{Event*SIZE}$	-0.0070768	-0.0023357**	32510230***	-0.0043749	-0.0014363***	0.0010173	0.0028185
5	β	0.0907416***	0.1073451	-368650782	-0.0076916	0.0155938	-0.0348507***	-0.245124***
	δ_{SIZE}	0.0035284***	0.0016367**	26040179**	0.000573	0.000256	-0.0016521***	-0.0084149
	$\lambda_{Event*SIZE}$	-0.0048962***	-0.0054729	17463158	0.0002568	-0.0008175	0.0016541***	0.0121965***
6	β	0.042682	0.0687499**	-315232920	0.0236766	0.028048*	-0.0111985**	0.1884259
	δ_{SIZE}	0.0041243***	0.000788***	35320687***	0.001251***	0.0000507	-0.0011288***	-0.0118801***
	$\lambda_{Event*SIZE}$	-0.0025881	-0.0034866**	16068795	-0.0013134	-0.0014237*	0.000438*	-0.0092217

SIZE decile	Independent Variables	Liquidity Measures						
		ACOR	AGIB	Amihud	ECOR	EGIB	QSPD	Zeros
7	β	0.1903544***	0.0615108**	-498862158***	0.0197314***	0.001005	-0.0256229***	0.0207304
	δ_{SIZE}	0.0015786	-0.0000281	65957197***	-0.0003943	-0.0003299***	-0.0012341***	-0.0043174
	$\lambda_{Event*SIZE}$	-0.009667***	-0.0030465**	26441772***	-0.0010833***	-0.000068	0.0011505***	-0.0011987
8	β	0.0346376	0.0549263**	67189649	0.000017	0.0172056**	-0.0038161	0.0767734
	δ_{SIZE}	-0.0017328**	0.0003133	103519839***	-0.0015089***	-0.0000388	-0.0005753***	-0.000232
	$\lambda_{Event*SIZE}$	-0.0021365	-0.0027076**	-637271	-0.0001379	-0.0008393**	0.0001223	-0.0041222
9	β	-0.0175628	-0.018185***	-2.88E+09	-0.0060768*	-0.0053043**	-0.0001331	-0.1124225
	δ_{SIZE}	-0.0010303**	-0.0008881***	177425651***	-0.0003707***	-0.0002877***	-0.0003542***	-0.0042589***
	$\lambda_{Event*SIZE}$	0.0003231	0.0006883	131477125	0.000135	0.000199	-0.0000373	0.0049114
10	β	0.0087965	0.0041228	-1.65E+09	0.0015689	0.0004716	0.0010433	0.014443
	δ_{SIZE}	-0.0009664***	-0.0007***	615183241***	0.0000346***	-0.0001071***	-0.0001398***	-0.0007791***
	$\lambda_{Event*SIZE}$	-0.0006943***	-0.0002734	84658109	-0.0001447	-0.0000419***	-0.0000623***	-0.0005359

Panel C *- NASDAQ sub-sample: 1,199,959 stock-day observations*

SIZE **decile**	***Independent Variables***	***Liquidity Measures*** ***ACOR***	***AGIB***	***Amihud***	***ECOR***	***EGIB***	***QSPD***	***Zeros***
1	β	-0.3315125*	-0.1278488	-51616227***	0.0048168	-0.0063108	-0.02234	-0.1016836***
	δ_{SIZE}	-0.01867*	-0.0092939*	1831490*	0.0002832	-0.0029735***	-0.0081818***	0.0041276*
	$\lambda_{Event*SIZE}$	0.0182629*	0.0069534	2976538***	-0.000492	0.0001692	0.0003014	0.0060334***
2	β	-0.1802421*	-0.0840024	-312414985	-0.0176754	0.0061419	0.0645926*	0.0673438
	δ_{SIZE}	-0.003087	-0.0031131	-6122901	0.0010502***	-0.0033366***	-0.0096638***	-0.018515***
	$\lambda_{Event*SIZE}$	0.0095988*	0.0045113	16201333	0.0008996	-0.0004779	-0.0041422**	-0.0034481
3	β	0.014432	0.0113942	-384350126	0.015332	-0.0007942	-0.0110288	-0.1425572
	δ_{SIZE}	0.0026489	0.0004053	1533244	0.0032082***	-0.0011625***	-0.0066935***	-0.0441004***
	$\lambda_{Event*SIZE}$	-0.0009376	-0.0006125	20986264	-0.0011486	-0.0000238	0.0003896	0.0080426
4	β	0.1470843	0.0526826**	-855329407***	0.0269792**	0.0316891	-0.0118189	-0.1330639
	δ_{SIZE}	0.0092237***	0.0024639**	22444136***	0.0011686***	-0.0006742**	-0.004189***	-0.0220564***
	$\lambda_{Event*SIZE}$	-0.0077579	-0.002773**	43827591***	-0.001597**	-0.0016981	0.0005296	0.0065225
5	β	-0.2073897***	-0.0910643**	92810936	0.0244812	0.0035301	-0.004542	0.0730642
	δ_{SIZE}	-0.0039247	-0.002807	46865081***	-0.0010687**	-0.0008176***	-0.0020304***	0.0048499
	$\lambda_{Event*SIZE}$	0.0105368***	0.0046725**	-3319296	-0.0014329	-0.0002509	0.0000981	-0.0039535
6	β	0.1387705	0.0601915	-415456743*	0.0401921*	0.0124432	0.0017869	0.1875961***
	δ_{SIZE}	0.0021621	0.0004565	55979629***	-0.0010404***	-0.0009487***	-0.0014266***	0.0011975
	$\lambda_{Event*SIZE}$	-0.0070026	-0.0029934	20449157*	-0.002115*	-0.0006555	-0.0001455	-0.0093794***

