# Agent Trading Models, Speed and Market Making Incentives

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# Summary

This study analysed the effect of the tick size pilot program implemented by the United States Securities and Exchange Commission on the trading behaviour of three market participant groups: proprietary trading companies, banks and agency firms. The purpose of the study was to provide an in-depth analysis of how the tick size pilot program affected those three groups, in order to infer the competitive advantages and liquidity preferences of each market participant category. First, this dissertation examined the effect of the policy change on market participants' competition for order flow, liquidity provision and transaction costs. The empirical findings indicated that the program encouraged proprietary trading companies to increase their liquidity provision, induced banks to cross the spread more often and move their order flow from BX to Nasdaq and increased agency firms' waiting costs. Second, the effect of the policy change on market participants' intraday order submission strategies and ability to establish time priority was examined. The current literature suggests that tick size consolidations exacerbate the need for speed and allow proprietary trading companies to extract rents from other traders by establishing time priority. Conversely, this study's empirical findings indicated that banks are as fast as proprietary trading companies but cross the spread more frequently to ensure full execution of their clients' orders. Thus, differences in business models seem to be more important compared to speed in explaining the trading strategies of banks and proprietary trading companies. Finally, the study examined the effects of policy change on two groups of proprietary trading companies: (i) those specialised in using opportunistically marketable orders and (ii) market makers. The results indicated that opportunistic traders were specialised in predicting short-term price movement and minimising adverse selection risk, while market makers were specialised in establishing time priority to capture the bid–ask quoted spread as much as possible. Nevertheless, both classes of proprietary traders increased their liquidity provision and trading revenues on treatment stocks by leveraging their specific competitive advantages.

# Statement

I certify that this thesis has not already been submitted for any degree and is not being submitted as part of candidature for any other degree.

I also certify that the thesis has been written by me and that any help that I have received in preparing this thesis and all sources used have been acknowledged in this thesis.

Signature of Candidate

Eugenio Piazza

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# Chapter 1: Introduction

Academics have long analysed how market liquidity is affected by the market participant's fundamental reason to trade or their order submission strategies. An early example of these studies is Kyle (1985) who analysed the effects of informed trading on market depth by modelling the trading behaviour of an informed trader, a dealer and an indistinct group of uninformed traders. Foucault (1999) progressed the literature and developed a game theory model of price formation and order placement decisions in a dynamic limit order market, suggesting that the proportion of limit orders in the order flow and the quoted spread are positively related to asset volatility.

Nonetheless, the advent of the electronic trading system, algorithmic trading and increased market fragmentation have drastically changed financial markets' structure and created a favourable environment for a new class of market participants: the high-frequency trader (i.e., proprietary trading company). The United States (US) Security and Exchange Commission (SEC, 2010) defined high-frequency traders (HFT) as proprietary traders who use their technological advantage to generate, route and execute orders, process direct data feeds sold by exchanges to minimise latency, quickly cancel their submitted orders and avoid overnight inventory positions.

The academic literature provides mixed empirical evidence regarding HFT. Empirical studies indicate that proprietary traders provide more liquidity at the inside compared to other market participants (Jarnecic & Snape, 2014), increase price efficiency by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors (Biais, Declerck & Moinas, 2016; Brogaard, Hendershott & Riordan, 2014) and supply liquidity when it is scarce while they consume it when it is plentiful (Carrion, 2013). Other studies split HFT between those who opportunistically place marketable orders to take advantage of price inefficiencies and those who act as market makers. The latter group tends to reduce volatility (Hangströmer & Nordén, 2013), while the former uses marketable orders to increases price efficiency (Benos & Sagade, 2016). Conversely, Busish, Cramton and Shim (2015) argue that high-frequency trading does not reduce the size or frequency of the arbitrage opportunities; rather, it only creates an expensive arms race to capture them. Similarly, Yao and Ye (2018) suggest that when the quoted spread of a security equals the minimum price variation, also known as tick size, proprietary trading companies use their innovative technology to establish time priority and extract rent from slow traders who are compelled to submit more marketable orders.

Nonetheless, the current academic literature overlooks the effect of new trading technologies on non-HFT who also rely on extremely fast speed to provide different services to their heterogeneous clientele (O'Hara, 2015; Yao & Ye, 2018). Instead, the US regulator supports the idea presented by Weild, Kim and Newport (2012) that markets are structured to favour proprietary trading companies, while they do not incentivise small investment banks and other institutions to make markets on small–medium market capitalisation stocks. The so-called tick size pilot should work as incentive for these institutions to supply liquidity on the so-called growth stocks and ultimately enhance market quality. This dissertation fills these two gaps in the literature by examining the effect of the policy change introduced by the SEC in 2016 on a group of market participants segregated by their declared business model. Using Nasdaq proprietary data and the *Financial and Operational Combined Uniform Single* (FOCUS) reports available on the SEC's (2017) website, we can assess the effect of the tick size pilot on the order submission, cancellation and execution of market participants classified as proprietary traders, banks or agency firms. First, I analyse the wealth effect produced by the market structure change on the three market participant's groups regarding trading volume distribution and execution quality. Then, the thesis focuses on the non-high-frequency trading companies to understand whether both banks and agency firms behave as liquidity traders, as defined by Admati and Pfleiderer (1988), and the effect of the policy change on their ability to establish time priority. The final part of the dissertation investigates whether the market making incentive created by the tick size pilot urges proprietary traders to use their specific technological advantage to supply liquidity. In this chapter, HFT are further divided into market makers and opportunistic traders who strategically place marketable orders to take advantage of price inefficiencies. The motivations of each specific topic examined in this dissertation are further detailed in the remaining part of this chapter.

## 1.1 Tick Size Pilot and Market Participants' Business Model

Since the beginning of the millennium, US financial markets have undergone a technological revolution. The rise of alternative trading systems (i.e., dark pools), algorithmic trading and increased market fragmentation have altered the financial industry by reducing institutional trading costs (Hendershott, Jones & Menkveld, 2011) and increasing the speed of trading (O'Hara, 2015) and by the overall complexity of the capital markets (Weild et al., 2012).

These changes in market structure have raised several concerns to the US regulator, as industry participants appear more focused on increasing profits from the capital allocation process rather than encouraging capital formation. This shift is particularly detrimental for small and medium enterprises that struggle to raise the necessary resources from capital markets to expand and create jobs in the economy. According to Weild et al. (2012), the reduction in minimum price increment as well as market fragmentation and high-frequency trading represent frictions that discourage investment banks from promoting and supporting emerging growth stocks.

In response, the SEC issued an order on 6 May 2015 to implement the tick size pilot program, which increases the minimum price increment, also known as the tick size, of growth stocks from $0.01 to $0.05. The rationale behind the tick size program is based on Weild et al.'s (2012) research, which posits that proprietary trading companies and large investment banks are the main beneficiaries of a low tick size environment, while small investment banks and agency-like institutions tend to lose money. These losses push the non-proprietary trading companies to produce less equity research on illiquid stocks and, therefore, promote less these stocks to their clients. Through tick size consolidation, the US government anticipates that an increase in expected return on liquidity-supplying activities should generate liquidity spillovers on growth stocks, which will ultimately 'bring back capital formation, jobs and investors' confidence' (Weild et al., 2012).

In this analysis, I assess the effect of tick size consolidation on market participants' competition, liquidity provision, implicit transaction costs and proprietary trading companies' gross trading revenues. Due to the great detail provided by Nasdaq proprietary data, this study segregates investors into three broad categories according to their declared business model (proprietary traders, agency firms and banks). The market participant identifier (MPID), which is tagged to each individual trade, provides a unique opportunity to examine whether the tick size consolidation actually enhances trading competition, increases non-proprietary trading companies' liquidity provision and boosts the overall trading volume on growth stocks. Moreover, the analysis is conducted across three lit markets (BX, PSX and Nasdaq) with varying priority and fee structures (i.e., taker–maker with price–time priority, maker–taker with pro-rata execution system and maker–taker with price–time priority), which will provide additional insights into the interactions between exchanges' incentive system and market participants' trading behaviour.

Findings from this research are relevant to US regulators, government, exchange operators and academics and can be readily applied to other overseas financial markets contemplating similar tick consolidation exercises. Empirical results suggest that, overall, tick size consolidation does not increase competition for order flow among market participants on securities affected by the policy change. However, agency firms are trading a larger share of their order flow through passive strategies on PSX while banks are now using a larger portion of market orders on BX to minimise their transaction costs. Nonetheless, agency firms face higher waiting costs on treatment securities. Further, the policy change has no effect on the trading behaviour of these market participants on stocks with a pre-pilot quoted spread higher than \$0.11. Conversely, it appears that the program engourages proprietary trading companies to supply liquidity on treatment securities and to reduce their order's cancellation rate to earn higher gross trading profits on securities with a pre-pilot average quoted spread lower than \$0.04. Overall, it appears that the tick size change has partially accomplished its desired results on very illiquid securities.

These findings should be interpreted with caution. Although this research partially overcomes the issues raised by Carrion (2013), the data cover only the trading activity in the three NASDAQ trading markets. Nevertheless, this analysis advances our understanding of incentive mechanisms, such as tick size consolidation, on different market participants in a multi-market environment.

## 1.2 Tick Size Pilot and Market Participants' Intraday Trading Behaviour: Does Speed Still Matter?

Recent technological advancements have pushed both regulators and industry professionals to reshape the financial industry as the new trading systems now strongly rely on the communication speed between the single broker/dealers and the exchanges. Specifically, exchanges spend a huge amount of resources to increase the stability and functionalities of their limit order books to allow market participants to best handle their order flows at any point. Some of these traders, also known as proprietary trading companies, are constantly developing their trading technology to be a step ahead by taking full advantage of all publicly available information and leveraging their superior ability to quickly communicate to the limit order book.

With the call for papers requested by the SEC in 2010 and the introduction of new rich databases, the academic community has focused its attention in understanding whether fast traders overall improve or damage market quality. A portion of the theoretical literature highlights that fast trading technologies may have detrimental side effects on market quality (Biais, Foucault & Moinas, 2015; Menkveld & Zoican, 2017). However, a large portion of the empirical literature indicates that fast traders reduce implicit transaction costs and improve price efficiency by trading against transitory price movements (Brogaard, Hagströmer, Nordén & Riordan, 2015; Brogaard, Hendershott & Riordan, 2014). The most recent analyses split market participants into slow traders, market maker and opportunistic fast traders. Fast market makers use their speed advantage to reduce their inventory constraints and improve the informativeness of their quotes while fast opportunistic traders seem to increase price efficiency by trading against stale quotes. Overall, the academic literature demonstrates that both opportunistic and market making fast traders optimise their order submission strategies by considering the trade-off between crossing the bid–ask spread and waiting costs (Hangströmer, Nordén & Dong, 2014).

My research, inspired by O'Hara (2015), tries to understand whether speed is still relevant in today's financial markets by analysing the effect of the tick pilot program on a sample of market participants' quoting and trading activity on Nasdaq and BX. Our novel approach differs from the existing literature as market participants are not classified based on their trading behaviour, but on their declared nature of business as reported on the SEC filings. Through this approach, I can characterise the market participants by classifying them as proprietary trading companies, banks or agency firms. Because of this classification, and the possibility to distinguish between principal and agency orders, I test Yao and Ye (2018)'s speculation that a tick size consolidation exacerbates the need for speed and creates a competitive advantage for fast traders. This allows me to test whether proprietary trading companies are capable of being at the front of the queue more often than all other market participants. Subsequently, I analyse the quoting behaviour of this study's sample of market participants by classifying each order based on its aggressiveness. Using the difference-in-differences methodology, it is possible to understand the causal effect of speed in explaining changes in market participants' order submission strategies.

Surprisingly, the current study results indicate that, as the pilot program starts, banks are as much at the front of the queue as proprietary trading companies, but wind up crossing the bid–ask spread more frequently. These results indicate that banks, which mostly trade on behalf of their clients, are as fast as proprietary traders, but are forced to consume liquidity as they trade close to their demand realisation. These findings are relevant to the literature as they clearly indicate that trading speed is not as important as it was as market participants choose whether to be fast or slow based on their business model. Therefore, researchers should shift their focus from studying the effect of fast trading on market quality to analysing when voluntary market makers, who trade only when it is convenient, play a significant role in ensuring market integrity, fairness and efficiency.

## 1.3 Tick Size Pilot and Heterogeneous High-Frequency Traders

Academics and regulators have long debated whether market maker obligations are still useful in modern financial markets. Some academics support the idea that the increased market competition and market fragmentation have effectively eliminated much of the profitability of the registered market makers as HFT now supply liquidity though their trading activity (Born et al., 2011). Nonetheless, the joint Commodity Futures Trading Commission and SEC advisory committee suggest that these two regulatory authorities should 'consider encouraging, through incentives or regulations, persons who regularly implement market maker strategies' (Born et al., 2011). Consistently, the SEC decided to commence on 3 October 2016 the tick size pilot program studying the effects of increasing the minimum price variation, also known as tick size, on growth stocks from \$0.01 to \$0.05 on market making. This speculation is based on Weild et al.'s (2012) study, which suggests that a thicker tick size should ultimately encourage liquidity on growth stocks and increase the number initial public offerings.

In this research, I demonstrate that the market making incentive introduced by the SEC encourages proprietary trading companies to use their specific technological advantages to increase their liquidity provision, their presence at the national best bid and offer (NBBO) and their intermediation activity. HFT specialised in news trading increased their liquidity supply mostly on securities with a pre-pilot quoted spread lower than \$0.11 using their superior ability to predict short-term price movements to minimise their adverse selection costs and maximise their realised spread. Conversely, those proprietary traders specialised in speed increase their liquidity provision on all treatment stocks using their technology to be on top of the books as much as possible to capture the bid–ask spread. Overall, the research suggests that both technologies allow high-frequency trading companies to increase their trading revenues on securities affected by the policy change.

## 1.4 Summary

This study examines the effect of the tick size pilot on the trading behaviour of banks, agency firms and proprietary traders to deepen our understanding of the relationship between tick size, speed, market participant's business models and voluntary market making.

The remainder of this dissertation is structured as follows: Chapter 2 introduces the relevant literature review for each topic examined in this dissertation, Chapter 3 provides the institutional settings and the methodology used to classify the three market participant groups, Chapter 4 analyses the effect of the tick size pilot program on the three groups, Chapter 5 focuses on examining the trading behaviour of banks and agency firms and Chapter 6 focuses on disentangling the effects of the policy change on market making and opportunistic HFT.

# Chapter 2: Literature Review

This chapter provides an overview of the relevant literature related to the three topics outlined in this dissertation to explain in further detail the contribution of these analyses to the existing theoretical and empirical literature.

## 2.1 Tick Size and Heterogeneous Market Participants

Academic papers analysing the effect of the minimum price movement changes can be split in two main categories: (i) those studying the effects of the policy change on market quality and (ii) those focused on the changes in the market participants' trading behaviour. This section of the dissertation is related to both topics as it provides important insights on institutional transaction costs and on the behaviour of different market participants after the introduction of the tick size consolidation.

The debate over the optimal tick size is not new in the literature as the gradual reduction in the minimum price variation across all the stock exchanges worldwide is well documented in the literature. However, academics provide mixed predictions and empirical results regarding the effects of the tick size reductions on the overall market quality.

Initially, Harris (1994) predicted through a cross-sectional regression model that the absence of a tick constraint reduces quoted spreads, decreases displayed quoted size and increases the average daily traded volume of securities priced below $10. Moreover, Harris (1996) demonstrated that traders are more willing to expose a larger order size on securities with larger tick size and lower volatility. Therefore, in 1997, he suggested that a larger tick size in conjunction with time priority may be positive for institutional investors as it renders front-running strategies more expensive. These results are consistent with papers published by other academics that provide both positive and negative effects of tick size reductions on market quality.

The debate over this topic is further revitalised by the NYSE's decision to reduce the minimum price variation from eighths to sixteenths. Goldstein and Kavajecz (2000) indicate that this market microstructure change decreases both quoted spreads and the total market depth throughout the entire limit order book. Thus, traders submitting small orders benefit from this policy change, while the execution costs increase for large orders in low priced illiquid stocks. This phenomenon is consistent with Jones and Lipson's (2001) results; their study used proprietary data regarding institutional orders and provided empirical evidence of increased institutional transaction costs after the NYSE tick size reduction. Additionally, this policy change inspired Kadan (2006) to develop a theoretical model that analysed the effect of a tick size reduction on dealers' competition.

Further, the US and Canadian regulators enforced a rule to set the tick size to 1 cent at the beginning of the millennium. These rules, also known as decimalisation, provide academics with new research opportunities to study the topic from different perspectives. Bessembinder (2003), who studied the effects of decimalisation on market quality in the US stock market, suggested that heavily traded large capitalisation NASDAQ-listed stocks benefit the most from the tick size reduction. Ahn, Cao and Choe (1998) analysed whether decimalisation in the Canadian market sparks order flow competition on stocks cross-listed in US stock exchanges. Their research indicated that despite an economically significant reduction in the spread on the Toronto Stock Exchange, orders do not migrate from US to Canadian market. Additionally, MacKinnon and Nemiroff (2004) suggested that decimalisation reduces the profitability of naïve liquidity provision strategies across stocks of all price and volume categories.

Over the same period, the US regulator introduced a sub-penny rule (Rule 612), which prohibits market participants from accepting or displaying orders or quotations in a pricing increment smaller than a penny, except for orders or quotations in stocks that are priced at less than $1.00 per share. Kwan, Masulis and McInish (2015) demonstrated that tick size influences dark trading as market participants use dark pools to obtain a finer pricing grid when the stock prices are tick constrained.

Recently, Weild et al. (2012) provided evidence that a smaller tick size is detrimental for growth stocks. Because of this research, the SEC issued an order in 2016 to commence a pilot program that aims to understand the effect of tick size consolidation on market quality. Lin, Swan and Mollica (2018), who studied the effect of the so-called nickel tick pilot on market quality, suggested that as consolidated trading volume decreases, the overall transaction costs and adverse selection costs increase significantly, while price discovery is enhanced for the most tick-constrained group and the lit market share increases for treatment securities subject to the '*trade-at*' rule. Comerton-Forde, Gregoire and Zhong (in press) suggested that the exogenous shock provided by the tick size pilot on inverted markets affects market quality as it improves price efficiency, increases liquidity and decreases volatility. However, the imposition of the trade-at rule appears to have a negative effect on price efficiency.

With the availability of new and richer databases, and because of the growing interest in HFT regulation, academics have recently focused their attention on the effects of tick size reduction and consolidation on the market participant's trading behaviour.