SIZE decile	*Independent Variables*	*Liquidity Measures*						
		ACOR	***AGIB***	***Amihud***	***ECOR***	***EGIB***	***QSPD***	***Zeros***
	β	0.1410882	0.0829807***	-949744641	0.0302207**	0.0154312	-0.0071719***	-0.0870334
7	δ_{SIZE}	0.0068124***	0.0025874***	99139781***	-0.0008803***	-0.0004569***	-0.0013981***	-0.010741***
	$\lambda_{Event*SIZE}$	-0.0069827	-0.0039949***	47950936	-0.0015967**	-0.0007762	0.0003058***	0.0042122
	β	-0.065724	-0.082515***	373248964	-0.0042511	-0.0097881	0.0021103	0.0003121
8	δ_{SIZE}	-0.0047047*	-0.00153*	208307992***	-0.0022535***	-0.0007012***	-0.0005244***	0.0032209
	$\lambda_{Event*SIZE}$	0.0022934	0.0037598***	-16123910	-0.0000229	0.0004055	-0.0001446	-0.0000934
	β	0.0468048	-0.020412**	-2.05E+09***	0.0167472	-0.0030751**	-0.0017132	0.2225788***
9	δ_{SIZE}	-0.0012179	-0.0022876**	317567336***	-0.0002105	-0.0006155***	-0.0005514	0.0052891***
	$\lambda_{Event*SIZE}$	-0.0029364	0.0006583**	93896101***	-0.0009409	0.0001089	0.0000657	-0.0106482***
	β	0.044938	0.0189892	-9.34E+10***	-0.0027734	0.0005054	0.0002804	-0.0107459
10	δ_{SIZE}	-0.0016465***	-0.0010847**	310763972	-0.0000936	-0.0001787*	-0.0000973***	-0.0014693*
	$\lambda_{Event*SIZE}$	-0.0033154*	-0.0012361	4244722258***	-0.0000344	-0.000053	-0.0000196***	0.0001811

Table 5: Estimation of equation 2 using a four-year window

Results for estimating Equation 2:

$$RET_{i,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \beta_{LIQLEV} LIQLEV_{i,t} + \beta_{LIQFAC} LIQFAC_t$$

$$+ \sum_{m=1}^{6} \lambda_m \, Dummy\ Interaction_{i,m,t} + \varepsilon_{i,t}$$

Where $RET_{i,t}$ is the daily return of stock *i* at day *t*, *MKT* is daily market excess return, *SMB* and *HML* are Fama and French daily small-minus-big and high-minus-low daily factors, respectively, *UMD* is the daily momentum factor, *LIQFAC* is a daily liquidity factor, and *LIQLEV* is a daily level liquidity measure which is calculated for each stock *i,* based on one of the seven liquidity measures (*LIQ*) at a time. The construction method of *LIQFAC* and *LIQLEV* is presented in the data and measures section. Liquidity measures are: quoted spreads (*QSPD*), effective spreads based on both Corwin and Schultz (2011) estimation method (*ECOR*) and the Gibbs estimator (*EGIB*) of Hasbrouck (2009), amortized spreads (*ACOR* and *AGIB*) based on the two estimations of effective spreads, Amihud's price impact measure (*Amihud*), and the Zeros measure (*Zeros*) of Lesmond *et al*. (1999). *RET* is regressed on these factors in addition to *Dummy Interaction* variables, which are interaction terms of *Event* (a dummy variable that takes the value of 1 (0) after (before) the implementation of Hybrid) with each of the abovementioned independent variables. Hybrid was phased-in gradually between October 6, 2006 and January 24, 2007. Observations pertaining to this period are excluded. Observations used are of the two years preceding Hybrid (October 2004 to September 2006) and the two years subsequent to its implementation (February 2007 to January 2009). Coefficients are estimated using generalized least squares method with adjustment for time and firm effects. Significance levels are indicated by *, **, and *** which denote significance at 10%, 5%, and 1% levels, respectively. Panel A presents results for the CRSP sample, whereas Panels B and C present results for NYSE and NASDAQ sub-samples, respectively.

Panel A *- CRSP sample: 5,381,304 stock-day observations*

Independent Variables	***LIQLEV Measures***						
	QSPD	***ECOR***	***EGIB***	***ACOR***	***AGIB***	***Amihud***	***Zeros***
α	0.000403***	0.000403***	0.000399***	0.000403***	0.0003988***	4.19E-04***	0.000403***
β_{MKT}	0.904446***	0.904443***	0.903227***	0.904437***	0.9032275***	9.31E-01***	0.9044396***
$\lambda_{Event*MKT}$	0.117264***	0.117308***	0.140602***	0.117319***	0.1406088***	0.103676***	0.1173147***
β_{SMB}	0.499508***	0.499502***	0.501826***	0.499507***	0.501828***	5.15E-01***	0.4995081***
$\lambda_{Event*SMB}$	-0.06084***	-0.06085***	-0.04769***	-0.06088***	-0.0476948***	-0.06782***	-0.060877***
β_{HML}	0.090581***	0.090585***	0.088271***	0.090597***	0.088273***	9.47E-02***	0.0906002***
$\lambda_{Event*HML}$	-0.11545***	-0.11536***	-0.10934***	-0.11541***	-0.1093297***	-0.12025***	-0.115418***
β_{UMD}	0.02753***	0.027539***	0.024149***	0.027531***	0.0241485***	2.66E-02***	0.027533***
$\lambda_{Event*UMD}$	-0.08697***	-0.08695***	-0.08792***	-0.08695***	-0.0879155***	-8.72E-02***	-0.086953***
β_{LIQLEV}	0.027366***	0.053676***	0.134391***	0.006184***	0.0151699***	0***	-0.002189***
$\lambda_{Event*LIQLEV}$	-0.02508***	-0.00904***	-0.115***	-0.0054***	-0.0120379***	0***	0.0016027
β_{LIQFAC}	0.205212***	0.205206***	0.205106***	0.205204***	0.2051077***	0.211555***	0.2052046***
$\lambda_{Event*LIQFAC}$	0.074941***	0.074992***	0.081476***	0.074997***	0.0814803***	6.95E-02***	0.074994***

Panel B *- NYSE sub-sample: 2,467,594 stock-day observations*

Independent Variables	***LIQLEV Measures***						
	QSPD	***ECOR***	***EGIB***	***ACOR***	***AGIB***	***Amihud***	***Zeros***
α	0.0002944*	0.0002975*	0.000376***	0.0003011*	0.0003223**	3.00E-04**	0.0002767*
β_{MKT}	0.8791297***	0.8763484***	0.8846212***	0.8773019***	0.8791014***	0.897416***	0.8767845***
$\lambda_{Event*MKT}$	0.2496932***	0.2517075***	0.2465027***	0.2507076***	0.2509643***	0.2377306***	0.251183***
β_{SMB}	0.3634335***	0.3626953***	0.3660888***	0.3629279***	0.3645465***	0.3734663***	0.3627851***
$\lambda_{Event*SMB}$	-0.033658	-0.03316	-0.0319752	-0.0332347	-0.0309426	-0.0384306	-0.033137
β_{HML}	0.2492915***	0.2469734***	0.2521919***	0.2480677***	0.2465523***	0.2561909***	0.2472694***
$\lambda_{Event*HML}$	-0.281701***	-0.279424***	-0.285995***	-0.2808461***	-0.2797838***	-0.2894421***	-0.279992***
β_{UMD}	0.0457556***	0.0465551***	0.0395274***	0.0461925***	0.0413408***	0.0450664***	0.0464878***
$\lambda_{Event*UMD}$	-0.135347***	-0.136262***	-0.1302328***	-0.1359902***	-0.1318109***	-0.1359026***	-0.136261***
β_{LIQLEV}	0.0235707	0.0014117	0.2269291***	0.0045208***	0.0477616***	0***	-0.002776***
$\lambda_{Event*LIQLEV}$	-0.03423***	0.0204688**	-0.2613395***	-0.0043583***	-0.0504252***	0***	0.0006496
β_{LIQFAC}	0.0898718***	0.0870614***	0.0962829***	0.0878753***	0.0908741***	0.0896228***	0.0875336***
$\lambda_{Event*LIQFAC}$	0.1985948***	0.2003176***	0.1972334***	0.1995427***	0.2008337***	0.1969339***	0.1997914***

Panel C - *NASDAQ sub-sample: 2,242,670 stock-day observations*

Independent Variables	***LIQLEV Measures***						
	QSPD	***ECOR***	***EGIB***	***ACOR***	***AGIB***	***Amihud***	***Zeros***
α	0.0005135***	0.0003805***	0.000462***	0.0005206***	0.0005099***	5.54E-04***	0.0005339***
β_{MKT}	0.9560281***	0.9568354***	0.9553647***	0.9553146***	0.9572688***	0.9869895***	0.9573295***
$\lambda_{Event*MKT}$	0.03266***	0.0317692***	0.0342366***	0.0318249***	0.0325427***	0.017988***	0.0315785***
β_{SMB}	0.7074071***	0.7078443***	0.7090299***	0.707166***	0.7095473***	7.30E-01***	0.7077354***
$\lambda_{Event*SMB}$	-0.00019	-0.000199	0.0005369	0.0001361	0.0001801	-0.0076973	-0.000392
β_{HML}	-0.087246***	-0.087265***	-0.0893963***	-0.0884916***	-0.0876418***	-8.77E-02***	-0.086492***
$\lambda_{Event*HML}$	0.1019646***	0.1027108***	0.1040965***	0.1027468***	0.1020504***	0.1023318***	0.1011425***
β_{UMD}	-0.034892***	-0.035188***	-0.0375334***	-0.0344882***	-0.0380851***	-3.78E-02***	-0.035125***
$\lambda_{Event*UMD}$	-0.031741*	-0.030685*	-0.0291773*	-0.0322841*	-0.0288931*	-3.06E-02	-0.031557*
β_{LIQLEV}	0.0226468***	0.0690759***	0.0866824***	0.007834***	0.0158051***	0***	-0.001575**
$\lambda_{Event*LIQLEV}$	-0.023616***	-0.00466	-0.0728619***	-0.0044112	-0.0061527	0***	0.0002918
β_{LIQFAC}	0.2855193***	0.2866497***	0.2839232***	0.2850943***	0.2858075***	0.2967481***	0.286917***
$\lambda_{Event*LIQFAC}$	-0.056742***	-0.058093***	-0.0579478***	-0.0582625***	-0.059302***	-6.54E-02***	-0.05775***