Hagströmer and Norden (2013) studied the stabilising role played by market making HFT on stocks' intraday volatility after the tick size consolidation in NASDAQ-OMX Stockholm. This paper appears to be the only one to use NASDAQ classification expertise to distinguish between pure agency traders and proprietary traders, classified as non-HFT and HFT. Similarly, O'Hara, Saar and Zhong (in press) reported that high-frequency market makers leave orders in the book longer, trade more aggressively and have higher profit margins as the ratio between the tick size and the price, also known as the relative tick size, increases. Ultimately, the authors suggested that the optimal minimum tick size is one that approximates a stock's normal unconstrained spread level. Therefore, the optimal tick size may be lower for active stocks and higher for inactive stocks. An analogous result on SGX-listed securities is provided by Lepone and Wong (2017), whose research indicated that pseudo market makers change their trading behaviour by trading more actively low-priced securities, as the yield from quoting these spreads is higher.

However, Yao and Ye (2018) supported the idea that tick size constraints lead to queue rationing, which favours HFT. Because of the difficulty in establishing time priority, slow traders are pushed to submit more market orders as the relative tick size increases despite the increased profitability of submitting limit orders.

The current study focuses on analysing the impact of the tick size consolidation and the '*trade-at*' rule on proprietary trading companies, banks, and agency firms. Specifically, the dissertation analyses how the tick size pilot program introduced by the SEC (2016) influences market participant's competition for order flow, liquidity provision, and implicit transaction costs across three Nasdaq trading venues.

## 2.2 Tick Size and Market Participants' Speed

The current analysis contributes to the existing literature using an exogenous event, the tick size pilot, to study the quoting behaviour of different market participants classified by their business models. As suggested by O'Hara (2015), all market participants have fair access to the existing technology, but choose to employ different intraday quoting strategies in accordance with their incentives structure. To validate this hypothesis, I test whether the tick size consolidation advantages proprietary trading companies in establishing time priority, as suggested by Yao and Ye (2018), and how other types of market participants adjust their order submission strategies when facing this regulatory change.

Previous academic literature regarding heterogeneous market participants focused on two main themes: (i) the effect of heterogeneous market participants on market quality and (ii) their optimal dynamic order submission strategies. Recent papers addressing these subjects use speed as a source of market participants' heterogeneity as this incentivises fast traders to exploit their technological advantage to maximise their gains from trading. However, papers published in the 1990s suggest that market participants' business models determine intraday trading volume patterns and traders' dynamic order submission strategies.

Specifically, Admati and Pfleiderer (1988) developed a theoretical model in which observed intraday trading volume and volatility patterns (e.g., McInish & Wood, 1992) can be explained by the trading behaviour of time-constrained traders, also known as discretionary liquidity traders, who are forced to trade close to their demand realisation. Conversely, Parlour (1998) suggested that the intraday trading patterns are endogenously created by market participants' strategic behaviours that induce them to consider other traders' order submission strategies. The empirical paper published by Anand, Chakravarty and Martell (2005) indicated that informed and liquidity traders have opposite behaviours during the trading day. The informed traders (liquidity traders) take (supply) liquidity at the beginning of the day while they supply (take) liquidity later in the trading session. Other papers published in that period regarding order submission strategies suggest that market participants tend to provide liquidity when quoted spreads and volatility are high and, hence, it is profitable to place limit orders (Bae, Jang & Park, 2003; Biais, Hillion & Spatt, 1995; Handa & Schwartz, 1996).

However, the most recent theoretical literature analyses the effect of speed-induced market participants' heterogeneity on market quality, traders' order submission strategies and utilitarian welfare. According to Menkveld (2016), it is possible to use the models developed by Kyle (1985) and Glosten and Milgrom (1985) to assess the effect of fast traders, also known as HFT, on market quality. If HFT behave as informed traders, their trading behaviour should exploit their informational advantage to maximise their gains from trading, which increases market makers' adverse selection costs. However, if HFT are market makers, they use their speed advantage to minimise their adverse selection costs by posting more informative quotes. Foucault, Hombert and Rosu (2016) update Kyle's model by assuming that informed traders have a speed advantage over other market participants and use this technological edge to engage in news trading strategies making their trades strongly correlated to pending news and short-run price reactions to news. Overall, the model suggests that fast informed traders' profits should decline with news informativeness. Menkveld and Zoican (2017) investigate the effect of exchange speed on market quality in a single market model characterised by opportunistic HFT, market maker HFT and liquidity traders. The authors assume that liquidity traders' arrival rate and the exchange latency represents an 'anti-sniping shield' for high-frequency market makers' quotes; thus, an exchange speed update may have detrimental effects on market quality. The effect of speed-induced heterogeneity on market participants' order submission strategy is tackled by Hoffman (2014), who developed a game theory model based on Foucault (1999) in which speed is a competitive advantage that allows fast traders to revise their quotes after news arrival. Hoffman concluded that fast traders induce slow traders to submit limit orders with lower execution probability while increasing their probability of being adverse selected. Overall, this model suggested that fast traders act as informed traders and use their speed advantage to trade only when it is most profitable. Biais et al. (2015) analysed the relationship between speed heterogeneity and utilitarian welfare by developing a multimarket model in which market participants choose whether to be fast or slow. The authors predicted that trades' informational content should be inversely related to the cost of becoming fast and that utilitarian welfare is maximised when both slow and fast traders coexist and the government enforces Pigovian taxes on trading technology.

With the introduction of rich databases, empirical researchers started testing theoretical models to assess how trading technology shaped modern financial markets. Earlier papers analysed the effect of exchange latency and algorithmic trading on market quality and indicated that increased low-latency activity improves spreads, depth in the limit order book and short-term volatility (Hasbrouck & Saar, 2013). Consistent empirical findings are also documented by Riodan and Storkenmaier (2012) and Conrad, Wahal and Xiang (2015) who studied the effect of a speed upgrade on the Deutsche Boerse and Tokyo Stock Exchange, while Chaboud, Chiquoine, Hjalmarsson and Vega (2014) ascertained that algorithmic traders Granger cause a reduction of arbitrage opportunities by trading against human-entered quotes. However, Budish, Cramton and Shim (2015) argued that the recent technological advancements do not reduce the size or frequency of arbitrage opportunities; rather, they create a costly arms race between market participants.

Other papers that leverage on proprietary data analyse the trading behaviour of market participants classified by their speed. Garvey and Fei (2010) studied the trading behaviour of market participants based on their distances from New York City; they discovered that traders that are very close to the servers have faster execution speeds and lower execution costs. They further argued that this competitive advantage helps fast traders to trade more often, hold their inventory positions for shorter periods and use more aggressive order types compared to the rest of the market. Likewise, Hirschey (2013) and Carrion (2013) used Nasdaq data to demonstrate that HFT possess intraday market timing ability as they tend to provide (consume) liquidity when it is scarce (plentiful) and their aggressive trades lead those of other investors. Further, Brogaard et al. (2014) used the same data to indicate that the effect of that trading behaviour improves price efficiency as HFT use marketable orders to trade in the direction of permanent price changes and in the opposite direction of transitory pricing errors. Menkveld (2013) used proprietary data from GETCO, an important proprietary trading company, to analyse its trading behaviour on Euronext and Chi-X Europe, and suggested that this market participant behaves as a market maker as it earns the bid–ask spread, while losing on its inventory position. This research also indicated that the introduction of a new trading platform incentivised GETCO to tight their quoted spread, indicating an intimate relationship between HFT trading activity and market fragmentation. Jarnecic and Snape (2014) analysed the market participants' order submissions strategies and discovered that HFT tended to provide more liquidity at the inside compared to non-HFT. Yao and Ye (2018) stated that HFT are more active on tick-constrained securities in which they can exploit that speed advantage against non-HFT, who are unable to establish time priority on tick-constrained securities and are forced to submit more market orders.

As suggested by O'Hara (2015), the latest empirical research papers split market participants between market making HFT, opportunistic HFT and slow traders to obtain a better understanding of how traders belonging to these three categories affect market quality. Hangströmer and Nordén (2013) and Hangströmer, Nordén and Dong (2014) used Nasdaq Nordic data to indicate that market making and opportunistic HFT consider the trade-off between waiting cost and the cost of crossing the bid–ask spread, while non-HFT are less responsive to that trade-off. However, they also suggest that both non-HFT and HFT reduce volatility by submitting less aggressive orders when the market is more volatile. Benos and Sagade (2016) stated that HFT trades contribute about 14% of all the trade-induced price discovery and opportunistic HFT account for two-thirds of this contribution. These findings are consistent with Biais et al. (2016), who suggest that proprietary traders, regardless of their speed, provide liquidity with contrarian marketable orders that stabilise the market. While these papers focus their attention on the three classes of market participants, Brogaard et al. (2015) and Kirilenko et al. (2017) focused their attention on market making HFT. The former suggested that market making HFT use their speed advantage to reduce their exposure to adverse selection costs and to relax their inventory constraints. The latter concluded that market making HFT do not alter their inventory dynamics when facing large liquidity shocks.

This research is innovative in that it analyses whether market participants' heterogeneous behaviours is mainly driven by differences in their execution speed or differences in their business model by looking at their National Best Bid or Offer price setting behaviour and their order submission strategy.

## 2.3 Heterogeneous High-Frequency Traders

Inspired by O'Hara (2015), this research joins a growing body of literature analysing the biodiversity of market participants. While most academic studies focused on the static trading behaviour of several trader types, I examine how changes in incentive structures influence proprietary trading companies' order submission strategies. Our results indicate that both opportunistic and market making HFT are profit motivated market participants that specialise in using their speed either to process information or to be at the front of the queue. Most of the current theoretical literature analyses these two classes of proprietary trading companies separately.

Academics have examined the strategic behaviour of specialised proprietary traders that use their superior speed and tread ahead of news release. For instance, Kandel and Marx (1999) analysed how price volatility and minimum tick size affect the quote sniping strategy employed by the so-called bandits. This theoretical model states that bandits' profits from sniping market makers' stale quotes are positively correlated to tick size changes. Within the same context, Foucault, Röell and Sandås (2003) developed a theoretical model to study the order submission strategies of liquidity traders, dealers and bandits. In this framework, bandits have superior information regarding asset value and profit from sniping dealers' stale quotes, while dealers face a trade-off between news and quote monitoring. Each dealer can either invest in news processing technology or match other dealers' quotes to share the risk of being picked off. Therefore, bandits can use dealers' quote updates to pick off the slowest market makers, leading to increased competition among liquidity providers. However, when adverse selection costs are too high, dealers may refuse to provide liquidity, resulting in dramatic consequences for market quality. Hoffman (2014) updated Foucault's (1999) theoretical model by introducing a fast trader who can revise its quotes based on news arrival. The introduction of such a market participant induces slow traders to enter limit orders with lower execution probability while facing higher adverse selection costs. Biais, Foucault and Moinas (2015) developed a multi-market model in which traders can choose to invest in speed before trading.

According to this theoretical model, traders' informational content should be inversely related to the cost of fast trading technology. Foucault et al. (2016) revised Kyle's (1986) work by formulating a model in which one market maker, one informed trader and one liquidity trader interact. This model, inspired by the empirical evidence regarding high-frequency trading, suggests that informed traders' trades are strongly correlated with pending news and short run price reaction to news. Further, informed traders' profits should decline with news informativeness. Similarly, Foucault, Kohzan and Tham (2017) presented a model of cross-market arbitrage in which two segregated market makers provide liquidity on two highly correlated securities to a speculator and a multitude of liquidity traders. The main message of this model is that the probability for a speculator of hitting a stale quote depends on its speed relative to the market maker.

Conversely, there are theoretical models focused on voluntary market making in high-frequency markets. One model, developed by Cartea and Penalva (2012), assumed that a market making high-frequency trader extracts rents from professional traders and liquidity traders. The presence of such an intermediary creates more market microstructure noise and pushes professional traders to upgrade their speed to become high-frequency market makers. This model suggests that volume-based liquidity metrics are biased as high-frequency market maker trades represent an intermediation cost for natural investors. Conversely, Ait-Sahalia and Sağlam (2013) studied the optimal quoting strategy of a market maker with two advantages over liquidity traders: (i) speed and (ii) the ability to observe a signal that is informative about the likely sign of the next incoming market order. According to the authors, speed allows market makers to improve their ability to control their inventories by predicting the sign of the next market order at a higher frequency. Ultimately, market makers in this model aim to trade as much as possible with a liquidity motivated market participant to earn the spread. Jovanovic and Menkveld (2016) studied whether a better-informed market maker can improve welfare by analysing its effect on investors' trading strategies. Investors experience a lower bid–ask spread after the introduction of a market maker; however, these market participants are forced out of earning the spread as their limit orders face the threat of being sniped by the intermediary. Therefore, the model suggested that a large spread reduction and volume increase are not necessary synonymous with better market quality.

The most current models on these topics try to blend high-frequency market makers and bandits or they allow proprietary trading companies to provide or consume liquidity based on relative convenience of each trading strategy. Menkveld and Zoiacan (2017) developed a game theory model with high-frequency bandits, high-frequency market makers and liquidity traders, analysing the effect of exchange latency on market quality. High-frequency bandits use their superior technological expertise to snipe stale quotes, while the uncertainty generated by the presence of liquidity traders and exchange latency constitute an anti-sniping shield for high-frequency market makers. Because of these assumptions, the authors predicted that a reduction in exchange latency may impair market quality as market makers suffer higher adverse selection costs. Instead, the model developed by Li, Wang and Ye (2018) assumed that proprietary trading companies choose when to provide liquidity and snipe stale quotes based on the stock's characteristics and relative tick size. In this theoretical research, algorithmic investors attempt to minimise their transaction costs using a mixture of limit and market orders. However, these market participants are not sufficient fast to compete with proprietary trading companies on tick-constrained securities in which time priority limits their ability to use market orders. Interestingly, the authors suggested that the tick size pilot primarily advantages proprietary trading companies, which set prices more often than algorithmic investors.

The empirical literature extensively tested these theories and provided invaluable insights regarding proprietary trading companies' strategies, its intimate relationship to speed and market fragmentation and its effects on market quality. Speed is an important topic in the market microstructure literature, as traders, who are physically closer to the market centres, tend to trade more frequently, cancel orders more often, submit more aggressive orders and reverse their inventory more quickly compared to other market participants (Garvey & Wu, 2010). Proprietary trading companies appear to invest extensively in trading technology to reduce their communication latency with the exchanges and engage in profitable intraday trading strategies (SEC, 2010). Thus far, the empirical literature analysing Nasdaq datasets suggests that proprietary traders provide liquidity when it is scarce, take liquidity when there is plentiful and lead other market participants' aggressive purchases and sales (Carrion, 2013; Hirschey, 2013). However, the liquidity supply of these market participants is sensitive to prolonged extreme price movements, as suggested by Brogaard et al. (2018), as position risk forces proprietary traders to switch from supplying to demand liquidity during periods of extreme price volatility. In contrast, evidence from the futures market suggest that proprietary trading companies do not alter their inventory dynamics when facing a large liquidity shock (Kirilenko, Kyle, Samadi & Tuzun, 2017). Further, Brogaard et al. (2014) determined that proprietary trading companies increase price efficiency on Nasdaq by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors. Papers analysing the Australian Stock Exchange and London Stock Exchange suggested that proprietary desks tend to cluster their limit orders close to the top of the book, while the opposite is true for other market participants (Aitken, Almeida, deB Harris & McInish, 2007; Jarnecic & Snape, 2014). Menkveld (2013) consistently determined that GETCO, a large proprietary trader, acts as a voluntary market maker in Dutch equity markets as the company loses on its inventory and earns the bid–ask spread. Menkveld established that bid–ask spreads declined when proprietary trading companies started trading on a new trading platform established in 2007, suggesting that cross-market trading strategies employed by proprietary traders have overall a positive effect on market quality. Brogaard et al. (2015) exploited a natural experiment on NASDAQ-OMX Stockholm and indicated that proprietary traders use superior trading speed to relax their inventory constraints and reduce their exposure to adverse selection risk. Overall, this natural experiment has a positive spillover effect as effective spreads decreases, while the NBBO depth increases. Conversely, Yao and Ye (2018) suggested that proprietary traders' speed advantage may hurt investors who are forced to submit more market orders on securities with high relative tick size. However, Kenvel and Menkveld (2018) indicated that investors are aware of proprietary traders' order submission strategies and trade optimally to minimise the likelihood of being detected.

More recently, academics have acknowledged that 'all trading is now fast, with technological improvements originally attaching to High Frequency Traders permeating throughout the marketplace' (O'Hara, 2015). With this new perspective in mind, researchers are now less invested in understanding how fast traders affect slow traders, as they are focusing more on understanding the biodiversity of market participants. Specifically, Hangströmer and Nordén (2013) calculated the percentage of liquidity providing volume and the percentage of times each market participant on Nasdaq-OMX Stockholm displays both the best bid and the best offer within a trading day to segregate proprietary traders into opportunistic and market makers. The authors indicated that when the tick size changes, market maker proprietary trading companies appear to reduce the stock's intraday volatility. Hangströmer, Nordén and Dong (2014) used the same data and classification to analyse market participant's order aggressiveness and concluded that proprietary trading companies consider the trade-off between waiting costs and the cost of crossing the spread, while the other traders do not. Further, the authors indicated that all market participants tend to submit less aggressive orders when facing market volatility. Similarly, Benos and Sagade (2016) studied the price discovery contribution of the proprietary trading companies classified as aggressive, neutral or passive based on their trading activity. According to this research, proprietary traders generate 14% of the trade-induced price discovery and the aggressive type account for 67%. Instead, O'Hara et al. (in press) used NYSE proprietary data to analyse the trading behaviour of market makers, quantitative traders and institutions. The former group comprises designated market makers

(DMMs) and supplementary liquidity suppliers (SLPs), the second group comprises program traders and arbitrageurs and the latter group comprises agency firms. The authors suggested that a larger tick size should be beneficial mainly for market makers, while it leads all other market participants to move their order flow away from stock exchanges. Biais, Declerk and Moinas (2016) divided market participants trading on European exchanges based on their latency and a proprietary flag that allowed the authors to distinguish each order as either principal or agent. Interestingly, proprietary trading companies, regardless of their speed, stabilised the market by supplying liquidity with contrarian marketable orders. Finally, Baron, Brogaard, Hangströmer and Kirilenko (2018) analysed whether the cross differences in speed had any explanatory power over proprietary trading companies' revenues. The empirical results suggest that differences in relative latency account for large differences in proprietary traders' trading performance and that when one of these firms co-locates, its trading performance improve.

This chapter contributes to the existing literature by indicating that opportunistic and market maker proprietary trading companies react similarly when facing certain incentives, but use their comparative advantage to maximise their total trading revenues.

# Chapter 3: Institutional Settings and Market Participants' Classification

This chapter explains the motivation behind the policy change introduced by the US regulator in 2016 while providing an appropriate description of the pilot program used as an exogenous event to study market participants' trading behaviour. Further, this section describes the methodology used to separate each MPID, which is central for testing the hypotheses formulated in each of the following chapters. Both the tick size pilot program and the classification methodology are the common theme of this analysis. The remainder of this chapter is structured as follows: first, I introduce the US tick size pilot implemented on 3 October 2018; second, I outline the methodology used to separate market participants into proprietary traders, banks and agency firms.