Table 6: Estimation of equation 2 for size deciles using a four-year window

Results for estimating Equation 2:

$$RET_{i,t} = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \beta_{LIQLEV}LIQLEV_{i,t} + \beta_{LIQFAC}LIQFAC_t + \sum_{m=1}^{6} \lambda_m \, Dummy\ Interaction_{i,m,t} + \varepsilon_{i,t}$$

Where $RET_{i,t}$ is the daily return *i* at day *t*, *MKT* is daily market excess return, *SMB* and *HML* are Fama and French daily small-minus-big and high-minus-low daily factors, respectively, *UMD* is the daily momentum factor, *LIQFAC* is a daily liquidity factor, and *LIQLEV* is a daily level liquidity measure which is calculated for each stock *i,* based on one of the seven liquidity measures (*LIQ*) at a time. The construction method of *LIQFAC* and *LIQLEV* is presented in the data and measures section. Liquidity measures are: quoted spreads (*QSPD*), effective spreads based on both Corwin and Schultz (2011) estimation method (*ECOR*) and the Gibbs estimator (*EGIB*) of Hasbrouck (2009), amortized spreads (*ACOR* and *AGIB*) based on the two estimations of effective spreads, Amihud's price impact measure (*Amihud*), and the Zeros measure (*Zeros*) of Lesmond *et al*. (1999). *RET* is regressed on these factors in addition to *Dummy Interaction* variables, which are interaction terms of *Event* (a dummy variable that takes the value of 1 (0) after (before) the implementation of Hybrid) with each of the abovementioned independent variables. Hybrid was phased-in gradually between October 6, 2006 and January 24, 2007. Observations pertaining to this period are excluded. Observations used are of the two years preceding Hybrid (October, 2004 to September, 2006) and the two years subsequent to its implementation (February 2007 to January 2009). Coefficients are estimated using generalized least squares method with adjustment for time and firm effects. Significance levels are indicated by *, **, and *** which denote significance at 10%, 5%, and 1% levels, respectively. Panel A presents results for the CRSP sample, whereas Panels B and C present results for NYSE and NASDAQ sub-samples, respectively. Presented results include estimates of *Event, SIZE,* and *Event*SIZE* variables only. The equation has been estimated for each size decile individually, where decile 1 (10) contains smallest (largest) stocks.

Panel A *- CRSP sample: 5,381,304 stock-day observations*

SIZE **decile**	***Independent Variables***	***LIQLEV Measures***						
		ACOR	***AGIB***	***Amihud***	***ECOR***	***EGIB***	***QSPD***	***Zeros***
1	β_{SMB}	0.2892015***	0.2882317***	0.309***	0.2882846***	0.2851286***	0.2868046***	0.2902633***
	$\lambda_{Event*SMB}$	-0.2010214***	-0.2142084***	-0.2148645***	-0.200218***	-0.2123787***	-0.2011679***	-0.202453***
	β_{LIQLEV}	0.0119168***	0.020511***	0***	0.1963945***	0.104792***	0.02357***	-0.0018773*
	$\lambda_{Event*LIQLEV}$	-0.0104149***	-0.0101763**	0***	-0.122993***	-0.1406466***	-0.0408349***	-0.0018155
2	β_{SMB}	0.2995685***	0.3033719***	0.3182842***	0.2981825***	0.3038917***	0.2999225***	0.2999559***
	$\lambda_{Event*SMB}$	-0.083432*	-0.0827688*	-0.091079**	-0.083368*	-0.0830759*	-0.0819462*	-0.0835167*
	β_{LIQLEV}	0.0053341	0.0158066	0***	0.0876957***	0.1112308***	0.035448***	-0.0029455***
	$\lambda_{Event*LIQLEV}$	-0.0049188	-0.0149782***	0***	-0.016498	0.0020927	-0.0001556	0.0043338*
3	β_{SMB}	0.4229367***	0.4233116***	0.4428092***	0.4224226***	0.4234388***	0.4230839***	0.4232679***
	$\lambda_{Event*SMB}$	0.0743377	0.0949919	0.0682514	0.0756191	0.0948984	0.0745021	0.0740173
	β_{LIQLEV}	0.0010443*	0.0063092	0***	0.0706722***	0.1965895***	0.0302668***	0.0001141
	$\lambda_{Event*LIQLEV}$	-0.0014349**	-0.0058023	0***	-0.016316	-0.0688571	0.0099112	0.0040794
4	β_{SMB}	0.7315754***	0.7325155***	0.7531405***	0.7310769***	0.731972***	0.7321545***	0.7316897***
	$\lambda_{Event*SMB}$	-0.001329	0.0232967	-0.0108273	-0.000434	0.0235441	-0.0010856	-0.0015126
	β_{LIQLEV}	0.0008741	0.0269335**	0***	0.1006073***	0.2653498***	0.0146261**	-0.0007173
	$\lambda_{Event*LIQLEV}$	-0.0007522	-0.0288032**	0***	-0.048783**	-0.0579726	0.03439***	0.0039295**
5	β_{SMB}	0.7832038***	0.7880075***	0.8046748***	0.7839047***	0.7875837***	0.7827745***	0.7830675***
	$\lambda_{Event*SMB}$	-0.0407484	-0.0247717	-0.0490022	-0.040748	-0.0243963	-0.0399976	-0.040477
	β_{LIQLEV}	0.0015124	0.0093001	0***	0.0140965**	0.2600354***	0.0601645***	-0.001688***
	$\lambda_{Event*LIQLEV}$	-0.0000305	-0.0041701	0***	0.0425452***	-0.0793908	-0.01384	0.0053063**