## 3.1 Institutional Setting

The tick pilot program is one initiative promoted by the *Jumpstart our Business Startups* (Jobs) Act (SEC, 2016), which introduces several reforms to encourage funding of small businesses in the US by easing the country's securities regulation. The Jobs Act amends Section 11A(c) of the Securities and Exchange Act of 1934 (15 USC. 78k-1[c]) by adding a new paragraph, which requires the SEC to conduct a study examining the effect of decimalisation and eventually allows the regulator to designate a minimum increment for the securities of emerging growth companies that is greater than $0.01 and lower than $0.10. Ultimately, this process led the SEC to implement a two-year pilot program to test whether a tick size consolidation incentivises non-HFT to act as market makers on the so-called *growth stocks* and ultimately enhance market liquidity[1] on these securities. The pilot program considers a universe of 2319 common stocks with a market capitalisation lower or equal to $3 billion, a consolidated average trading volume during the measurement period of one million shares or less, a closing price of at least $2.00 on the last day of the measurement period, a closing price on every US trading day during the measurement period that is not less than $1.50 and a measurement period volume-weighted average price of at least $2.00. The main reason that three out of five selection criteria focus on the stock's price level is that the SEC wants to avoid companies that may be subject to Rule 612, which dictates that securities with a price lower or equal to $1 must be traded at sub-penny increments. The selected stocks are divided into four groups, each characterised by specific trading rules imposed by the SEC from 3 October 2016 onwards. One set

[1] In market microstructure, liquidity measures the ability to buy or sell securities within a short time frame at a price close to the securities' consensus value (Foucault, Pagano, & Röell, 2013).

of securities is not affected by the policy change and serves as a control group to quantify the effect of the tick size consolidation. *Test Group One* contains stocks that are quoted in $0.05 minimum increments, but continues to trade at any price increment that is currently permitted. However, midpoint executions and participant-oriented retail liquidity programs continue to be accepted at their current price increment. Treatment securities in *Test Group Two* and *Test Group Three* are both quoted and traded in $0.05 minimum increments, but the latter is also subject to the trade-at prohibition. The trade-at prohibition:

> prevents an exchange that was not quoting from price-matching protected quotations and permits an exchange that was quoting at the NBBO to execute orders at that level, but only up to the amount of its displayed size (SEC, 2015).

In the following chapters, I refer to these groups as control, G1, G2 and G3.

## 3.1 Market Participants' Classification

The classification of the MPIDs, a four-character code used by the exchange and FINRA for regulatory purposes, is critical to examine changes in each group's trading behaviour. Each registered broker/dealer trading on Nasdaq owns a set of identifiers that are used at the company's discretion to handle their message traffic within the exchange. The classification, developed in this chapter, categorises each analysed MPID as a proprietary trading company, bank or agency firm.

For each of the 48 most active market participants' IDs from 1 April 2016 to 30 April 2017, which represent 91.53% of the total order messages, I collected the FOCUS report filings and classified the MPID based on their reported nature of business/operations. Proprietary trading companies stated on their FOCUS report that they 'trade on their own account … and are market-makers'. Identifiers of companies claiming to be 'electronic agency' institutions or that they only 'execute and clear securities and commodities transaction for customers' were categorised as agency firms, while those market participants stating on their FOCUS report that they 'facilitate client transactions and make markets … primarily with institutional clients' were classified as banks.

For clarity regarding these terms, proprietary trading companies trade on their own account to maximise profits. Based on an analysis of the trading data, it is observed that agency firms are providers of trading execution technology and serve as agencies for trades by the end users. However, the predominant activities of banks involved execution on behalf of mainly institutions and passing the trade to the end clients. The distinctions between agency and bank classifications are as follows: (i) the facilitation business model of agencies versus the execution services provided by banks and (ii) the mainly institutional focus of banks. Importantly, the Volcker rule, enforced by the US government following the 2008 financial crisis, does not allow banks to engage in proprietary trading and, hence, makes it possible to clearly distinguish the two business models.

Of the 48 MPIDs, 15 were proprietary traders, 17 were banks and 16 were agency firms. To understand the goodness of fit for our classification, I calculated the percentage of dollar traded value on all control and treatment securities that were not excluded from the pilot program during the analysed period according to market participant group and capacity flag. The capacity flag is a field in Nasdaq data indicating whether a broker/dealer who is entering an order in the trading system is buying or selling on its own account (*principal*) or on its client's account (*agency*, *riskless*, *other*).

**Table 3.1**

**Market Participants' Classification Cross-Validation**

| **Market participant type** | Orders' capacity | | | |
|---|---|---|---|---|
| | *Agency* | *Principal* | *Riskless* | *Other* |
| Proprietary trading companies | 0.44% | 22.02% | 0.14% | 0.00% |
| Banks | 45.08% | 10.49% | 0.00% | 0.00% |
| Agency firms | 12.79% | 0.57% | 0.00% | 0.00% |
| Not classified | 6.61% | 1.77% | 0.01% | 0.08% |

*Note.* Percentage of the total traded value executed by each market participant group per Nasdaq broker–dealer's capacity from 1 April 2016 to 1 April 2017 for 2183 tick pilot securities.

Table 3.1, which sums to 100%, indicates that our classification is consistent with the observed proportion of principal and agency trades employed by the market participants: 22.02% out of 22.60% of proprietary traders' dollar traded volume is labelled as principal, 12.79% out of 13.36% of the agency firms' trades are labelled as agency and banks are the only market participants with a consistent mixture of agency and principal trading. Although this classification is not perfect, I am confident that this current study's results are significant, as our methodology underestimates the true differences in trading behaviour among these three types of market participants[2].

[2] Differences among market participants are maximized when each market participant is perfectly classified. Conversely, if market participants were randomly selected, there would be no differences among their trading behaviors. By acknowledging that some MPIDs may be misclassified, I implicitly claim that the empirical evidences found in this analysis somewhat underestimate the true differeces in trading behavior among these three types of market participants.

# Chapter 4: Tick Size Pilot and Market Participants' Business Models

This chapter aims to disentangle the effect of a tick size change on heterogeneous buy side-focused market participants. As theorised by Li et al. (2018), so-called liquidity traders are not all the same as some can be more sophisticated than others. Instead, the classification used in this research implies that liquidity traders differ mainly due to their business models, as banks can commit capital on a principal basis to satisfy their clients' needs, while agency firms offer trading technologies to allow institutional and retail investors to manage their own orders. These two very different business models have strong implications for the possible effects of the policy change on the trading behaviour of these market participants. Banks, which need to execute clients' orders within a certain period, are probably more sensitive to waiting costs while institutions trading through agency firms can directly time their orders as they please. Moreover, small investment banks and long-term institutions are the main focus of the tick size pilot as the program is designed to incentivise this class of market participants to actively provide liquidity on small–medium market capitalisation stocks. Weild et al. (2012) suggest that the reduction of the tick size in conjunction with the advent of HFT disincentives small investment banks to provide liquidity and promote, through their equity research services, small–medium capitalisation stocks. Moreover, the lower tick size induces HFT to become market makers, who do not have any incentive to promote the so-called '*growth stocks*' as they only seek to quickly profit by identifying short-term price discrepancies. Hence, the tick size pilot should incentivise non-proprietary trading companies to provide liquidity on securities issued by small and medium enterprises because of the increased profitability. The SEC believes that the positive externality generated by the program will ultimately lead to positive liquidity spillovers for the analysed securities. Similarly, the CEO of Knight Capital Group (as cited in Weild et al., 2012), which is an important electronic market maker, expressed the following view:

> if spreads widen, market makers might have the opportunity to have a more profitable business and it might attract more sponsorship for more companies. I think that is something that is a likely outcome if spreads widened in an appropriate fashion … and there are a lot of firms that will tie research coverage to market making.

Because of the importance of this topic and its central relevance to the public debate, this chapter analyses the effects of the tick size pilot on market competition, implicit trading costs, waiting costs and revenues of HFT.

First, the changes in trading competition between market participants are analysed. Based on previous academic literature and on the expectations set by Weild et al. (2012), the tick size pilot should enhance competition among market participants by attracting a larger number of MPIDs and increasing the distribution of dollar trading value among the three groups. Specifically, the number of unique MPIDs belonging to proprietary trading companies, banks and agency firms should increase on growth stocks across all the Nasdaq Group exchanges and the concentration of the dollar trading volume should decrease. Further, Yao and Ye (2018) suggested that proprietary traders should be more active on those securities in which the quoted spread equals the tick size due to their technological advantage. The first hypothesis is as follows:

H1: The tick size consolidation increases market competition in the treatment securities.

In this chapter, I test whether market participants change their behaviour across the three exchanges after the program's introduction. Since liquidity provision strategies are now more profitable, all market participants have an incentive to execute their orders through passive strategies. However, as predicted by Yao and Ye (2018), proprietary trading companies should have a competitive advantage over the other market participants for tick constraint securities. Therefore, the next hypothesis is:

H2: The tick size consolidation increases proprietary traders' liquidity provision across different 'lit' venues with varying fee structures *and* incentives for treatment securities.

Later in this chapter, I analyse the effect of the tick size pilot program on market participants' trading costs and on HFT revenues. The profits or losses from trading should depend on the number of times each market participant manages to execute their trades through a passive order. If everything else is equal, net liquidity makers should have higher trading revenues after the introduction of the tick pilot, while net liquidity takers should experience higher transaction costs. However, because of the nature of their business, it is reasonable to expect that banks and agency firms face higher transaction costs, while proprietary traders' revenues should increase. Therefore, the last two hypotheses addressed in this chapter are as follows:

H3: The tick size consolidation increases implicit transaction costs *and* the waiting costs for non-proprietary trading companies in treatment securities.

H4: The tick consolidation increases proprietary trading companies' revenues in treatment securities.

## 4.1 Data Description and Sample Selection

### 4.1.1 Data overview

This research uses two datasets provided by Nasdaq—the Security Information Processor (SIP) data and Nasdaq proprietary data—from 1 April 2016 to 30 April 2017. SIP data are publicly available information regarding top of the book NBBO quotes and trades information across all US equity markets. Nasdaq data comprise all order submission, cancellation and execution messages generated across three stock exchanges: BX, PSX and Nasdaq.

This chapter uses trade SIP data to calculate the end-of-day volume-weighted average price (VWAP) per security day. Each trade record contains the following fields: reference date, timestamps in milliseconds, security symbol, exchange identifier, trade price, trade volume and sale conditions. Trades on Nasdaq-listed securities (AMEX, BATS, NYSE, NYSE Arca) with sale conditions equal to E, M, Q, 8 and 9 (M, Q, 8 and 9) are excluded from the VWAP calculations.

The following analysis requires Nasdaq order submission, cancellation and execution data. The relevant fields in Nasdaq proprietary execution tables are as follows: reference date, security symbol, timestamp in nanoseconds, execution price, executed volume, MPID of the liquidity provider, MPID of the liquidity taker, buy–sell indicator and the unique order sequence number. It is important to note that each execution generated two messages: (i) for liquidity taker and (ii) for liquidity maker. Each message provides a special code called an '*addremove*' flag that identifies who initiated the trade and a liquidity code identifying the fee/rebate paid/earned by the market participant.

Similarly, the order submission and cancellation tables contain the following fields: reference date, security symbol, timestamp in nanoseconds, order price, submitted (cancelled) volume, MPID, buy–sell indicator and the unique order sequence number. Most measures used in this chapter are split by exchange as each stock market has different trading rules that allow market participants to execute their orders strategically throughout proprietary smart order routing systems. BX is a taker–maker market in which liquidity makers pay a fee to post liquidity, while liquidity takers are paid by the exchange to execute their orders. Conversely, Nasdaq is a maker–taker market in which liquidity consumers pay an exchange fee while the liquidity suppliers receive a small rebate from the exchange. Both markets use the price–time priority to decide which order is executed first.

PSX is a maker–taker market with a pro-rata priority structure, which guarantees a 40% allocation to the price setting order when incoming marketable orders are executed, while the remaining 60% is executed against resting orders via a size pro rata allocation. As the trading behaviours of market participants also depend on the exchange's priority and fee structures, it is reasonable to expect that the tick size pilot encourages the three groups of traders to rearrange their order submission strategies across these three stock markets to minimise (maximise) their transaction costs (revenues).

### 4.1.2 Sample selection

To properly ascertain the effect of the policy change on market quality, the SEC provides a group of stocks to control for changes in trading behaviour that are driven by factors other than the tick size alteration. This study uses this feature by matching the stocks in the pilot with the control stocks. The SEC suggests dividing the tick pilot securities sample into 27 subgroups based on three stock characteristics: market capitalisation, price and average daily volume. Nonetheless, not all the reported combinations are possible due to the strong correlation between market capitalisation with the other two variables. Figure 1 indicates that the average daily quoted spread, which is greatly affected by this policy change, is log–log linearly associated with the company's size, price and trading activity. As this chapter focuses on market participants' heterogeneity rather than optimal tick size, the tick pilot stocks are split based on the security's pre-pilot average daily dollar quoted spread quantiles. Those securities with a pre-pilot average daily dollar spread lower than \$0.04 are classified as a low quoted spread, those stocks with a quoted spread that is higher than \$0.11 are classified as a high quoted spread and the remainder of the sample securities are classified as a medium quoted spread. All securities subject to merger, acquisition, delisting or with a price drop below \$2.00 during the analysed period were excluded from this research.

Figure 1 displays the relationship between the pre-pilot average daily dollar quoted spread and the linear combination of the pre-pilot average daily market capitalisation, volume-weighted average price and volume. The linear combination of the stock's characteristics was obtained through linear regression. The plotted results were the average daily dollar quoted spread and the fitted values generated by the linear model.

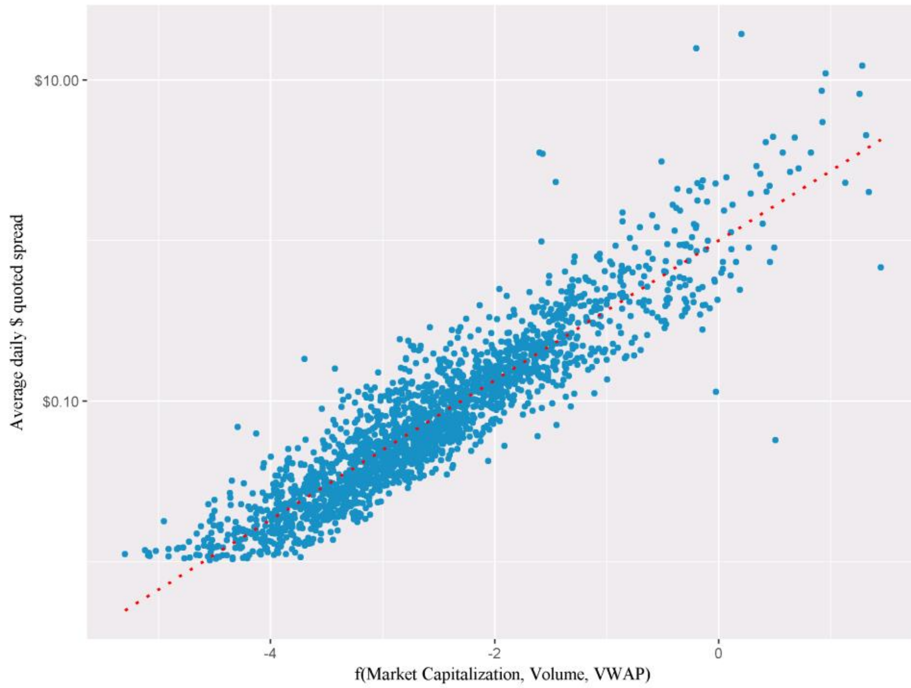


**Figure 1: Relationship between quoted spread in dollars and stock characteristics.**

The securities were matched within their quoted spread group with an approach similar to Huang and Stoll (1996), who minimised the sum of squared relative differences in the market capitalisation and the last sale price. Mathematically, each treatment stock *i* was matched to a control stock *j* within its quoted spread group so that it minimised the following score:

$$score_{ij} = \left[\frac{Price_i - Price_j}{(Price_i + Price_j) \times 0.5}\right]^2 + \left[\frac{Mkt\ Cap_i - Mkt\ Cap_j}{(Mkt\ Cap_i + Mkt\ Cap_j) \times 0.5}\right]^2$$

*Price* is the closing price and *Mkt Cap* is the market value of the securities on 1 April 2016. If two treatment securities were matched with the same control stock, the pair with the highest score was excluded from the sample. Smith and Todd (2005) suggest that matching with replacement would increase the average quality of our matches, but increase the variance of the estimator.

This procedure generated three samples of treatment and control stocks with similar pre-pilot stock characteristics for market capitalisation, volume-weighted average price and average daily volume (see Table 4.1).

**Table 4.1: Descriptive Statistics of the Matched Stocks**

| *Panel A: Low quoted spread* | Treatment stocks | Control stocks |
|---|---|---|
| Number of securities | 209 | 209 |
| Number of trading days | 128 | 128 |
| Volume-weighted average price | $14.60 | $14.70 |
| Avg. daily market capitalisation | $821,672,989 | $808,813,106 |
| Avg. daily volume | 418,423 | 397,159 |
| Avg. daily quoted spread (USD) | $0.03 | $0.03 |
| Avg. daily market share NASDAQ Group (lit) | 41.00% | 40.98% |
| *Panel B: Medium quoted spread* | Treatment stocks | Control stocks |
| Number of securities | 209 | 209 |
| Number of trading days | 128 | 128 |
| Volume-weighted average price | $32.41 | $31.67 |
| Avg. daily market capitalisation | $817,477,207 | $810,828,696 |
| Avg. daily volume | 178,966 | 190,966 |
| Avg. daily quoted spread (USD) | $0.07 | $0.07 |
| Avg. daily market share Nasdaq Group (lit) | 46.21% | 45.99% |
| *Panel C: High quoted spread* | Treatment stocks | Control stocks |
| Number of securities | 202 | 202 |
| Number of trading days | 128 | 128 |
| Volume-weighted average price | $52.18 | $51.29 |
| Avg. daily market capitalisation | $553,355,385 | $560,028,793 |
| Avg. daily volume | 61,042 | 66,132 |
| Avg. daily quoted spread (USD) | $0.46 | $0.57 |
| Avg. daily market share Nasdaq Group (lit) | 50.79% | 49.81% |

*Note.* The descriptive statistics were calculated from the period 1 April 2016 to 3 October 2016. The matched stocks were chosen in a manner similar to Huang and Stoll (1996). The quoted spread was calculated as the time-weighted difference between the ask price and the bid price over the continuous trading session. If no quote was entered after 9:30 am, only the last quote available before the beginning of the trading session was considered.

Consistent with Figure 1, market capitalisation, average daily volume and the volume-weighted average price were inversely correlated with the average daily dollar quoted spread. On average, low quoted spread securities were priced at about $14.60, had a market capitalisation slightly above than $800 million and had an average daily volume of about 400,000 shares. Medium quoted spread securities have a similar market capitalisation as the low quoted spread group, but differ on volume-weighted average price and average number of traded shares. *Panel C* suggests that high quoted spread securities had an average daily VWAP of $51, an average market capitalisation of $500 million and an average daily volume of about 60,000 shares.

On average, the securities in the samples had a price higher than $14, suggesting that it is unlikely that the prices of these securities dropped below $1, triggering Rule 612.

Finally, it is worth stressing that the results of this analysis should be interpreted with caution. While I am confident that the presented empirical findings underestimate the true differences between the three market participant groups, our results cannot be used to assess the impact of the tick size pilot on market quality as Nasdaq data only cover about half of the U.S. total lit trading activity.

## 4.2 Methodology

This section provides an in-depth exposition of the methodology used to test the relevant hypotheses for this chapter. First, this section briefly describes the difference-in-differences methodology. Second, there is an in-depth presentation of the variables of interest used to test each hypothesis.

### 4.2.1 Econometric model

Because of the structure of the pilot program, the natural methodology to use to analyse the effect of the policy change on market participants' trading behaviours is the difference-in-differences methodology. As suggested by Bertrand, Duflo and Mullainathan (2004), the dependent variables are collapsed into pre- and post-tick pilot implementation stock averages to minimise the likelihood of false positive results due to autocorrelation in the variables of interest. Although the tick size pilot officially commences on October 3rd 2016, treatment securities do not start trading in nickles all at the same time. Most of G1 and G2 stocks start trading in nickles between October 3rd 2016 and October 17th 2016, while the last commencement day for G3 securities is on October 30th 2016. To be consistent across the three treatment groups, post-pilot averages are calculated using all observation after November 1st 2016. Mathematically, this econometric model comprises the following linear regression model:

$$\bar{y}_{it} = \alpha + \beta_1 Group_i + \beta_2 Pilot_t + \beta_3 Group_i \times Pilot_t + \varepsilon_{it} \tag{4.1}$$

$\bar{y}_{it}$ is the average daily variable of interest per stock pilot period, $Group_i$ is a dummy variable that equals 1 if the security is affected by the policy change and 0 if otherwise, and $Pilot_t$ is a dummy variable that equals 0 for the pre-pilot averages and 1 for the post-pilot averages. The coefficient $\beta_3$ associated with the interaction variable between $Group_i$ and $Pilot_t$ measures the effect of the tick size pilot on market participants' competition, liquidity provision, transaction costs and proprietary traders' revenues. As suggested by the literature, standard errors are adjusted using White's (1980) sandwich estimator.

### 4.2.2 Variables of Interest

One aim of the tick size pilot is to promote liquidity on small–medium market capitalisation stocks by enhancing competition among liquidity providers. Nonetheless, past empirical literature on this topic has suggested that this policy change should attract more HFT because of the increased trading revenues for fast traders, such as designated market makers and supplementary liquidity providers (O'Hara, Saar, & Zhong, in press). However, there are no explicit predictions of the effects of the tick size pilot on banks and agency firms.

H1 fills this gap by examining whether there are more banks and agency firms trading tick pilot stocks across the three trading venues and whether there is greater competition for order flow across the three market participant groups. Competition for order flow is measured as trading activity concentration, measured in dollar trading volume, across the market participant groups.

These two measures of market competition are inspired by previous literature regarding the effect of market participant competition on market quality. Laux (1995) used the size of both the dealers' and the institutional investors' populations to analyse the effect of competition on bid–ask spreads. The results suggest that the institutional investors' presence in a stock increases the average trade size and the average quoted spread while the number of dealers does not necessarily improve market quality. Bennett and Wei (2006) studied the effects of order flow fragmentation, measured as the concentration index of the dollar traded volume, which is also known as the Herfindahl–Hirschman Index (HHI), and total number of market participants trading on the NYSE and Nasdaq regarding market quality. This research suggested that order flow consolidation improved market quality and was particularly valuable for the most illiquid stocks.

H1 is tested in line with Bennett and Wei (2006) by assessing the effect of the tick size pilot program on the Nasdaq Group exchanges through two metrics: (i) the normalised HHI and (ii) the number of unique MPIDs trading pilot stocks.

The HHI index is widely used in microeconomic research to study the degree of competition among different market participants within the same industry. The normalised HHI index is calculated as follows:

$$H = \sum_{g=1}^{4} s_g^2 \qquad (4.2)$$

$$Normalized\ HHI\ = 1 - \frac{H - \frac{1}{n}}{1 - \frac{1}{n}} \tag{4.3}$$

$s_i$ represents the daily dollar trading volume market share for each market participants' group $g$ on each security and $n$ represents the total number of market participant groups (proprietary trading companies, banks, agency firms or not classified). When there is high (low) competition, the index approaches one (zero). According to Weild et al. (2012), competition should increase and the normalised HHI should be closer to one for treatment securities.

The second measure used in this research is the total number of unique MPIDs trading tick pilot stocks for each market participants' group on each stock exchange as a percentage of the total number of classified identifiers for each group. Formally, the variable is calculated as:

$$\%\ MPIDs_{git}\ = \frac{MPID\ count_{git}}{Total\ \#\ MPID_{git}} \tag{4.4}$$

where MPID count represents the number of unique market identifiers codes for each stock-day-group divided by the total number of classified MPIDs available, which are 48 when analysing all market participant groups, 15 for proprietary trading companies, 17 for banks, and 16 for agency firms. According to the existing literature, the program should increase the number of proprietary trading companies for growth stocks (O'Hara, Saar, & Zhong, in press; Yao & Ye, 2018), while there is no prediction regarding the effects of these types of policy changes for banks and agency firms.

H2 relates to the effect of the tick size pilot on market participants' liquidity provision. Part of the literature suggests that HFT tend to engage in market making strategies in low priced stocks in which the minimum price variation equals the security's quoted spread (Lepone & Wong, 2017; O'Hara, Saar, & Zhong, in press; Yao & Ye, 2018). HFT tend to have a stabilising effect on the intraday volatility of stocks after tick size consolidation due to their market making activity (Hagströmer & Norden, 2013). Moreover, the empirical literature on tick size consolidation has suggested that a tick size consolidation forces market participants to ascertain a finer price grid or to jump the queue by trading either in dark pools (Foley & Putniņš, 2016; Kwan, Masulis & McInish, 2015) or in inverted markets in which the liquidity provider pays a fee to post a limit order while the liquidity consumer earns a rebate to enter a marketable order (Li, Wang & Ye, 2018).

The methodology used in this research analyses the effect of the tick size consolidation on the liquidity provision of proprietary traders, banks and agency firms in a multivenue environment. Thanks to matching engine proprietary data, it is possible to study the dynamics of liquidity provision across different participants in an inverted market, a market with a price setter pro rata model and in a normal maker–taker market. The database differentiates between liquidity taker and maker for each trade based on the 'addremove' flag attached to each trade. Thus, we can observe whether non-proprietary trading companies are more likely to adopt liquidity providing strategies to execute their clients' orders after the tick size consolidation.

H2 depends on two main factors: (i) the per-group total trading volume and (ii) percentage of shares executed through passive orders. If market participants trade fewer treatment stocks while increasing their percentage of passive orders, it is likely that that specific market participant group is now avoiding lit markets and is trying to minimise (maximise) its transaction costs (revenues) by executing a small portion of its order flow through passive orders. Meanwhile, a true increase in liquidity provision requires an all else equal increased percentage of volume executed through passive orders. While the average daily trading volume per market participant group is a straightforward calculation, the percentage of passive orders requires the use of the '*addremove*' flag to distinguish the liquidity providers from the liquidity taker in each transaction. Following Carrion (2013), liquidity provision (i.e., the proportion of shares executed through passive orders for each exchange by each market participant group) is expressed as:

$$\text{LiquidityProvision}_{\text{git}} = \frac{\text{\# Shares Executed Through Passive Orders}_{\text{git}}}{\text{\# Shares Executed}_{\text{it}}} \tag{4.5}$$

*g* represents the market participant group (proprietary trading companies, banks and agency firms), *i* is the security and *t* is the trading day. These results are subsequently split by stock exchange (BX, PSX and Nasdaq).

The third and fourth hypotheses test the effect of the tick size pilot program on proprietary traders' revenues and market participants' implicit costs and waiting costs. Recent academic literature has suggested that a tick size consolidation should be an incentive for proprietary trading companies to engage in market making strategies (Lepone & Wong, 2017; Yao & Ye, 2018), while the trade-at rule encourages market participants to ascertain a finer price grid outside the lit markets (Foley & Putniņš, 2016; Kwan, Masulis & McInish, 2015). Overall, these papers suggested that the policy change may also have a detrimental effect on banks' and agency firms' transaction costs as HFT force other market participants to use a larger portion of marketable orders (Li, Wang & Ye, 2018).

Although the previous literature highlights the effects of market structure changes on proprietary trading companies, this chapter focuses on understanding the joint effect of both tick size consolidation and trade-at rule on proprietary traders' revenues and non-HFT trading costs decomposed into the cost of crossing the spread and waiting costs.

To properly estimate the effect of the policy change on institutional trading costs, it is necessary to possess information regarding each investor's parent order and the connected child orders. Because of the nature of our sample data, it is only possible to estimate the implicit trading costs measure and the waiting costs. Implicit trading costs are usually measured as the difference between the prices paid by each market participant and a benchmark price. The typical benchmark prices are: the bid-ask midpoint price, which proxies the true value of the undelying security; and the end-of-day volume weighted average price (VWAP), which measures average execution price across all market participants. In line with Hu (2009), the implicit trading costs, estimated in this analysis, are calculated as follows:

$$implicit\ trading\ costs = \ side \times \frac{(P - VWAP)}{P} \times 10000 \qquad (4.6)$$

*P* is the execution price of each transaction from the perspective of the liquidity taker, *VWAP* is the end-of-day volume-weighted average price calculated based on SIP's consolidated total traded value and volume and *side* is an indicator that equals 1 for buy transactions and –1 for otherwise. At the end of each trading day, the metric is volume weighted to provide the end-of-day average result for each market participant group. Implicit trading costs should be affected by the policy change as tick-constrained securities now have a 400% higher quoted spread. However, a larger minimum price variation should also increase the quoted depth, making it harder for market order and aggressively priced limit orders to walk through the books.

Waiting costs are estimated using order submission, cancellation and executions for each market participant group. Specifically, two measures are used to understand whether the tick size pilot increases the proportion of orders that are either fully cancelled or fully executed. Through the sequence number, it is possible to track any order entered in Nasdaq and observe whether this order is fully executed, partially executed, fully cancelled, partially cancelled or just submitted before 4:30 pm for each trading day. The waiting cost proxies analysed in this chapter are calculated as follows:

$$\%\ executions_{git} = \frac{\#\ orders\ fully\ executed_{git}}{\#\ orders_{git}} \tag{4.7}$$

$$\%\ cancellations_{git} = \frac{\#\ orders\ fully\ cancelled_{git}}{\#\ orders_{git}} \tag{4.8}$$

*% executions* (*% cancellations*) measures the proportion of fully executed (*cancelled*) orders entered by the market participant group *g* on the security *i*, during the trading day *t*. If Equation 4.6's result increases, this indicates that the average market participant's order is fully executed more frequently than before. If *% executions* decrease, the average market participant enters a larger portion of orders that are not filled. The cancellation rate measures the propensity of any market participant to display an order for a longer period.

The last variable of interest analysed in this chapter is the proprietary traders' fee-adjusted trading revenues before and after the commencement of the tick size pilot. In line with Carrion (2013), I assume that proprietary trading companies do not hold inventory overnight and trade the inventory in excess on other exchanges at the volume-weighted average price. The assumptions made by this methodology are consistent with proprietary trading companies' trading behaviour, which avoid overnight inventory positions, but it is not suitable to estimate banks and agency firms' revenues. Mathematically, the metric is calculated as follows:

$$VWAP = \sum_{t=1}^{T} \frac{(P + Side \times Fee) \times Volume}{Volume} \tag{4.9}$$

$$Revenues_{git} = \left(VWAP\ Sell_{git} - VWAP\ Buy_{git}\right) \times max\left(Volume\ Sell_{\ git}, Volume\ Buy_{git}\right) \tag{4.10}$$

*P* is the transaction price, *Side* is the direction of the trade and equals 1 if it is a buy order and –1 if otherwise, *Volume* is the number of shares executed on each transaction and *Fee* is the fee/rebate that the market participant pays/receives from the exchange. The rebates and fees paid by HFT are estimated using the liquidity code attached to each transaction. Each liquidity code is associated with a fee/rebate schedule based on the trading venue (see Table A1). Proprietary traders' revenues are calculated as the *VWAP* difference between buy and sell orders multiplied by the maximum between the buy and sell traded volume. All observations in which the market participant only buys or sells a security throughout the entire trading day are removed. According to the empirical literature, a tick size consolidation should increase the revenues of proprietary trading companies. The next section provides the results of this empirical research.

## 4.3 Empirical Findings

This section presents the empirical results of each test separately based on the hypothesis tested for that specific subsection.

### 4.3.1 Tick size pilot and market participant's competition

This section tests the first hypothesis by analysing the effects of the tick size consolidation on the competition for order flow, as measured by the HHI, and on market participants' presence, measured by the MPIDs count.

The pre-pilot summary statistics reported in Table 4.2 suggest that the difference in the percentage of classified MPIDs between low and high quoted spread securities is about 26%. There are, on average, 56.17%, 67.87% and 49.33% of proprietary traders, banks and agency firms' identifiers, respectively, trading low quoted spread securities and approximately 20% fewer MPIDs trading high quoted spread stocks across all market participant groups. Banks are trading more actively small capitalisation stocks compared to other groups, as more than 40% of the banks' identifiers trade these securities. Most proprietary trading companies predominantly trade low quoted spread securities while only one-quarter trade securities belonging to the high quoted spread group. Agency firms seem less active compared to proprietary trading companies for low quoted spread stocks and more active for the high quoted spread group. The average normalized HHI is approximately 0.70 across all the samples, suggesting that the dollar traded volume is fairly well-distributed among market participants. Low quoted spread securities, characterised by large capitalisation companies, exhibit much lower standard deviations compared to the high quoted spread samples.

**Table 4.2: Pre-Pilot Summary Statistics for the Competition Variables Analysed**

| *Panel A: Normalised Herfindahl–Hirschman Index* | All | BX | PSX | Nasdaq |
|---|---|---|---|---|
| Low quoted spread | 0.81 | 0.74 | 0.75 | 0.80 |
| | (0.10) | (0.17) | (0.20) | (0.10) |
| Medium quoted spread | 0.79 | 0.66 | 0.65 | 0.79 |
| | (0.13) | (0.20) | (0.26) | (0.13) |
| High quoted spread | 0.78 | 0.67 | 0.58 | 0.78 |
| | (0.18) | (0.23) | (0.30) | (0.18) |
| *Panel B: Proportion of all market participant identifiers* | All | BX | PSX | Nasdaq |
| Low quoted spread | 58.03% | 34.58% | 17.36% | 55.37% |
| | (15.76%) | (15.62%) | (11.61%) | (15.80%) |
| Medium quoted spread | 48.79% | 26.38% | 9.57% | 47.04% |
| | (20.27%) | (17.67%) | (10.04%) | (20.10%) |
| High quoted spread | 32.20% | 13.10% | 3.69% | 31.07% |
| | (22.32%) | (15.17%) | (7.12%) | (21.89%) |
| *Panel C: Proportion of classified proprietary trader* identifiers | All | BX | PSX | Nasdaq |
| Low quoted spread | 56.17% | 37.41% | 19.84% | 53.00% |
| | (20.46%) | (20.20%) | (14.16%) | (20.43%) |
| Medium quoted spread | 44.51% | 26.81% | 10.58% | 43.05% |
| | (24.26%) | (21.16%) | (12.37%) | (24.16%) |
| High quoted spread | 26.36% | 14.13% | 3.73% | 25.48% |
| | (23.82%) | (18.12%) | (8.44%) | (23.55%) |
| *Panel D: Proportion of classified bank identifiers* | All | BX | PSX | Nasdaq |
| Low quoted spread | 67.87% | 43.44% | 22.69% | 66.32% |
| | (15.51%) | (18.12%) | (15.69%) | (15.83%) |
| Medium quoted spread | 59.74% | 35.39% | 13.66% | 58.21% |
| | (21.79%) | (21.84%) | (14.30%) | (21.90%) |
| High quoted spread | 41.71% | 17.85% | 5.40% | 40.56% |
| | (27.18%) | (19.62%) | (10.38%) | (26.96%) |
| *Panel E: Proportion of classified agency firm identifiers* | All | BX | PSX | Nasdaq |
| Low quoted spread | 49.33% | 22.53% | 9.36% | 45.96% |
| | (16.61%) | (13.54%) | (8.89%) | (16.67%) |
| Medium quoted spread | 41.19% | 16.39% | 4.27% | 38.92% |
| | (18.97%) | (13.84%) | (6.42%) | (18.57%) |
| High quoted spread | 27.59% | 7.10% | 1.85% | 26.24% |
| | (19.05%) | (10.30%) | (4.40%) | (18.39%) |

*Note.* The average daily values of the competition variables from 1 April 2016 to 1 October 2016 by quoted spread group and exchange. The normalised HHI was calculated for the total dollar volume executed by each market participant group (proprietary trading companies, banks and agencies). The other metrics only consider the unique number of the MPIDs divided by the total number of classified MPIDs belonging to each group. Standard deviations are reported in parentheses.

The difference-in-differences regressions for the normalised HHI (see Table 4.3a) suggest two main dimensions driving the results: (i) the quoted spread quantile and (ii) the restrictions imposed by the program. The results of the regressions for the HHI suggest that market participants' competition only increases for securities with a pre-pilot quoted spread lower than $0.11 on BX. These results suggest that the policy change effect is negatively correlated to the security's pre-pilot dollar quoted spread. Overall, this empirical evidence suggests that market participants are now trading more actively on the inverted market in which liquidity takers receive a rebate from the exchange while liquidity providers pay a fee to execute their limit orders.

Table 4.3b indicates that the policy change neither increases nor decreases the total number of market participants' presence for tick pilot stocks, suggesting that the policy change does not encourage competition on treatment securities. However, the difference-in-differences coefficients estimated using BX data for low quoted spread securities affected by the trade-at rule are positive and significant. This result indicates that market participants, who cannot access a finer price grid in the dark, are encouraged to use more actively inverted markets.