SIZE decile	Independent Variables	LIQLEV Measures						
		ACOR	AGIB	Amihud	ECOR	EGIB	QSPD	Zeros
6	β_{SMB}	0.7797138***	0.7863484***	0.7973809***	0.7801438***	0.7865048***	0.7808288***	0.7795617***
	$\lambda_{Event*SMB}$	-0.0401362	-0.0339153	-0.0502918	-0.04024	-0.0339712	-0.0408164	-0.0399929
	β_{LIQLEV}	0.0014467	0.0126256	0***	0.0217016***	0.4329578***	0.0883051***	-0.0019924
	$\lambda_{Event*LIQLEV}$	-0.0011003	-0.0142347***	0***	0.0307588***	-0.245208***	-0.0706075***	0.0036244**
7	β_{SMB}	0.737074***	0.7417886***	0.7505705***	0.7373053***	0.7368926***	0.7380703***	0.7427521***
	$\lambda_{Event*SMB}$	-0.0671353**	-0.0463718	-0.0745451**	-0.066664**	-0.067066**	-0.0678193**	-0.0468061
	β_{LIQLEV}	0.0003623	0.011348*	0***	0.0203382***	-0.0024693***	0.032879***	0.383555***
	$\lambda_{Event*LIQLEV}$	0.0001877	-0.0067991	0***	0.0217958**	0.001043	-0.0466258**	-0.238855**
8	β_{SMB}	0.589321***	0.5884495***	0.5990898***	0.589339***	0.5908007***	0.5914444***	0.5889262***
	$\lambda_{Event*SMB}$	-0.0863397***	-0.0779793***	-0.0927856***	-0.08627***	-0.0794905***	-0.0877924***	-0.08615***
	β_{LIQLEV}	0.0026013**	0.008009**	0***	0.0223706*	0.3960267***	0.0687466***	-0.0012485
	$\lambda_{Event*LIQLEV}$	-0.0012984	-0.0043883	0***	0.0190592	-0.2995951**	-0.0871604***	0.0012467
9	β_{SMB}	0.3159609***	0.3175488***	3.21E-01***	0.31575***	0.3199649***	0.3189253***	0.3163153***
	$\lambda_{Event*SMB}$	-0.0842498***	-0.0871991***	-8.64E-02***	-0.084107***	-0.0887036***	-0.0857253***	-0.0841748***
	β_{LIQLEV}	0.0017871***	0.0052228	0***	0.0115854	0.3231085***	0.0659607*	0.0003366
	$\lambda_{Event*LIQLEV}$	0.0017136	0.0082778	0***	0.013065	-0.2677402***	-0.0991388***	-0.0042661**
10	β_{SMB}	0.0452306***	0.046053***	0.0467***	0.0448974***	0.049101***	0.0477866***	0.0456358***
	$\lambda_{Event*SMB}$	-0.0770921***	-0.0757803***	-0.0775***	-0.077028***	-0.0778973***	-0.0787339***	-0.0773466***
	β_{LIQLEV}	-0.0033239	0.048429***	0***	-0.029255*	0.2941178***	0.0637129**	-0.0000661
	$\lambda_{Event*LIQLEV}$	0.0040207	-0.0486289***	0***	0.0415413**	-0.3005159***	-0.0776408**	-0.0025417*