Consistently, Table 4.3c indicates that the number of proprietary trading companies increases for low quoted spread securities trading on BX by 9.84% for G1, 8.34% for G2 and 6.82% for G3. This result alone is inconsistent with the previous literature that suggests that HFT tend to act as liquidity providers on securities with a large relative tick size (Yao & Ye, 2018). Therefore, if proprietary traders want to maximise their revenues, they should provide more liquidity in maker–taker markets rather than in the inverted markets. Nonetheless, Table 4.3d indicates that the tick size pilot program leads agency firms to reduce their presence on Nasdaq while increasing it on BX for low quoted spread securities.

The number of agency identifiers increased by 5.26%, 4.47% and 6.48% for G1, G2 and G3 securities, respectively, on BX; conversely, they decreased by 6.41%, 6.20% and 5.83% for G1, G2 and G3, respectively, on Nasdaq. Therefore, Tables 4.3b and 4.3d complement each other and suggest that proprietary trading companies increase their presence on BX primarily due to the increased presence of liquidity traders in that trading venue.

## Table 4.3a: Difference-in-Differences Regression for the Average Daily Percentage of the Normalised Herfindahl–Hirschman Index

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 0.80 | 0.71 | 0.69 | 0.80 | 0.79 | 0.64 | 0.60 | 0.79 | 0.77 | 0.60 | 0.48 | 0.76 |
| | (135.45)*** | (52.54)*** | (42.1)*** | (133.6)*** | (104.02)*** | (38.13)*** | (29.94)*** | (104.04)*** | (57.6)*** | (35.73)*** | (25.34)*** | (57.20)*** |
| Group | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 | 0.02 | 0.01 |
| | (0.95) | (0.58) | (0.34) | (0.67) | (0.53) | (0.51) | (0.26) | (0.48) | (0.53) | (0.06) | (0.88) | (0.54) |
| Pilot | 0.00 | –0.04 | –0.02 | 0.01 | 0.01 | –0.01 | 0.01 | 0.01 | 0.02 | –0.01 | 0.00 | 0.02 |
| | (0.25) | (2.08)** | (0.70) | (1.69)* | (0.58) | (0.42) | (0.51) | (1.42) | (0.85) | (0.61) | (0.11) | (1.00) |
| Group*Pilot | 0.01 | 0.09 | 0.01 | 0.00 | –0.01 | 0.08 | –0.01 | –0.02 | –0.02 | 0.04 | 0.01 | –0.02 |
| | (0.85) | (3.93)*** | (0.30) | (0.37) | (0.43) | (3.05)*** | (0.30) | (1.46) | (0.92) | (1.15) | (0.26) | (0.72) |
| Adjusted $R^2$ | 0.01 | 0.11 | –0.01 | 0.00 | –0.01 | 0.10 | –0.01 | 0.00 | –0.01 | 0.00 | 0.00 | –0.01 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 240 | 240 | 280 | 280 | 280 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 0.81 | 0.74 | 0.74 | 0.81 | 0.78 | 0.65 | 0.59 | 0.79 | 0.75 | 0.56 | 0.47 | 0.75 |
| | (157.26)*** | (51.97)*** | (47.78)*** | (150.17)*** | (110.72)*** | (49.55)*** | (33.94)*** | (108.86)*** | (56.61)*** | (25.43)*** | (20.47)*** | (55.18)*** |
| Group | 0.00 | 0.01 | 0.00 | 0.00 | 0.01 | 0.00 | –0.02 | 0.01 | 0.00 | 0.02 | 0.01 | 0.01 |
| | (0.12) | (0.33) | (0.09) | (0.27) | (1.45) | (0.12) | (0.83) | (1.57) | (0.17) | (0.64) | (0.50) | (0.28) |
| Pilot | –0.01 | –0.05 | –0.03 | 0.00 | 0.01 | –0.02 | 0.00 | 0.02 | 0.02 | 0.01 | 0.01 | 0.02 |
| | (1.34) | (2.48) | (1.44) | (0.20) | (0.96) | (1.06) | (0.20) | (1.99)** | (0.90) | (0.30) | (0.30) | (1.21) |
| Group*Pilot | 0.02 | 0.07 | 0.01 | 0.01 | –0.01 | 0.10 | 0.04 | –0.02 | –0.01 | 0.04 | –0.02 | –0.02 |
| | (1.47) | (2.88)*** | (0.23) | (0.72) | (0.68) | (4.53)*** | (1.14) | (1.92)* | (0.56) | (0.98) | (0.51) | (0.65) |
| Adjusted $R^2$ | 0.00 | 0.07 | 0.00 | –0.01 | 0.00 | 0.12 | 0.00 | 0.01 | –0.01 | 0.02 | –0.01 | –0.01 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 352 | 352 | 264 | 264 | 264 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 0.81 | 0.74 | 0.72 | 0.81 | 0.77 | 0.62 | 0.56 | 0.77 | 0.77 | 0.60 | 0.52 | 0.77 |
| | (152.79)*** | (60.96)*** | (48.71)*** | (157.43)*** | (75.91)*** | (38.37)*** | (26.09)*** | (74.00)*** | (55.78)*** | (29.51)*** | (29.12)*** | (54.98)*** |
| Group | 0.00 | 0.00 | 0.01 | 0.00 | –0.01 | –0.01 | –0.01 | –0.01 | 0.00 | 0.00 | –0.03 | 0.00 |
| | (0.53) | (0.05) | (0.45) | (0.43) | (0.90) | (0.61) | (0.37) | (0.98) | (0.14) | (0.13) | (1.09) | (0.16) |
| Pilot | –0.01 | –0.06 | –0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.03 | 0.01 | –0.01 | –0.06 | 0.01 |
| | (1.01) | (3.47)*** | (1.15) | (0.93) | (1.23) | (0.26) | (0.84) | (1.79) | (0.29) | (0.49) | (1.73)* | (0.59) |
| Group*Pilot | 0.00 | 0.10 | 0.01 | –0.01 | 0.00 | 0.11 | 0.03 | –0.02 | –0.01 | 0.04 | 0.07 | –0.01 |
| | (0.10) | (4.52)*** | (0.26) | (1.04) | 0.00 | (3.68)*** | (0.62) | (1.13) | (0.55) | (0.99) | (1.68)* | (0.25) |
| Adjusted $R^2$ | 0.00 | 0.11 | 0.00 | –0.01 | 0.01 | 0.13 | 0.00 | 0.03 | –0.01 | 0.00 | 0.00 | –0.01 |
| N. Observations | 300 | 300 | 300 | 300 | 244 | 244 | 244 | 244 | 264 | 264 | 264 | 264 |

*Note.* The difference-in-differences regressions used to measure the effect of the tick size program on the normalised HHI, which quantifies the traded value concentration among market participant groups. The independent variables are as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses are calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

## Table 4.3b: Difference-in-Differences Regressions for Number of Market Participant Identifiers

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 55.64% | 33.18% | 16.10% | 52.83% | 50.27% | 27.10% | 10.14% | 48.60% | 31.76% | 12.58% | 3.16% | 30.58% |
| | (31.03)*** | (19.61)*** | (14.57)*** | (29.60)*** | (20.88)*** | (12.88)*** | (9.59)*** | (20.51)*** | (12.57)*** | (7.86)*** | (4.49)*** | (12.29)*** |
| Group | 0.52% | –0.17% | 0.78% | 0.73% | 0.76% | 0.59% | 0.41% | 0.79% | 0.28% | –0.14% | 0.02% | 0.37% |
| | (0.20) | (0.07) | (0.46) | (0.29) | (0.22) | (0.20) | (0.26) | (0.23) | (0.08) | (0.06) | (0.02) | (0.11) |
| Pilot | 3.02% | 3.26% | 2.48% | 2.81% | 4.43% | 4.46% | 4.47% | 4.05% | 2.73% | 1.64% | 1.97% | 2.68% |
| | (1.21) | (1.38) | (1.52) | (1.13) | (1.31) | (1.52) | (2.65)*** | (1.22) | (0.75) | (0.71) | (1.62) | (0.75) |
| Group*Pilot | –0.41% | 6.27% | –2.01% | –3.45% | –2.69% | 3.07% | –2.34% | –5.09% | –0.16% | 4.01% | –0.26% | –1.77% |
| | (0.11) | (1.81)* | (0.82) | (0.95) | (0.55) | (0.71) | (0.95) | (1.04) | (0.03) | (1.18) | (0.16) | (0.36) |
| Adjusted $R^2$ | 0.00 | 0.05 | 0.00 | 0.00 | 0.00 | 0.03 | 0.02 | 0.00 | –0.01 | 0.02 | 0.01 | –0.01 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 240 | 240 | 280 | 280 | 280 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 59.49% | 35.56% | 18.36% | 57.07% | 50.62% | 28.21% | 10.75% | 48.92% | 29.65% | 11.43% | 3.36% | 28.74% |
| | (33.47)*** | (21.55)*** | (16.49)*** | (32.16)*** | (24.15)*** | (15.87)*** | (11.72)*** | (23.66)*** | (10.90)*** | (6.28)*** | (4.38)*** | (10.80)*** |
| Group | 0.32% | 1.06% | 0.54% | –0.09% | –0.51% | –1.51% | –1.40% | –0.62% | 0.35% | 0.71% | 0.06% | 0.11% |
| | (0.12) | (0.44) | (0.33) | (0.03) | (0.18) | (0.63) | (1.12) | (0.23) | (0.09) | (0.28) | (0.05) | (0.03) |
| Pilot | 3.38% | 4.01% | 3.45% | 3.18% | 3.27% | 2.95% | 3.46% | 2.93% | 3.01% | 1.86% | 2.04% | 2.89% |
| | (1.39) | (1.75)* | (2.04)** | (1.30) | (1.15) | (1.20) | (2.41)*** | (1.04) | (0.77) | (0.71) | (1.58) | (0.76) |
| Group*Pilot | –0.74% | 5.03% | –3.00% | –3.49% | –0.05% | 6.32% | –0.59% | –2.53% | 0.11% | 3.58% | –0.75% | –1.41% |
| | (0.20) | (1.49) | (1.24) | (0.93) | (0.01) | (1.87)* | (0.30) | (0.67) | (0.02) | (0.95) | (0.43) | (0.27) |
| Adjusted $R^2$ | 0.00 | 0.08 | 0.01 | 0.00 | 0.00 | 0.04 | 0.03 | 0.00 | –0.01 | 0.01 | 0.00 | –0.01 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 352 | 352 | 264 | 264 | 264 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 59.04% | 34.78% | 17.12% | 56.36% | 45.29% | 24.17% | 8.11% | 43.40% | 35.11% | 15.24% | 4.79% | 33.82% |
| | (42.71)*** | (24.01)*** | (16.37)*** | (41.14)*** | (18.11)*** | (11.75)*** | (8.22)*** | (17.64)*** | (12.87)*** | (7.86)*** | (5.64)*** | (12.80)*** |
| Group | –0.10% | 0.38% | 0.32% | 0.00% | –1.18% | –0.72% | –0.02% | –1.10% | –0.41% | –0.38% | –0.44% | –0.28% |
| | (0.05) | (0.18) | (0.22) | (0.00) | (0.31) | (0.23) | (0.02) | (0.30) | (0.11) | (0.14) | (0.37) | (0.08) |
| Pilot | 2.45% | 4.02% | 3.07% | 2.19% | 4.75% | 4.61% | 4.43% | 4.40% | 2.09% | 1.28% | 1.99% | 1.97% |
| | (1.21) | (1.93)* | (1.96)** | (1.08) | (1.33) | (1.56) | (2.60)*** | (1.26) | (0.53) | (0.46) | (1.41) | (0.52) |
| Group*Pilot | –0.73% | 5.81% | –1.46% | –4.14% | –0.05% | 5.96% | –0.62% | –3.17% | 0.92% | 5.13% | –0.13% | –0.94% |
| | (0.24) | (1.98)** | (0.67) | (1.35) | (0.01) | (1.35) | (0.25) | (0.61) | (0.17) | (1.29) | (0.07) | (0.18) |
| Adjusted $R^2$ | 0.00 | 0.09 | 0.01 | 0.00 | 0.00 | 0.05 | 0.03 | 0.00 | –0.01 | 0.01 | 0.00 | –0.01 |
| N. Observations | 300 | 300 | 300 | 300 | 244 | 244 | 244 | 244 | 264 | 264 | 264 | 264 |

*Note.* The effect of the program on the average daily percentage of classified MPIDs trading tick pilot stocks. The effects of the policy change on competition were quantified through the difference-in-differences regression in which the dependent variable was the percentage of unique MPIDs and the independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table 4.3d indicates that banks’ presence is not sensitive to market structure changes such as tick size consolidations and trade-at rule as the empirical results across the three trading venues (*All*) are not statistically significant. The only difference-in-differences coefficient that is statistically significant is the one associated with banks’ presence on *low quoted spread G2* securities in PSX, indicating that this type of market participant tends to be less active on the pro-rata execution system stock exchange, which is designed to shield slow traders from fast traders.

In summary, the empirical findings in this section suggest that the tick size pilot: (i) does not increase market competition across the three stock exchanges, (ii) decreases market concentration measured by the HHI on BX and (iii) increases the presence of proprietary trading companies and agency firms on inverted markets. In the next section, I analyse the effect of the tick size pilot on market participants’ liquidity provision across BX, PSX and Nasdaq.

## Table 4.3c: Difference-in-Differences Regression for the Number of Proprietary Trading Company Identifiers

| | Low quoted spread | | | | Medium quoted spread | | | | High quoted spread | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 52.82% | 34.99% | 18.13% | 49.71% | 45.64% | 27.42% | 11.33% | 44.26% | 25.71% | 13.19% | 3.10% | 24.72% |
| | (22.77)*** | (15.69)*** | (13.43)*** | (21.82)*** | (15.99)*** | (11.07)*** | (8.85)*** | (15.63)*** | (9.80)*** | (6.92)*** | (3.82)*** | (9.51)*** |
| Group | 1.42% | 0.81% | 0.90% | 1.44% | 1.66% | 1.23% | 0.59% | 1.59% | –0.14% | –0.02% | –0.06% | –0.02% |
| | (0.43) | (0.25) | (0.44) | (0.44) | (0.40) | (0.34) | (0.31) | (0.38) | (0.04) | (0.01) | (0.06) | (0.01) |
| Pilot | 2.94% | 3.31% | 2.78% | 3.30% | 5.21% | 5.00% | 4.61% | 4.98% | 3.40% | 2.20% | 2.17% | 3.45% |
| | (0.93) | (1.08) | (1.38) | (1.06) | (1.32) | (1.46) | (2.32)** | (1.27) | (0.91) | (0.81) | (1.55) | (0.93) |
| Group*Pilot | 4.34% | 9.84% | –1.61% | 1.21% | 1.88% | 7.10% | –1.75% | –1.19% | 1.80% | 4.30% | –0.06% | –0.83% |
| | (0.95) | (2.24)*** | (0.54) | (0.26) | (0.32) | (1.38) | (0.59) | (0.20) | (0.34) | (1.09) | (0.03) | (0.16) |
| Adjusted $R^2$ | 0.02 | 0.07 | 0.00 | 0.00 | 0.01 | 0.05 | 0.02 | 0.00 | 0.00 | 0.02 | 0.01 | –0.01 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 240 | 240 | 280 | 280 | 280 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 58.58% | 39.11% | 21.46% | 55.60% | 46.84% | 28.94% | 11.85% | 45.48% | 23.62% | 12.25% | 3.38% | 22.92% |
| | (25.55)*** | (17.58)*** | (15.45)*** | (24.81)*** | (18.91)*** | (13.65)*** | (10.62)*** | (18.58)*** | (8.15)*** | (5.67)*** | (3.95)*** | (8.02)*** |
| Group | 0.47% | 1.44% | 0.20% | 0.03% | –1.07% | –1.62% | –1.59% | –1.24% | 0.51% | 0.87% | 0.19% | 0.31% |
| | (0.14) | (0.45) | (0.10) | (0.01) | (0.32) | (0.55) | (1.05) | (0.38) | (0.13) | (0.29) | (0.15) | (0.08) |
| Pilot | 2.88% | 3.56% | 3.45% | 3.50% | 3.32% | 3.44% | 3.45% | 3.19% | 3.47% | 2.03% | 2.06% | 3.47% |
| | (0.91) | (1.15) | (1.64) | (1.12) | (0.99) | (1.19) | (2.03)** | (0.96) | (0.84) | (0.67) | (1.44) | (0.86) |
| Group*Pilot | 3.97% | 8.34% | –2.18% | 1.19% | 5.68% | 11.08% | 0.33% | 1.95% | 1.87% | 3.97% | –0.60% | –0.69% |
| | (0.86) | (1.91)* | (0.75) | (0.25) | (1.23) | (2.71)*** | (0.14) | (0.42) | (0.32) | (0.90) | (0.30) | (0.12) |
| Adjusted $R^2$ | 0.01 | 0.08 | 0.00 | 0.00 | 0.02 | 0.07 | 0.02 | 0.00 | 0.00 | 0.01 | 0.00 | –0.01 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 352 | 352 | 264 | 264 | 264 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 56.75% | 37.14% | 19.53% | 53.47% | 40.05% | 23.81% | 8.93% | 38.53% | 30.07% | 16.78% | 5.05% | 29.13% |
| | (29.03)*** | (19.06)*** | (15.34)*** | (28.08)*** | (13.89)*** | (9.80)*** | (7.34)*** | (13.41)*** | (9.92)*** | (7.16)*** | (4.99)*** | (9.79)*** |
| Group | 0.22% | 0.99% | 0.59% | 0.40% | –0.14% | –0.23% | –0.12% | –0.13% | –0.96% | –0.37% | –0.72% | –0.89% |
| | (0.08) | (0.35) | (0.33) | (0.14) | (0.03) | (0.06) | (0.07) | (0.03) | (0.23) | (0.11) | (0.52) | (0.21) |
| Pilot | 2.29% | 3.55% | 2.89% | 2.91% | 5.26% | 5.15% | 4.73% | 5.24% | 2.16% | 1.46% | 1.93% | 2.04% |
| | (0.83) | (1.28) | (1.50) | (1.08) | (1.29) | (1.49) | (2.30)** | (1.29) | (0.51) | (0.44) | (1.20) | (0.49) |
| Group*Pilot | 1.17% | 6.82% | –2.14% | –2.91% | 2.61% | 8.26% | –0.74% | –2.63% | 0.65% | 3.26% | –0.11% | –2.74% |
| | (0.30) | (1.81)* | (0.82) | (0.73) | (0.43) | (1.62) | (0.26) | (0.43) | (0.11) | (0.72) | (0.05) | (0.47) |
| Adjusted $R^2$ | 0.00 | 0.06 | 0.00 | –0.01 | 0.01 | 0.06 | 0.03 | 0.00 | –0.01 | 0.00 | 0.00 | –0.01 |
| N. Observations | 300 | 300 | 300 | 300 | 244 | 244 | 244 | 244 | 264 | 264 | 264 | 264 |

*Note.* The effect of the program on the percentage of classified MPIDs belonging to proprietary trading companies trading tick pilot securities. The effects of the policy change on competition were quantified through the difference-in-differences regression in which the dependent variable was the total number of proprietary trading companies and the independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