Panel B *- NYSE sub-sample: 2,467,594 stock-day observations*

***SIZE* decile**	***Independent Variables***	***LIQLEV Measures* *ACOR***	***AGIB***	***Amihud***	***ECOR***	***EGIB***	***QSPD***	***Zeros***
1	β_{SMB}	0.170818***	0.1807598***	0.1796096***	0.1695413***	0.180352***	0.1701116***	0.170187***
	$\lambda_{Event*SMB}$	-0.20937***	-0.2142493***	-0.2134136***	-0.2073013***	-0.21359***	-0.2087304***	-0.20887***
	β_{LIQLEV}	0.00812	0.0078005	0***	0.0384288	0.03607	0.006559	-0.00131
	$\lambda_{Event*LIQLEV}$	-0.00893	-0.039731***	0***	0.0132169	-0.12497	0.0025725	-0.000064
2	β_{SMB}	0.160411***	0.1600239***	0.1707966***	0.1600368***	0.160095***	0.1599151***	0.16016***
	$\lambda_{Event*SMB}$	-0.08372	-0.0865064	-0.0869945	-0.0838614	-0.08676	-0.0841929	-0.08385
	β_{LIQLEV}	0.020347*	0.0272454	0***	0.0033556	0.035473	-0.0051872	-0.00252**
	$\lambda_{Event*LIQLEV}$	-0.01853*	-0.0420612	0***	-0.0053446	-0.1603*	-0.0135479	0.003641
3	β_{SMB}	0.233047***	0.2348895***	0.245761***	0.2326153***	0.235344***	0.2334009***	0.234198***
	$\lambda_{Event*SMB}$	0.066025	0.0691445	0.063229	0.0662823	0.068442	0.066775	0.06524
	β_{LIQLEV}	-0.00106	0.0402075	0***	-0.0358031**	0.095455	0.0191528**	-0.00166
	$\lambda_{Event*LIQLEV}$	0.003878	-0.0534442	0***	0.0583269***	-0.26344**	0.0255256	0.004709
4	β_{SMB}	0.44163***	0.443944***	0.4608989***	0.4410635***	0.444933***	0.4411293***	0.441527***
	$\lambda_{Event*SMB}$	0.008691	0.0155099	-0.0003344	0.0091951	0.014752	0.0090085	0.008595
	β_{LIQLEV}	0.009236	0.0585367*	0***	0.0102712	0.217378***	0.0679414***	-0.00286**
	$\lambda_{Event*LIQLEV}$	-0.01087	-0.0622933**	0***	0.0136329	-0.28416**	-0.066513***	0.003851*
5	β_{SMB}	0.464323***	0.4678607***	0.4828717***	0.4642448***	0.46814***	0.4622162***	0.464367***
	$\lambda_{Event*SMB}$	0.107946***	0.1130574***	0.1027788***	0.1078689***	0.112908***	0.1108219***	0.107847***
	β_{LIQLEV}	0.006539	0.0754503**	0***	0.0035528	0.244737**	0.0697462***	-0.00179*
	$\lambda_{Event*LIQLEV}$	-0.00468	-0.0842838***	0***	0.0388035**	-0.26645**	0.0466597	0.004295

***SIZE* decile**	***Independent Variables***	***LIQLEV Measures***						
		ACOR	***AGIB***	***Amihud***	***ECOR***	***EGIB***	***QSPD***	***Zeros***
6	β_{SMB}	0.644968***	0.6494919***	0.6649994***	0.6448789***	0.650607***	0.6458978***	0.644941***
	$\lambda_{Event*SMB}$	-0.00476	-0.004065	-0.0170469	-0.0038859	-0.00484	-0.0053492	-0.00478
	β_{LIQLEV}	0.001178	0.055401**	0***	-0.0137987	0.323368***	0.0652247***	-0.00159**
	$\lambda_{Event*LIQLEV}$	-0.001	-0.0657019**	0***	0.06185***	-0.27492***	-0.0684193**	0.002614***
7	β_{SMB}	0.657737***	0.6574928***	0.6712252***	0.6579661***	0.659244***	0.6590381***	0.657968***
	$\lambda_{Event*SMB}$	-0.03787	-0.0281823	-0.0445913	-0.0376164	-0.02932	-0.039022	-0.03817
	β_{LIQLEV}	0.008471***	0.0449235**	0***	0.0161832***	0.299369***	0.022919***	-0.00262***
	$\lambda_{Event*LIQLEV}$	-0.0075***	-0.0412362**	0***	0.0147416***	-0.27714***	-0.0547134***	-0.0017
8	β_{SMB}	0.533206***	0.5286986***	0.5439424***	0.5333495***	0.530689***	0.5357233***	0.533179***
	$\lambda_{Event*SMB}$	-0.04864**	-0.0475754**	-0.0559631***	-0.0490043***	-0.0488**	-0.0504021***	-0.04868**
	β_{LIQLEV}	0.001396	0.0370917*	0***	0.0137626	0.335559***	0.0544276**	-0.00144
	$\lambda_{Event*LIQLEV}$	-0.00185	-0.0346395*	0***	0.0117132	-0.26317**	-0.094427***	-0.00054
9	β_{SMB}	0.298208***	0.3013276***	0.3038032***	0.2982295***	0.303607***	0.3010808***	0.298617***
	$\lambda_{Event*SMB}$	-0.08601***	-0.0907029***	-0.0896182***	-0.0861457***	-0.09215***	-0.0877663***	-0.08636***
	β_{LIQLEV}	0.005038***	0.0331165*	0***	0.0060907	0.288025***	0.0601332	0.000552
	$\lambda_{Event*LIQLEV}$	-0.00516***	-0.0256904	0***	-0.0016209	-0.25796**	-0.0949269***	-0.00375**
10	β_{SMB}	0.03179**	0.0332291**	0.0340749**	0.0315449**	0.035657***	0.0343236***	0.032049**
	$\lambda_{Event*SMB}$	-0.08706***	-0.0867237***	-0.0879***	-0.0870958***	-0.08844***	-0.0886776***	-0.08725***
	β_{LIQLEV}	-0.00271	0.0603419***	0***	-0.0215342	0.280513***	0.0685968**	-0.0002
	$\lambda_{Event*LIQLEV}$	0.002271	-0.0657832***	0***	0.0307446*	-0.29446**	-0.0819683**	-0.00193