## Table 4.3d: Difference-in-Differences Regression for the Number of Bank Identifiers

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 66.21% | 42.59% | 21.50% | 64.43% | 61.42% | 36.40% | 14.31% | 59.95% | 41.48% | 17.65% | 4.74% | 40.21% |
| | (40.61)*** | (23.77)*** | (15.58)*** | (38.45)*** | (24.43)*** | (14.53)*** | (10.08)*** | (23.94)*** | (13.70)*** | (8.76)*** | (4.81)*** | (13.37)*** |
| Group | –0.35% | –1.25% | 0.38% | –0.14% | –0.61% | –0.01% | 0.28% | –0.45% | 0.46% | –0.45% | –0.02% | 0.61% |
| | (0.15) | (0.47) | (0.18) | (0.06) | (0.18) | 0.00 | (0.13) | (0.13) | (0.11) | (0.16) | (0.02) | (0.15) |
| Pilot | 3.20% | 5.36% | 4.42% | 2.47% | 4.33% | 6.62% | 7.03% | 3.89% | 3.73% | 2.91% | 3.21% | 3.47% |
| | (1.41) | (2.15)** | (2.17)** | (1.06) | (1.24) | (1.88)* | (3.05)*** | (1.12) | (0.86) | (0.96) | (1.86)* | (0.80) |
| Group*Pilot | –2.62% | 4.07% | –4.86% | –4.79% | –3.94% | 0.29% | –5.01% | –5.70% | –1.37% | 4.46% | –0.56% | –2.39% |
| | (0.78) | (1.12) | (1.62) | (1.37) | (0.80) | (0.06) | (1.53) | (1.14) | (0.23) | (1.02) | (0.25) | (0.40) |
| Adjusted $R^2$ | 0.00 | 0.05 | 0.01 | 0.00 | 0.00 | 0.02 | 0.04 | 0.00 | –0.01 | 0.02 | 0.01 | –0.01 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 240 | 240 | 280 | 280 | 280 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 68.79% | 44.47% | 24.06% | 67.43% | 61.53% | 37.38% | 15.47% | 60.18% | 38.56% | 15.36% | 4.80% | 37.68% |
| | (39.76)*** | (25.65)*** | (16.93)*** | (38.29)*** | (27.83)*** | (17.74)*** | (12.49)*** | (27.10)*** | (12.08)*** | (6.93)*** | (4.57)*** | (11.92)*** |
| Group | 0.07% | 0.40% | 0.31% | –0.25% | 0.37% | –1.20% | –1.97% | 0.09% | 0.50% | 1.26% | 0.09% | 0.11% |
| | (0.03) | (0.15) | (0.15) | (0.10) | (0.13) | (0.42) | (1.17) | (0.03) | (0.11) | (0.41) | (0.06) | (0.03) |
| Pilot | 3.89% | 6.72% | 5.74% | 3.17% | 3.99% | 5.11% | 5.52% | 3.35% | 3.89% | 3.50% | 3.41% | 3.65% |
| | (1.69)* | (2.80)*** | (2.65)*** | (1.34) | (1.35) | (1.77)* | (2.82)*** | (1.13) | (0.85) | (1.07) | (1.87)* | (0.81) |
| Group*Pilot | –3.35% | 2.65% | –6.78% | –5.07% | –2.80% | 3.51% | –2.17% | –3.95% | –0.73% | 3.58% | –1.36% | –1.73% |
| | (0.96) | (0.74) | (2.24)** | (1.40) | (0.70) | (0.90) | (0.84) | (0.98) | (0.11) | (0.76) | (0.55) | (0.28) |
| Adjusted $R^2$ | 0.00 | 0.08 | 0.04 | 0.01 | 0.00 | 0.03 | 0.04 | 0.00 | –0.01 | 0.02 | 0.01 | –0.01 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 352 | 352 | 264 | 264 | 264 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 69.35% | 44.12% | 22.54% | 67.94% | 56.46% | 33.20% | 11.61% | 54.66% | 44.81% | 20.36% | 6.88% | 43.62% |
| | (56.7)*** | (29.8)*** | (17.54)*** | (54.65)*** | (21.46)*** | (13.7)*** | (8.82)*** | (20.83)*** | (13.99)*** | (8.53)*** | (5.77)*** | (13.85)*** |
| Group | –0.67% | –0.20% | 0.02% | –0.69% | –1.83% | –1.59% | 0.14% | –1.68% | –0.41% | –0.40% | –0.43% | –0.38% |
| | (0.35) | (0.09) | (0.01) | (0.35) | (0.46) | (0.43) | (0.07) | (0.43) | (0.09) | (0.12) | (0.26) | (0.09) |
| Pilot | 2.62% | 6.56% | 5.37% | 1.55% | 4.87% | 6.76% | 6.82% | 4.28% | 3.02% | 2.59% | 3.42% | 2.77% |
| | (1.47) | (3.10)*** | (2.79)*** | (0.84) | (1.29) | (1.91)* | (2.94)*** | (1.14) | (0.65) | (0.74) | (1.70)* | (0.61) |
| Group*Pilot | –1.75% | 4.29% | –3.48% | –3.64% | –1.22% | 4.85% | –1.96% | –2.62% | 1.70% | 6.84% | –0.35% | 0.71% |
| | (0.63) | (1.41) | (1.31) | (1.25) | (0.22) | (0.93) | (0.59) | (0.47) | (0.26) | (1.36) | (0.13) | (0.11) |
| Adjusted $R^2$ | 0.00 | 0.10 | 0.03 | 0.01 | 0.00 | 0.04 | 0.04 | 0.00 | –0.01 | 0.02 | 0.01 | –0.01 |
| N. Observations | 300 | 300 | 300 | 300 | 244 | 244 | 244 | 244 | 264 | 264 | 264 | 264 |

*Note.* The effect of the program on the percentage of classified MPIDs belonging to proprietary trading companies trading tick pilot securities. The effects of the policy change on competition were quantified through the difference-in-differences regression in which the dependent variable was the total number of proprietary trading companies and the independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White’s standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

## Table 4.3e: Difference-in-Differences Regression for the Number of Agency Firm Identifiers

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 47.05% | 21.49% | 8.45% | 43.42% | 42.78% | 16.94% | 4.59% | 40.61% | 27.09% | 6.62% | 1.53% | 25.84% |
| | (28.08)*** | (17.85)*** | (12.72)*** | (26.46)*** | (20.86)*** | (11.84)*** | (8.99)*** | (20.55)*** | (13.11)*** | (6.99)*** | (4.85)*** | (12.94)*** |
| Group | 0.58% | 0.06% | 1.10% | 0.99% | 1.36% | 0.64% | 0.39% | 1.36% | 0.48% | 0.08% | 0.14% | 0.47% |
| | (0.25) | (0.04) | (1.01) | (0.43) | (0.46) | (0.31) | (0.52) | (0.47) | (0.17) | (0.06) | (0.34) | (0.17) |
| Pilot | 2.92% | 0.98% | 0.15% | 2.69% | 3.79% | 1.67% | 1.63% | 3.36% | 1.04% | –0.24% | 0.48% | 1.14% |
| | (1.22) | (0.57) | (0.16) | (1.16) | (1.28) | (0.83) | (1.96)** | (1.18) | (0.35) | (0.18) | (0.89) | (0.39) |
| Group*Pilot | –2.51% | 5.26% | 0.65% | –6.41% | –5.65% | 2.26% | –0.05% | –8.10% | –0.73% | 3.25% | –0.14% | –2.01% |
| | (0.74) | (2.02)** | (0.42) | (1.94)* | (1.31) | (0.75) | (0.04) | (1.96)** | (0.18) | (1.64) | (0.19) | (0.52) |
| Adjusted $R^2$ | 0.00 | 0.04 | 0.00 | 0.01 | 0.00 | 0.01 | 0.02 | 0.01 | –0.01 | 0.02 | –0.01 | –0.01 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 240 | 240 | 280 | 280 | 280 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 50.47% | 22.76% | 9.39% | 47.45% | 42.58% | 17.78% | 4.70% | 40.18% | 25.84% | 6.50% | 1.80% | 24.70% |
| | (31.35)*** | (19.41)*** | (15.03)*** | (29.35)*** | (24.06)*** | (14.79)*** | (11.21)*** | (23.46)*** | (11.79)*** | (5.74)*** | (4.54)*** | (11.83)*** |
| Group | 0.45% | 1.42% | 1.10% | –0.03% | –0.91% | –1.75% | –0.63% | –0.79% | 0.03% | –0.01% | –0.10% | –0.09% |
| | (0.18) | (0.81) | (1.08) | (0.01) | (0.40) | (1.08) | (1.08) | (0.36) | (0.01) | (0.01) | (0.19) | (0.03) |
| Pilot | 3.31% | 1.54% | 1.02% | 2.88% | 2.45% | 0.20% | 1.30% | 2.25% | 1.66% | –0.04% | 0.55% | 1.55% |
| | (1.47) | (0.94) | (1.10) | (1.29) | (0.98) | (0.12) | (1.84)* | (0.93) | (0.52) | (0.02) | (0.88) | (0.52) |
| Group*Pilot | –2.37% | 4.47% | 0.24% | –6.20% | –2.51% | 4.86% | 0.24% | –5.24% | –0.65% | 3.21% | –0.26% | –1.75% |
| | (0.68) | (1.75)* | (0.16) | (1.80)* | (0.76) | (2.07)** | (0.25) | (1.65)* | (0.15) | (1.4) | (0.31) | (0.43) |
| Adjusted $R^2$ | 0.00 | 0.07 | 0.01 | 0.02 | 0.00 | 0.02 | 0.02 | 0.01 | –0.01 | 0.01 | –0.01 | –0.01 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 352 | 352 | 264 | 264 | 264 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 50.24% | 22.63% | 9.10% | 46.76% | 38.32% | 14.92% | 3.63% | 36.01% | 29.53% | 8.35% | 2.31% | 27.81% |
| | (39.96)*** | (21.14)*** | (13.80)*** | (37.37)*** | (17.48)*** | (10.47)*** | (8.10)*** | (17.16)*** | (14.15)*** | (7.39)*** | (6.49)*** | (14.22)*** |
| Group | 0.19% | 0.42% | 0.39% | 0.37% | –1.45% | –0.25% | –0.11% | –1.38% | 0.11% | –0.36% | –0.19% | 0.38% |
| | (0.10) | (0.27) | (0.43) | (0.19) | (0.44) | (0.12) | (0.16) | (0.44) | (0.04) | (0.23) | (0.35) | (0.13) |
| Pilot | 2.43% | 1.76% | 0.78% | 2.19% | 4.14% | 1.83% | 1.61% | 3.75% | 1.03% | –0.29% | 0.51% | 1.06% |
| | (1.25) | (1.11) | (0.81) | (1.15) | (1.32) | (0.9) | (2.05)** | (1.25) | (0.34) | (0.18) | (0.81) | (0.37) |
| Group*Pilot | –1.44% | 6.48% | 1.33% | –5.83% | –1.31% | 4.98% | 0.91% | –4.28% | 0.36% | 5.05% | 0.10% | –1.01% |
| | (0.51) | (2.80)*** | (0.97) | (2.05)** | (0.28) | (1.58) | (0.73) | (0.97) | (0.08) | (2.05)** | (0.1) | (0.25) |
| Adjusted $R^2$ | 0.00 | 0.10 | 0.02 | 0.02 | 0.00 | 0.04 | 0.04 | 0.00 | –0.01 | 0.03 | –0.01 | –0.01 |
| N. Observations | 300 | 300 | 300 | 300 | 244 | 244 | 244 | 244 | 264 | 264 | 264 | 264 |

*Note.* The effect of the program on the percentage of classified MPIDs belonging to agency firms trading tick pilot securities. The effects of the policy change on competition were quantified through the difference-in-differences regression in which the dependent variable was the total number of banks and the independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

### 4.3.2 Tick size pilot and market participant's liquidity provision

This section outlines how the tick size pilot program affected market participants' liquidity provision across three Nasdaq exchanges (BX, PSX and Nasdaq) and whether the policy change led non-proprietary trading companies to use more limit orders than before, as hypothesized in *H2*. The analysis comprises two parts: (i) the analysis of the number of shares traded and (ii) the examination of market participants' liquidity provision.

**Table 4.4: Pre-Pilot Summary Statistics for the Average Daily Log Volume**

| Panel A: Proprietary trading companies | All | BX | PSX | Nasdaq |
|---|---|---|---|---|
| Low quoted spread | 9.82 | 7.89 | 6.91 | 9.61 |
| | (1.52) | (1.36) | (1.34) | (1.53) |
| Medium quoted spread | 8.74 | 7.10 | 6.07 | 8.56 |
| | (1.87) | (1.52) | (1.33) | (1.87) |
| High quoted spread | 7.44 | 6.24 | 5.50 | 7.30 |
| | (2.10) | (1.71) | (1.41) | (2.09) |
| **Panel B: Banks** | **All** | **BX** | **PSX** | **Nasdaq** |
| Low quoted spread | 10.65 | 8.62 | 7.02 | 10.45 |
| | (1.29) | (1.26) | (1.41) | (1.31) |
| Medium quoted spread | 9.71 | 8.01 | 6.40 | 9.52 |
| | (1.71) | (1.43) | (1.37) | (1.72) |
| High quoted spread | 8.11 | 6.84 | 5.84 | 7.97 |
| | (2.20) | (1.75) | (1.51) | (2.17) |
| **Panel C: Agency firms** | **All** | **BX** | **PSX** | **Nasdaq** |
| Low quoted spread | 9.27 | 7.16 | 6.07 | 9.08 |
| | (1.27) | (1.21) | (1.28) | (1.30) |
| Medium quoted spread | 8.43 | 6.38 | 5.41 | 8.29 |
| | (1.56) | (1.28) | (1.23) | (1.58) |
| High quoted spread | 7.14 | 5.54 | 5.37 | 7.04 |
| | (1.93) | (1.49) | (1.48) | (1.92) |

*Note.* Average daily log volume per market participant group and stock exchange from 1 April 2016 to 1 October 2016. Standard deviations are reported in parentheses.

The average daily volume indicates whether there is a substitution effect across the different markets or whether changes in tick size and the trade-at rule encourages market participants to increase their trading activity in the lit markets. Table 4.4 indicates that the average daily natural logarithm for the trading volume was not evenly distributed among the three market participant groups. Banks were the major players in these markets as they traded, on average, 42,343, 16,488 and 3,317 shares for *low*, *medium* and *high quoted spread* stocks, respectively. The average number of shares was calculated by applying the exponential function on the numbers reported in the table (e.g., $e^{10.65} = 42{,}343$). Agency firms were the least active market participant for small–medium capitalisation stocks. Table 4.4 also indicates that market participants used to trade more active on Nasdaq, while they only marginally included BX and PSX in their order submission strategies.

The difference-in-differences regressions indicate that the magnitude of the effects of the tick size pilot on market participants' trading volume was consistent across the three quoted spread groups, but it was mostly significant on *low quoted spread* securities. Consistent with Lin et al. (2018), the results for securities with a pre-pilot quoted spread lower than $0.04 suggested that the tick size consolidation encouraged non-proprietary trading companies to shift their trading activity from the time priority maker–taker stock exchange (Nasdaq) to the inverted market (BX). Further, Table 4.5c indicates that agency firms marginally reduce their trading activity across the three markets only for G2 securities, but not for G3 stocks. These results are consistent with Kwan et al. (2015), who determined that market participants search for a finer price grid outside the lit market for securities with tick-constrained dollar quoted spreads. Conversely, proprietary trading companies appear to significantly increase their trading volume only on BX, suggesting that their order submission strategies are sensitive to changes in banks' and agency firms' trading activity.

Overall, the analysis shows that non-proprietary trading companies only marginally reduce their trading activity across the three Nasdaq trading venues on low quoted spread G2 securities, while it clearly demonstrates that the tick size consolidation creates a substitution effect between Nasdaq and BX. This result suggests that market participants are now either looking for a finer price grid or minimising the costs of crossing the spread by shifting their trading activity from the maker-taker to the taker-maker venue[3].

[3] It is worth highlighting that the volume results cannot be generalized to make inference on the effects of the program on the consolidated volume. Instead, the results provide a good proxy for analysing the change in trading behavior of the three participants' groups when choosing whether to submit their orders on a BX, PSX, or Nasdaq.

## Table 4.5a: Difference-in-Differences Regressions for the Natural Logarithm of the Volume Traded by Proprietary Trading Companies

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 9.83 | 7.64 | 6.41 | 9.63 | 9.01 | 6.65 | 5.09 | 8.87 | 6.95 | 4.81 | 2.67 | 6.81 |
| | (66.45)*** | (44.77)*** | (31.82)*** | (65.01)*** | (44.13)*** | (27.48)*** | (18.81)*** | (44.2)*** | (28.96)*** | (17.12)*** | (8.04)*** | (28.50)*** |
| Group | 0.10 | 0.12 | 0.04 | 0.11 | 0.03 | 0.11 | 0.11 | 0.03 | 0.15 | –0.21 | 0.40 | 0.17 |
| | (0.48) | (0.49) | (0.13) | (0.51) | (0.11) | (0.32) | (0.30) | (0.09) | (0.47) | (0.53) | (0.85) | (0.52) |
| Pilot | 0.33 | 0.46 | 0.16 | 0.32 | 0.47 | 0.57 | 0.55 | 0.45 | 0.40 | 0.42 | 0.59 | 0.37 |
| | (1.64) | (1.90)* | (0.56) | (1.57) | (1.68)* | (1.66)* | (1.36) | (1.62) | (1.16) | (1.00) | (1.20) | (1.10) |
| Group*Pilot | –0.03 | 1.08 | 0.00 | –0.41 | –0.26 | 0.78 | –0.52 | –0.55 | –0.01 | 0.57 | 0.07 | –0.12 |
| | (0.10) | (3.31)*** | (0.01) | (1.40) | (0.61) | (1.62) | (0.90) | (1.33) | (0.02) | (0.96) | (0.09) | (0.26) |
| Adjusted $R^2$ | 0.01 | 0.16 | –0.01 | 0.00 | 0.00 | 0.08 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 232 | 240 | 280 | 268 | 198 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 10.24 | 8.03 | 6.86 | 10.06 | 9.09 | 6.81 | 5.18 | 8.93 | 6.87 | 4.51 | 2.78 | 6.77 |
| | (67.70)*** | (47.33)*** | (33.90)*** | (66.79)*** | (53.33)*** | (34.37)*** | (22.85)*** | (52.31)*** | (27.23)*** | (14.86)*** | (7.41)*** | (27.28)*** |
| Group | –0.07 | 0.00 | –0.01 | –0.08 | –0.13 | –0.05 | –0.22 | –0.13 | 0.11 | –0.08 | 0.20 | 0.07 |
| | (0.29) | (0.01) | (0.03) | (0.33) | (0.59) | (0.21) | (0.71) | (0.58) | (0.31) | (0.18) | (0.39) | (0.21) |
| Pilot | 0.34 | 0.53 | 0.28 | 0.31 | 0.41 | 0.54 | 0.39 | 0.39 | 0.57 | 0.54 | 0.69 | 0.56 |
| | (1.61) | (2.24)** | (0.91) | (1.50) | (1.85)* | (2.14)** | (1.21) | (1.76)* | (1.63) | (1.21) | (1.29) | (1.64) |
| Group*Pilot | –0.11 | 0.93 | –0.39 | –0.49 | 0.01 | 0.96 | 0.07 | –0.29 | –0.18 | 0.50 | –0.18 | –0.33 |
| | (0.34) | (2.77)*** | (0.86) | (1.52) | (0.02) | (2.83)*** | (0.15) | (1.01) | (0.37) | (0.80) | (0.25) | (0.70) |
| Adjusted $R^2$ | 0.00 | 0.17 | –0.01 | 0.01 | 0.02 | 0.12 | 0.00 | 0.01 | 0.00 | 0.02 | 0.00 | 0.00 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 338 | 352 | 264 | 250 | 182 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 10.06 | 7.80 | 6.69 | 9.89 | 8.69 | 6.45 | 4.59 | 8.53 | 7.30 | 4.99 | 3.26 | 7.16 |
| | (79.15)*** | (52.18)*** | (37.32)*** | (78.44)*** | (45.77)*** | (28.16)*** | (17.55)*** | (45.33)*** | (28.76)*** | (14.74)*** | (8.82)*** | (28.96)*** |
| Group | 0.08 | 0.08 | 0.09 | 0.07 | –0.33 | –0.31 | –0.05 | –0.32 | 0.10 | 0.01 | –0.01 | 0.11 |
| | (0.42) | (0.39) | (0.34) | (0.41) | (1.03) | (0.87) | (0.13) | (1.01) | (0.30) | (0.03) | (0.01) | (0.32) |
| Pilot | 0.31 | 0.54 | 0.26 | 0.27 | 0.47 | 0.56 | 0.68 | 0.45 | 0.39 | 0.35 | 0.33 | 0.39 |
| | (1.70)* | (2.55)*** | (1.00) | (1.51) | (1.69)* | (1.70)* | (1.80)* | (1.63) | (1.08) | (0.73) | (0.59) | (1.12) |
| Group*Pilot | 0.06 | 1.34 | –0.08 | –0.47 | 0.29 | 1.60 | 0.11 | –0.16 | 0.05 | 0.88 | 0.41 | –0.15 |
| | (0.24) | (4.73)*** | (0.22) | (1.88)* | (0.66) | (3.34)*** | (0.20) | (0.37) | (0.10) | (1.37) | (0.56) | (0.31) |
| Adjusted $R^2$ | 0.02 | 0.28 | 0.00 | 0.01 | 0.02 | 0.15 | 0.02 | 0.01 | 0.00 | 0.03 | 0.00 | 0.00 |
| N. Observations | 300 | 300 | 298 | 300 | 244 | 242 | 234 | 244 | 264 | 252 | 204 | 264 |

*Note.* The difference-in-differences regressions used to measure the effect of the tick size program on the natural logarithm for the average daily volume traded by proprietary trading companies. The independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

## Table 4.5b: Difference-in-Differences Regressions for the Natural Logarithm of the Volume Traded by Banks

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 10.76 | 8.66 | 7.03 | 10.57 | 10.04 | 7.84 | 6.01 | 9.88 | 8.13 | 5.60 | 3.76 | 8.00 |
| | (91.11)*** | (65.57)*** | (50.30)*** | (88.16)*** | (56.16)*** | (38.10)*** | (31.59)*** | (55.84)*** | (38.08)*** | (18.09)*** | (14.32)*** | (37.90)*** |
| Group | 0.05 | –0.07 | –0.05 | 0.07 | 0.07 | 0.06 | –0.02 | 0.07 | 0.05 | –0.01 | 0.16 | 0.06 |
| | (0.27) | (0.34) | (0.25) | (0.38) | (0.27) | (0.19) | (0.08) | (0.27) | (0.17) | (0.03) | (0.39) | (0.21) |
| Pilot | 0.23 | 0.47 | 0.22 | 0.19 | 0.37 | 0.50 | 0.52 | 0.33 | 0.19 | 0.23 | 0.27 | 0.19 |
| | (1.38) | (2.43)*** | (1.00) | (1.10) | (1.45) | (1.62) | (1.70)* | (1.33) | (0.60) | (0.52) | (0.66) | (0.61) |
| Group*Pilot | –0.15 | 0.73 | –0.19 | –0.41 | –0.35 | 0.34 | –0.46 | –0.51 | 0.06 | 0.59 | 0.07 | –0.07 |
| | (0.60) | (2.65)*** | (0.57) | (1.69)* | (0.97) | (0.81) | (1.04) | (1.43) | (0.14) | (0.97) | (0.12) | (0.16) |
| Adjusted $R^2$ | 0.00 | 0.13 | 0.00 | 0.00 | 0.00 | 0.04 | 0.00 | 0.00 | –0.01 | 0.01 | –0.01 | –0.01 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 234 | 240 | 280 | 272 | 238 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 11.02 | 8.85 | 7.23 | 10.85 | 10.16 | 7.95 | 6.03 | 10.00 | 8.07 | 5.38 | 3.76 | 7.97 |
| | (89.65)*** | (66.77)*** | (47.33)*** | (86.91)*** | (70.52)*** | (45.36)*** | (35.75)*** | (69.92)*** | (36.99)*** | (18.94)*** | (13.38)*** | (37.20)*** |
| Group | –0.05 | 0.01 | 0.03 | –0.06 | –0.17 | –0.12 | –0.15 | –0.18 | 0.02 | 0.24 | –0.04 | –0.01 |
| | (0.27) | (0.04) | (0.12) | (0.33) | (0.88) | (0.51) | (0.63) | (0.93) | (0.06) | (0.61) | (0.09) | (0.05) |
| Pilot | 0.32 | 0.55 | 0.43 | 0.28 | 0.30 | 0.49 | 0.40 | 0.26 | 0.40 | 0.58 | 0.45 | 0.38 |
| | (1.85)* | (2.83)*** | (1.71)* | (1.59) | (1.61) | (2.16)** | (1.55) | (1.4) | (1.28) | (1.45) | (1.02) | (1.27) |
| Group*Pilot | –0.29 | 0.54 | –0.51 | –0.56 | –0.12 | 0.49 | –0.14 | –0.29 | –0.09 | 0.31 | –0.10 | –0.20 |
| | (1.10) | (1.96)** | (1.39) | (2.11)** | (0.49) | (1.62) | (0.39) | (1.15) | (0.21) | (0.54) | (0.16) | (0.48) |
| Adjusted $R^2$ | 0.01 | 0.15 | 0.01 | 0.03 | 0.01 | 0.06 | 0.01 | 0.02 | 0.00 | 0.02 | –0.01 | 0.00 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 350 | 352 | 264 | 256 | 230 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 10.92 | 8.76 | 7.12 | 10.75 | 9.83 | 7.68 | 5.56 | 9.65 | 8.42 | 5.95 | 4.18 | 8.29 |
| | (116.62)*** | (80.09)*** | (53.38)*** | (114.21)*** | (63.62)*** | (39.37)*** | (25.91)*** | (62.78)*** | (37.85)*** | (18.84)*** | (13.21)*** | (38.32)*** |
| Group | 0.04 | 0.02 | 0.02 | 0.04 | –0.24 | –0.22 | –0.08 | –0.22 | 0.08 | 0.00 | 0.29 | 0.08 |
| | (0.25) | (0.11) | (0.11) | (0.28) | (0.92) | (0.72) | (0.25) | (0.88) | (0.25) | (0.01) | (0.72) | (0.28) |
| Pilot | 0.28 | 0.62 | 0.44 | 0.21 | 0.36 | 0.51 | 0.70 | 0.32 | 0.17 | 0.24 | 0.37 | 0.17 |
| | (1.96)** | (4.02)*** | (2.27)** | (1.44) | (1.64) | (1.80)* | (2.27)** | (1.46) | (0.53) | (0.55) | (0.78) | (0.55) |
| Group*Pilot | 0.06 | 1.03 | –0.12 | –0.37 | 0.18 | 0.98 | –0.12 | –0.07 | 0.23 | 0.90 | –0.09 | 0.07 |
| | (0.29) | (4.61)*** | (0.44) | (1.78)* | (0.51) | (2.3)** | (0.26) | (0.22) | (0.53) | (1.45) | (0.16) | (0.16) |
| Adjusted $R^2$ | 0.02 | 0.32 | 0.02 | 0.01 | 0.02 | 0.10 | 0.02 | 0.01 | 0.00 | 0.02 | –0.01 | –0.01 |
| N. Observations | 300 | 300 | 300 | 300 | 244 | 242 | 242 | 244 | 264 | 254 | 228 | 264 |

*Note.* The difference-in-differences regressions used to measure the effect of the tick size program for the natural logarithm of the average daily volume traded by banks. The independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

## Table 4.5c: Difference-in-Differences Regressions for the Natural Logarithm of the Volume Traded by Agency Firms

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 9.41 | 7.08 | 5.62 | 9.25 | 8.78 | 6.07 | 4.58 | 8.67 | 7.18 | 4.06 | 3.72 | 7.10 |
| | (86.16)*** | (51.74)*** | (34.48)*** | (83.84)*** | (56.33)*** | (28.01)*** | (24.68)*** | (55.96)*** | (39.49)*** | (14.35)*** | (16.75)*** | (39.27)*** |
| Group | 0.13 | 0.02 | 0.08 | 0.14 | 0.09 | 0.07 | 0.19 | 0.10 | 0.12 | 0.00 | 0.12 | 0.11 |
| | (0.83) | (0.11) | (0.33) | (0.88) | (0.40) | (0.23) | (0.71) | (0.44) | (0.47) | (0.00) | (0.37) | (0.43) |
| Pilot | 0.11 | 0.05 | –0.23 | 0.13 | 0.31 | 0.21 | 0.18 | 0.31 | 0.03 | 0.08 | –0.70 | 0.06 |
| | (0.76) | (0.25) | (0.95) | (0.83) | (1.40) | (0.68) | (0.63) | (1.44) | (0.12) | (0.21) | (2.02)** | (0.22) |
| Group*Pilot | –0.21 | 0.98 | 0.36 | –0.48 | –0.48 | 0.49 | –0.40 | –0.62 | 0.04 | 0.64 | –0.10 | –0.03 |
| | (0.96) | (3.56)*** | (0.99) | (2.18)** | (1.51) | (1.18) | (0.91) | (1.94)* | (0.11) | (1.23) | (0.19) | (0.10) |
| Adjusted $R^2$ | –0.01 | 0.11 | 0.00 | 0.01 | 0.00 | 0.02 | –0.01 | 0.01 | –0.01 | 0.01 | 0.03 | –0.01 |
| N. Observations | 308 | 308 | 306 | 308 | 240 | 240 | 226 | 240 | 280 | 268 | 202 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 9.65 | 7.35 | 5.96 | 9.48 | 8.88 | 6.19 | 4.81 | 8.77 | 7.16 | 3.68 | 3.33 | 7.07 |
| | (87.71)*** | (53.44)*** | (35.06)*** | (84.89)*** | (68.9)*** | (36.09)*** | (30.33)*** | (68.16)*** | (36.86)*** | (12.09)*** | (11.51)*** | (36.66)*** |
| Group | 0.05 | 0.05 | 0.15 | 0.04 | –0.12 | –0.08 | –0.31 | –0.13 | 0.04 | 0.31 | 0.45 | 0.02 |
| | (0.28) | (0.23) | (0.61) | (0.22) | (0.76) | (0.36) | (1.41) | (0.81) | (0.15) | (0.78) | (1.23) | (0.10) |
| Pilot | 0.24 | 0.10 | –0.04 | 0.27 | 0.19 | 0.11 | –0.01 | 0.19 | 0.27 | 0.28 | –0.45 | 0.29 |
| | (1.59) | (0.53) | (0.15) | (1.77)* | (1.12) | (0.47) | (0.04) | (1.14) | (0.98) | (0.69) | (1.07) | (1.07) |
| Group*Pilot | –0.39 | 0.74 | 0.08 | –0.65 | –0.19 | 0.79 | 0.05 | –0.34 | –0.14 | 0.48 | –0.45 | –0.20 |
| | (1.68)* | (2.57)*** | (0.23) | (2.78)*** | (0.89) | (2.69)*** | (0.15) | (1.57) | (0.37) | (0.88) | (0.79) | (0.54) |
| Adjusted $R^2$ | 0.01 | 0.09 | –0.01 | 0.05 | 0.01 | 0.05 | 0.00 | 0.02 | –0.01 | 0.02 | 0.02 | –0.01 |
| N. Observations | 228 | 228 | 226 | 228 | 352 | 352 | 330 | 352 | 264 | 256 | 198 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 9.59 | 7.24 | 5.91 | 9.43 | 8.62 | 5.87 | 4.34 | 8.50 | 7.43 | 4.43 | 4.18 | 7.31 |
| | (111.65)*** | (62.38)*** | (38.59)*** | (110.24)*** | (66.8)*** | (28.09)*** | (24.07)*** | (66.25)*** | (39.44)*** | (14.27)*** | (18.28)*** | (40.18)*** |
| Group | 0.05 | –0.01 | 0.14 | 0.05 | –0.30 | –0.26 | –0.36 | –0.29 | 0.04 | –0.10 | –0.40 | 0.07 |
| | (0.37) | (0.06) | (0.7) | (0.41) | (1.36) | (0.82) | (1.25) | (1.33) | (0.14) | (0.23) | (1.22) | (0.28) |
| Pilot | 0.18 | 0.12 | –0.04 | 0.19 | 0.29 | 0.32 | 0.31 | 0.28 | 0.02 | –0.11 | –1.00 | 0.07 |
| | (1.38) | (0.76) | (0.19) | (1.47) | (1.62) | (1.07) | (1.17) | (1.58) | (0.06) | (0.27) | (2.66)*** | (0.23) |
| Group*Pilot | –0.01 | 1.37 | 0.23 | –0.42 | 0.02 | 1.17 | 0.25 | –0.21 | 0.20 | 1.17 | 0.25 | 0.10 |
| | (0.06) | (5.78)*** | (0.77) | (2.19)** | (0.06) | (2.68)*** | (0.56) | (0.68) | (0.52) | (2.12)** | (0.48) | (0.26) |
| Adjusted $R^2$ | 0.00 | 0.27 | 0.00 | 0.01 | 0.02 | 0.09 | 0.01 | 0.02 | –0.01 | 0.03 | 0.04 | –0.01 |
| N. Observations | 300 | 300 | 298 | 300 | 244 | 242 | 230 | 244 | 264 | 248 | 212 | 264 |

*Note.* The difference-in-differences regressions used to measure the effect of the tick size program for the natural logarithm of the average daily volume traded by agency firms. The independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

After analysing the effects of the tick size pilot program on market participants' average daily volume, this section examines the effect of the policy change on liquidity provision. In line with Carrion (2013), liquidity provision is defined as the number of shares executed through passive limit orders divided by the total number of shares traded split by market participant group. By construction, the sum of the percentage of passive orders among the three market participant groups reported in Table 4.6 roughly equals 50%. At first glance, the descriptive statistics in Table 4.6 are very different from those reported by Carrion (2013), who indicated that HFT passive orders executed are approximately 23.2% of the total traded volume on Nasdaq. These differences are probably due to differences in the samples. Carrion's (2013) trading volume summary statistics suggested that the analysed securities are very liquid, while the stocks used for this current investigation comprise mostly small and medium market capitalisation stocks.

**Table 4.6: Pre-Pilot Summary Statistics for the Average Daily Percentage of Passive Traded Volume**

| Panel A: Proprietary trading companies | All | BX | PSX | Nasdaq |
|---|---|---|---|---|
| Low quoted spread | 9.37% | 10.24% | 17.53% | 9.23% |
| | (0.06) | (0.09) | (0.15) | (0.06) |
| Medium quoted spread | 6.26% | 10.33% | 12.55% | 5.66% |
| | (0.05) | (0.10) | (0.15) | (0.05) |
| High quoted spread | 5.90% | 13.90% | 6.30% | 5.20% |
| | (0.07) | (0.14) | (0.13) | (0.07) |
| **Panel B: Banks** | **All** | **BX** | **PSX** | **Nasdaq** |
| Low quoted spread | 29.14% | 27.62% | 23.40% | 29.64% |
| | (0.08) | (0.12) | (0.16) | (0.08) |
| Medium quoted spread | 29.37% | 31.72% | 28.62% | 29.34% |
| | (0.10) | (0.12) | (0.18) | (0.10) |
| High quoted spread | 22.89% | 24.63% | 26.72% | 23.23% |
| | (0.13) | (0.16) | (0.21) | (0.14) |
| **Panel C: Agency firms** | **All** | **BX** | **PSX** | **Nasdaq** |
| Low quoted spread | 7.24% | 8.79% | 7.13% | 6.83% |
| | (0.05) | (0.08) | (0.11) | (0.06) |
| Medium quoted spread | 8.65% | 5.35% | 4.81% | 9.06% |
| | (0.08) | (0.08) | (0.11) | (0.08) |
| High quoted spread | 12.50% | 4.78% | 6.86% | 13.12% |
| | (0.12) | (0.09) | (0.14) | (0.13) |

*Note.* The summary statistics of the average daily percentage of shares traded as liquidity maker by each market participant group from 1 April 2016 to 1 October 2016. Standard deviations are reported in parentheses.

The pre-pilot summary statistics in Table 4.6 indicate that banks were the largest liquidity provides for these securities followed by agency firms and proprietary trading companies. Further, the summary statistics also suggest that, while agency firms tended to provide more liquidity on high quoted spread securities, proprietary traders tended to supply proportionally more liquidity on low quoted spread stocks. The liquidity provision of agency firms was 7.24%, 8.65% and 12.50% for the low, medium and high quoted spread, respectively, while proprietary trading companies supplied 9.37%, 6.26% and 5.90% of the total number of passive orders in the same spread groups, respectively. While there were clear liquidity provision patterns across market participants and quoted spread groups, there appeared to be no clear pattern for the liquidity provision across stock exchanges.

Regarding the average daily trading volume, market participant groups dramatically changed their liquidity provision on treatment securities across the three markets. Proprietary trading companies significantly increased their liquidity provisions' market share on the inverted market, doubling their liquidity supply (see Table 4.7a). Conversely, banks, which are the largest liquidity providers for control securities, significantly decreased their liquidity provision on all treatment stocks with a pre-pilot spread lower than $0.11 (see Table 4.7b). This effect was particularly strong on low quoted spread securities in which banks reduced their liquidity provision by 3.72%, 4.40% and 5.33% across G1, G2 and G3, respectively.