Panel C - *NASDAQ sub-sample: 2,242,670 stock-day observations*

***SIZE* decile**	***Independent Variables***	***LIQLEV Measures***						
		ACOR	***AGIB***	***Amihud***	***ECOR***	***EGIB***	***QSPD***	***Zeros***
1	β_{SMB}	0.3741632***	0.367035***	0.4029933***	0.372303***	0.362082***	0.3718824***	0.376894***
	$\lambda_{Event*SMB}$	-0.2164937***	-0.21381***	-0.2326511***	-0.21514***	-0.21107***	-0.2176689***	-0.21973***
	β_{LIQLEV}	0.0120933***	0.020147***	0***	0.218202***	0.099598***	0.0220248**	-0.00245
	$\lambda_{Event*LIQLEV}$	-0.0088234***	0.002583	0***	-0.12512***	-0.13443***	-0.039652***	-0.0022*
2	β_{SMB}	0.3854685***	0.395838***	0.4102942***	0.38499***	0.397761***	0.3875048***	0.38657***
	$\lambda_{Event*SMB}$	-0.0089343	-0.01642	-0.015615	-0.01072	-0.01722	-0.0074214	-0.00907
	β_{LIQLEV}	0.0053959	0.012566***	0***	0.094155***	0.101449***	0.0382122***	-0.00248**
	$\lambda_{Event*LIQLEV}$	0.0000464	-0.00793	0***	-0.0048	0.038633	0.0023056	0.004252
3	β_{SMB}	0.5556519***	0.558148***	0.58021***	0.557743***	0.55975***	0.5561305***	0.556735***
	$\lambda_{Event*SMB}$	0.2276809	0.225677	0.2251788	0.226858	0.224618	0.2276291	0.226483
	β_{LIQLEV}	0.0020923**	0.003814	0***	0.041941***	0.24381***	0.0854701***	0.003086***
	$\lambda_{Event*LIQLEV}$	0.0055548	0.012905	0***	0.011995	0.040151	-0.0239146	0.002406
4	β_{SMB}	0.9697009***	0.966115***	0.989878***	0.971527***	0.966351***	0.9689446***	0.969296***
	$\lambda_{Event*SMB}$	0.106707***	0.114348***	0.0995682***	0.107164***	0.114615***	0.1071876***	0.107054***
	β_{LIQLEV}	-0.0009939	0.017907	0***	0.0035320	0.275214***	0.1170646***	0.004171***
	$\lambda_{Event*LIQLEV}$	-0.0008245	-0.01541	0***	0.055582***	0.17743***	-0.0537921	0.002454
5	β_{SMB}	1.0320893***	1.036568***	1.0522601***	1.034223***	1.035866***	1.0325064***	1.031839***
	$\lambda_{Event*SMB}$	-0.022228	-0.01959	-0.0319621	-0.02265	-0.01901	-0.0224917	-0.0221
	β_{LIQLEV}	0.002264	0.008805	0***	0.017463**	0.197285***	0.0518723**	8.11E-05
	$\lambda_{Event*LIQLEV}$	-0.0009495	-0.01672	0***	0.054045***	0.20197***	-0.0425678	0.005702**

***SIZE* decile**	***Independent Variables***	***LIQLEV Measures***						
		ACOR	***AGIB***	***Amihud***	***ECOR***	***EGIB***	***QSPD***	***Zeros***
6	β_{SMB}	0.9565385***	0.959582***	0.970484***	0.95749***	0.956924***	0.9580816***	0.956317***
	$\lambda_{Event*SMB}$	-0.0141698	-0.01568	-0.0216141	-0.01546	-0.01346	-0.0155231	-0.01396
	β_{LIQLEV}	-0.0000885	-0.0051	0***	0.02695***	0.446822***	0.1224594**	0.000864
	$\lambda_{Event*LIQLEV}$	-0.0008105	-0.00056	0***	0.030806***	-0.1224	-0.0871934	0.00284
7	β_{SMB}	0.8945918***	0.898499***	0.9073942**	0.89505***	0.896674***	0.8960722***	0.894085***
	$\lambda_{Event*SMB}$	-0.0516838*	-0.05428**	-0.0601599**	-0.05134*	-0.05227*	-0.0531064**	-0.05189*
	β_{LIQLEV}	-0.0018891	0.024802***	0***	0.017509	0.386019***	0.0632335**	-0.00017
	$\lambda_{Event*LIQLEV}$	0.0058102	-0.00141	0***	0.037907**	-0.06321	-0.0719931**	0.003039
8	β_{SMB}	0.7590138***	0.759733***	0.767239***	0.759593***	0.761176***	0.762289***	0.759126***
	$\lambda_{Event*SMB}$	-0.095014***	-0.09639***	-0.0997482***	-0.09437***	-0.09731***	-0.097692***	-0.09595***
	β_{LIQLEV}	0.0059658***	0.019446**	0***	0.032162***	0.472949***	0.0904183*	0.000428
	$\lambda_{Event*LIQLEV}$	-0.0011312	-0.01493	0***	0.034864	-0.28465*	-0.1089046***	0.000773
9	β_{SMB}	0.4041514***	0.400341***	4.10E-01***	0.404293***	0.402826***	0.4086288***	0.405386***
	$\lambda_{Event*SMB}$	-0.0923612***	-0.08504***	-9.30E-02***	-0.0937***	-0.08642***	-0.0948298***	-0.09296***
	β_{LIQLEV}	0.0084916***	0.028434***	0***	0.026032*	0.448333***	0.0751305***	0.000054
	$\lambda_{Event*LIQLEV}$	-0.0018061	-0.02191	0***	0.039698**	-0.32057***	-0.1201487***	-0.00736***
10	β_{SMB}	0.1369826**	0.140014***	0.140**	0.136155**	0.143529***	0.1391352**	0.137946**
	$\lambda_{Event*SMB}$	-0.0285135	-0.02904	-0.032	-0.02828	-0.03147	-0.0299763	-0.02942
	β_{LIQLEV}	-0.0072495*	0.042998***	0***	-0.05529***	0.382692***	0.0885997*	0.000726
	$\lambda_{Event*LIQLEV}$	0.009378**	-0.03964**	0***	0.088546***	-0.34694**	-0.0599562	-0.00588**

Figure 1: Percentage of stocks with declining spreads

Percentage of stocks witnessing a decline in quoted spreads / effective spreads according to Corwin and Schultz (2011) estimation method, after the implementation of the Hybrid, for NYSE-listed (Figure 1.A) and NASDAQ-listed (Figure 1.B) stocks. The analysis is made for each size decile individually as presented on the horizontal axis, where decile 1 (10) contains smallest (largest) stocks, respectively. Percentages of stocks with declining spreads are on the vertical axis.

Figure 1.A *- NYSE sub-sample*

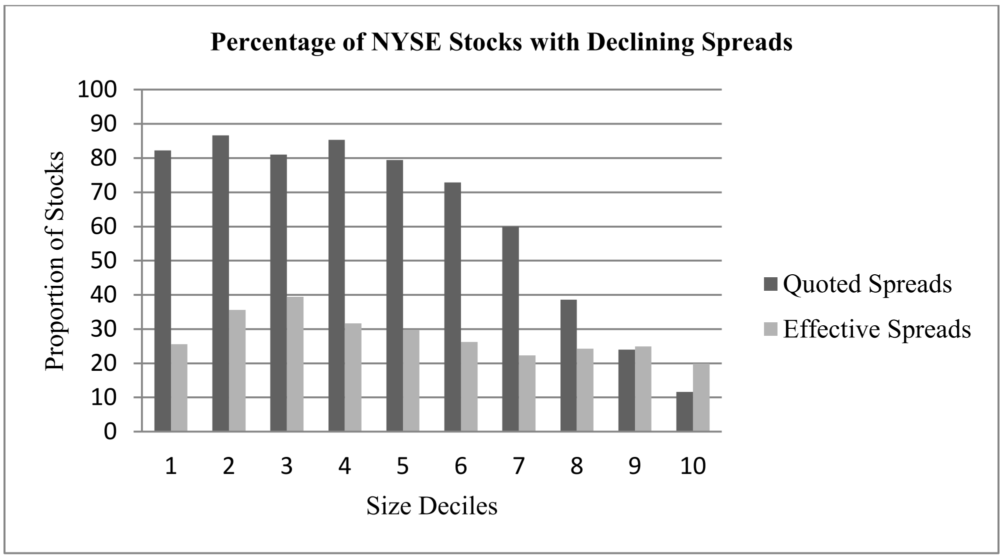

Figure 1.B *– NASDAQ sub-sample*

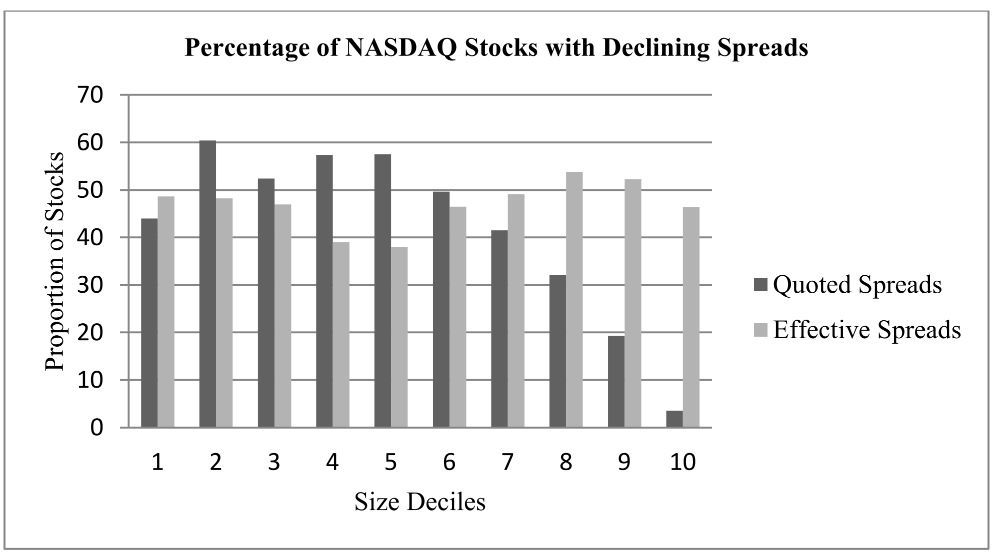

Figure 2: Correlation between size and liquidity

Monthly absolute Pearson correlation values between size, measured by the natural log of market capitalization values, and both quoted / effective spreads according to Corwin and Schultz (2011) estimation method, for the CRSP sample (A) as well as NYSE (B) and NASDAQ (C) sub-samples, for the period from October 2005 until January 2008 - the two-year period around the Hybrid implementation, including the four-month system roll-out period which is marked on graphs by rectangular boxes.