Conversely, Table 4.7c indicates that agency firms did not significantly change their liquidity supply across the three markets, although they appeared to significantly increase their liquidity provision on PSX for low quoted sp*read* securities. This empirical result, which appear contradictory, is due to PSX playing a small role in agency firms' order submission strategies as this trading venue only represents 4% of agency firms' trading activity. Overall, these results are consistent with Yao and Ye (2018) who suggested that proprietary trading companies establish time priority, forcing banks to use a larger proportion of marketable orders. Nonetheless, the results presented also suggest that agency firms (non-proprietary trading companies) did not reduce their liquidity provision across the three markets and that banks moved their order flow from Nasdaq to BX to minimise the cost of using marketable orders. These two novel results are consistent with O'Hara (2015) and suggest that speed may not be the only factor driving market participants' order submission strategies.

## Table 4.7a: Difference-in-Differences Regression for the Percentage of Shares Traded by Proprietary Trading Companies as Liquidity Providers

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 8.66% | 9.29% | 15.16% | 8.50% | 6.53% | 9.97% | 11.79% | 6.04% | 5.67% | 12.41% | 3.90% | 4.90% |
| | (27.22)*** | (21.55)*** | (18.59)*** | (24.94)*** | (26.82)*** | (20.04)*** | (13.5)*** | (23.17)*** | (24.3)*** | (14.72)*** | (7.8)*** | (21.95)*** |
| Group | 0.72% | 1.93% | 0.33% | 0.73% | –0.42% | 0.98% | 0.13% | –0.57% | 0.22% | –0.69% | –0.12% | 0.45% |
| | (1.29) | (2.57)*** | (0.28) | (1.20) | (1.34) | (1.30) | (0.10) | (1.69)* | (0.69) | (0.62) | (0.17) | (1.42) |
| Pilot | 0.18% | –1.77% | –2.14% | 0.58% | 0.65% | 0.25% | –1.13% | 0.78% | 1.86% | 4.33% | 0.27% | 1.57% |
| | (0.38) | (2.91)*** | (2.05)** | (1.15) | (1.82)* | (0.31) | (0.92) | (2.01)** | (5.08)*** | (3.35)*** | (0.35) | (4.69)*** |
| Group*Pilot | 3.62% | 9.53% | –1.95% | 0.41% | 3.91% | 8.47% | –2.91% | 1.04% | 0.41% | –1.46% | 0.23% | –0.02% |
| | (5.24)*** | (10.11)*** | (1.23) | (0.53) | (8.34)*** | (7.51)*** | (1.77)* | (2.02)** | (0.83) | (0.87) | (0.19) | (0.05) |
| Adjusted $R^2$ | 0.26 | 0.52 | 0.04 | 0.02 | 0.49 | 0.45 | 0.05 | 0.10 | 0.20 | 0.06 | –0.01 | 0.14 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 234 | 240 | 280 | 274 | 250 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 10.06% | 10.65% | 18.19% | 9.95% | 6.29% | 10.66% | 10.43% | 5.67% | 5.45% | 11.37% | 4.16% | 4.95% |
| | (18.90)*** | (16.04)*** | (20.33)*** | (18.04)*** | (36.00)*** | (22.53)*** | (16.19)*** | (34.25)*** | (19.12)*** | (14.42)*** | (6.47)*** | (17.71)*** |
| Group | –0.10% | –0.28% | –0.76% | –0.03% | 0.24% | 0.67% | –0.22% | 0.17% | 0.07% | 1.62% | 0.04% | –0.09% |
| | (0.14) | (0.37) | (0.59) | (0.04) | (0.90) | (0.89) | (0.24) | (0.63) | (0.20) | (1.28) | (0.05) | (0.27) |
| Pilot | –0.32% | –0.63% | –3.94% | –0.21% | 0.91% | –0.30% | –1.39% | 1.04% | 1.76% | 2.64% | 0.37% | 1.67% |
| | (0.43) | (0.61) | (3.61)*** | (0.28) | (3.64)*** | (0.48) | (1.51) | (3.89)*** | (4.6)*** | (2.12)** | (0.35) | (4.38)*** |
| Group*Pilot | 4.14% | 10.40% | –2.98% | 0.59% | 3.53% | 8.23% | –1.44% | 0.84% | 0.67% | –1.31% | 0.43% | –0.16% |
| | (4.22)*** | (8.65)*** | (1.87)* | (0.56) | (8.90)*** | (8.53)*** | (1.21) | (2.00)** | (1.30) | (0.73) | (0.30) | (0.31) |
| Adjusted $R^2$ | 0.16 | 0.46 | 0.19 | –0.01 | 0.50 | 0.39 | 0.04 | 0.14 | 0.20 | 0.01 | –0.01 | 0.12 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 350 | 352 | 264 | 262 | 240 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 9.02% | 9.42% | 16.60% | 8.87% | 5.98% | 9.76% | 10.42% | 5.42% | 5.81% | 12.19% | 4.50% | 5.12% |
| | (22.77)*** | (21.51)*** | (24.98)*** | (20.78)*** | (23.79)*** | (17.61)*** | (11.90)*** | (19.92)*** | (22.92)*** | (13.69)*** | (7.02)*** | (22.68)*** |
| Group | 0.42% | 0.92% | 1.13% | 0.38% | –0.10% | 0.46% | –0.87% | –0.13% | 0.27% | 1.22% | –0.44% | 0.26% |
| | (0.75) | (1.53) | (1.13) | (0.62) | (0.28) | (0.59) | (0.73) | (0.34) | (0.82) | (1.09) | (0.52) | (0.80) |
| Pilot | 0.06% | –1.42% | –3.46% | 0.40% | 0.70% | 0.88% | –1.43% | 0.80% | 1.50% | 3.54% | –0.33% | 1.44% |
| | (0.12) | (2.18)** | (4.12)*** | (0.67) | (2.00)** | (1.10) | (1.18) | (2.08)** | (4.34)*** | (2.88)*** | (0.37) | (4.23)*** |
| Group*Pilot | 4.47% | 11.33% | –2.71% | 0.05% | 4.85% | 9.97% | 1.50% | 0.76% | 0.59% | –1.17% | 2.26% | –0.44% |
| | (6.03)*** | (12.47)*** | (1.94)* | (0.06) | (8.53)*** | (8.03)*** | (0.84) | (1.34) | (1.15) | (0.75) | (1.63) | (0.85) |
| Adjusted $R^2$ | 0.29 | 0.60 | 0.14 | 0.00 | 0.51 | 0.48 | –0.01 | 0.06 | 0.17 | 0.04 | 0.01 | 0.07 |
| N. Observations | 300 | 300 | 300 | 300 | 244 | 242 | 242 | 244 | 264 | 258 | 232 | 264 |

*Note.* The difference-in-differences regressions used to measure the effect of the tick size program on the average daily percentage of volume traded by proprietary trading companies as liquidity providers. The independent variables are as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics are calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

## Table 4.7b: Difference-in-Differences Regression for the Percentage of Shares Traded by Banks as Liquidity Providers

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 29.65% | 29.00% | 26.24% | 30.01% | 29.28% | 31.42% | 28.94% | 29.27% | 22.16% | 23.95% | 22.74% | 22.35% |
| | (66.66)*** | (47.07)*** | (31.24)*** | (59.91)*** | (40.38)*** | (58.06)*** | (38.28)*** | (37.35)*** | (27.32)*** | (22.34)*** | (17.32)*** | (26.15)*** |
| Group | –0.96% | –1.89% | –1.29% | –0.81% | –0.26% | –0.63% | –1.03% | –0.27% | –0.70% | –1.91% | 0.44% | –0.72% |
| | (1.41) | (2.03)** | (1.05) | (1.10) | (0.26) | (0.70) | (0.79) | (0.24) | (0.60) | (1.28) | 0.22 | (0.59) |
| Pilot | 0.14% | 5.41% | 5.18% | –1.06% | –0.50% | 1.46% | 5.10% | –1.22% | –1.19% | –1.98% | 11.32% | –1.46% |
| | (0.21) | (6.80)*** | (4.32)*** | (1.48) | (0.46) | (1.50) | (3.80)*** | (1.08) | (1.00) | (1.27) | (5.13)*** | (1.20) |
| Group*Pilot | –3.72% | –12.07% | –3.13% | –0.36% | –2.45% | –10.74% | –1.36% | 0.16% | 1.53% | 1.85% | –1.52% | 1.38% |
| | (3.90)*** | (10.5)*** | (1.72)* | (0.34) | (1.68)* | (7.88)*** | (0.67) | (0.10) | (0.89) | (0.85) | (0.46) | (0.78) |
| Adjusted $R^2$ | 0.16 | 0.49 | 0.08 | 0.02 | 0.04 | 0.41 | 0.07 | 0.00 | –0.01 | 0.00 | 0.13 | –0.01 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 234 | 240 | 280 | 274 | 250 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 28.77% | 27.17% | 22.58% | 29.30% | 29.23% | 31.15% | 29.11% | 29.29% | 22.38% | 24.61% | 25.15% | 22.48% |
| | (52.54)*** | (34.99)*** | (26.78)*** | (49.12)*** | (51.02)*** | (58.28)*** | (35.78)*** | (48.16)*** | (25.97)*** | (27.73)*** | (16.34)*** | (24.58)*** |
| Group | 0.05% | –0.43% | 0.20% | 0.16% | –0.24% | –0.31% | 0.96% | –0.33% | –1.01% | –1.19% | –2.09% | –0.85% |
| | (0.06) | (0.42) | (0.17) | (0.18) | (0.28) | (0.38) | (0.83) | (0.36) | (0.80) | (0.84) | (1.01) | (0.63) |
| Pilot | 0.64% | 5.17% | 7.58% | –0.48% | 0.10% | 2.36% | 5.96% | –0.72% | –1.33% | 0.13% | 7.05% | –1.61% |
| | (0.77) | (4.57)*** | (6.66)*** | (0.55) | (0.12) | (3.12)*** | (4.66)*** | (0.83) | (1.06) | (0.08) | (2.98)*** | (1.24) |
| Group*Pilot | –4.40% | –11.74% | –2.32% | –0.98% | –3.13% | –10.91% | –2.62% | –0.59% | 1.55% | –1.82% | 2.61% | 1.45% |
| | (3.86)*** | (8.44)*** | (1.35) | (0.79) | (2.65)*** | (9.74)*** | (1.49) | (0.46) | (0.84) | (0.83) | (0.84) | (0.76) |
| Adjusted $R^2$ | 0.13 | 0.40 | 0.19 | 0.00 | 0.05 | 0.39 | 0.07 | 0.00 | –0.01 | 0.01 | 0.10 | –0.01 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 350 | 352 | 264 | 262 | 240 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 29.57% | 28.18% | 23.95% | 30.09% | 29.59% | 32.82% | 29.53% | 29.35% | 22.48% | 23.85% | 23.75% | 23.05% |
| | (64.73)*** | (45.99)*** | (32.61)*** | (60.90)*** | (42.75)*** | (51.87)*** | (29.95)*** | (38.68)*** | (25.66)*** | (21.66)*** | (17.80)*** | (24.21)*** |
| Group | –0.39% | –0.17% | –0.76% | –0.43% | –0.03% | –0.94% | 0.27% | 0.18% | 0.50% | 0.68% | 3.29% | 0.22% |
| | (0.64) | (0.2) | (0.72) | (0.63) | (0.03) | (1.02) | (0.18) | (0.16) | (0.40) | (0.45) | (1.75)* | (0.16) |
| Pilot | 0.45% | 6.15% | 7.73% | –0.92% | –1.26% | 0.20% | 4.05% | –2.02% | 0.13% | –0.09% | 10.49% | –0.45% |
| | (0.65) | (7.35)*** | (7.65)*** | (1.26) | (1.15) | (0.23) | (2.41)*** | (1.75)* | (0.10) | (0.06) | (5.1)*** | (0.33) |
| Group*Pilot | –5.33% | –15.25% | –3.08% | –0.41% | –4.06% | –12.98% | –3.16% | –0.30% | –0.25% | –2.50% | –5.75% | –0.49% |
| | (5.84)*** | (13.87)*** | (1.89)* | (0.37) | (2.58)*** | (8.99)*** | (1.30) | (0.17) | (0.14) | (1.10) | (1.87)* | (0.26) |
| Adjusted $R^2$ | 0.25 | 0.57 | 0.18 | 0.01 | 0.10 | 0.51 | 0.02 | 0.01 | –0.01 | 0.00 | 0.10 | –0.01 |
| N. Observations | 300 | 300 | 300 | 300 | 244 | 242 | 242 | 244 | 264 | 258 | 232 | 264 |

*Note.* The difference-in-differences regressions used to measure the effect of the tick size program on the average daily percentage volume traded by banks as liquidity providers. The independent variables are as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses are calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

## Table 4.7c: Difference-in-Differences Regression for the Percentage of Shares Traded by Agency Firms as Liquidity Providers

| | *Low quoted spread* | | | | *Medium quoted spread* | | | | *High quoted spread* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Group 1* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 7.31% | 8.34% | 6.42% | 7.01% | 8.74% | 5.80% | 5.86% | 9.03% | 12.69% | 6.08% | 11.09% | 13.51% |
| | (26.97)*** | (21.99)*** | (15.12)*** | (21.87)*** | (21.72)*** | (16.74)*** | (12.27)*** | (21.18)*** | (21.32)*** | (6.22)*** | (8.95)*** | (22.37)*** |
| Group | 0.29% | –0.04% | 0.89% | 0.22% | 0.54% | 0.04% | 0.00% | 0.64% | 0.44% | 0.18% | 1.14% | 0.23% |
| | (0.62) | (0.08) | (1.45) | (0.41) | (0.78) | (0.06) | (0.00) | (0.89) | (0.50) | (0.16) | (0.58) | (0.26) |
| Pilot | –0.41% | –3.28% | –2.98% | 0.21% | –0.43% | –1.46% | –3.46% | –0.11% | –1.68% | –1.05% | –7.67% | –1.84% |
| | (1.04) | (7.35)*** | (5.71)*** | (0.46) | (0.66) | (3.13)*** | (4.25)*** | (0.16) | (2.11)** | (0.91) | (4.76)*** | (2.3)** |
| Group*Pilot | –0.34% | 1.37% | 4.73% | –0.58% | –1.29% | 0.60% | 4.47% | –1.04% | 0.25% | 2.51% | 0.60% | 0.68% |
| | (0.58) | (2.33)** | (5.98)*** | (0.83) | (1.40) | (0.80) | (3.86)*** | (1.06) | (0.21) | (1.55) | (0.24) | (0.57) |
| Adjusted $R^2$ | 0.00 | 0.21 | 0.25 | –0.01 | 0.02 | 0.03 | 0.12 | 0.00 | 0.02 | 0.01 | 0.12 | 0.02 |
| N. Observations | 308 | 308 | 308 | 308 | 240 | 240 | 234 | 240 | 280 | 274 | 250 | 280 |
| *Panel B: Group 2* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 6.89% | 8.85% | 7.37% | 6.41% | 8.66% | 5.58% | 6.16% | 9.01% | 13.46% | 5.97% | 9.53% | 14.03% |
| | (27.42)*** | (21.23)*** | (11.97)*** | (22.15)*** | (24.93)*** | (20.16)*** | (9.81)*** | (25.41)*** | (19.04)*** | (10.4)*** | (8.24)*** | (19.73)*** |
| Group | 0.50% | 0.53% | –0.17% | 0.40% | 0.11% | –0.41% | –0.76% | 0.25% | 0.68% | 0.14% | 1.20% | 0.78% |
| | (1.18) | (0.85) | (0.21) | (0.83) | (0.21) | (1.09) | (0.96) | (0.46) | (0.63) | (0.16) | (0.71) | (0.73) |
| Pilot | –0.47% | –3.74% | –3.59% | 0.22% | –1.22% | –1.82% | –3.94% | –0.96% | –1.05% | 0.20% | –5.10% | –1.20% |
| | (1.32) | (7.67)*** | (5.1)*** | (0.53) | (2.51)*** | (5.15)*** | (5.44)*** | (1.9)* | (1.03) | (0.21) | (3.34)*** | (1.19) |
| Group*Pilot | –0.05% | 0.63% | 5.97% | –0.06% | 0.14% | 1.34% | 4.35% | 0.25% | –1.25% | 1.11% | 0.75% | –0.55% |
| | (0.10) | (0.89) | (5.76)*** | (0.09) | (0.19) | (2.76)*** | (4.66)*** | (0.32) | (0.83) | (0.73) | (0.33) | (0.37) |
| Adjusted $R^2$ | 0.01 | 0.30 | 0.21 | –0.01 | 0.02 | 0.07 | 0.11 | 0.01 | 0.01 | 0.00 | 0.06 | 0.01 |
| N. Observations | 228 | 228 | 228 | 228 | 352 | 352 | 350 | 352 | 264 | 262 | 240 | 264 |
| *Panel C: Group 3* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* | *All* | *BX* | *PSX* | *Nasdaq* |
| Intercept | 7.11% | 9.10% | 7.17% | 6.67% | 8.23% | 4.98% | 5.81% | 8.74% | 13.24% | 6.36% | 11.89% | 13.57% |
| | (31.15)*** | (25.91)*** | (17.57)*** | (26.71)*** | (24.75)*** | (16.78)*** | (7.43)*** | (23.92)*** | (17.16)*** | (7.69)*** | (8.49)*** | (18.00)*** |
| Group | 0.00% | –0.59% | –0.03% | 0.08% | 0.50% | 0.49% | 0.35% | 0.43% | –0.83% | –1.09% | –3.27% | –0.54% |
| | (0.01) | (1.22) | (0.05) | (0.22) | (0.84) | (1.18) | (0.26) | (0.69) | (0.84) | (1.18) | (1.77)* | (0.56) |
| Pilot | –0.40% | –3.97% | –3.46% | 0.36% | –0.07% | –1.23% | –1.80% | 0.19% | –2.06% | –0.85% | –7.35% | –1.91% |
| | (1.17) | (9.49)*** | (6.85)*** | (0.95) | (0.12) | (3.09)*** | (1.49) | (0.31) | (1.98)** | (0.69) | (4.03)*** | (1.88)* |
| Group*Pilot | 0.46% | 2.17% | 4.95% | 0.12% | –0.60% | 1.16% | 2.43% | –0.18% | 0.07% | 2.36% | 3.51% | 0.71% |
| | (1.02) | (3.67)*** | (6.28)*** | (0.22) | (0.72) | (1.98)** | (1.35) | (0.19) | (0.05) | (1.52) | (1.43) | (0.54) |
| Adjusted $R^2$ | 0.00 | 0.26 | 0.21 | 0.00 | –0.01 | 0.07 | 0.01 | –0.01 | 0.03 | 0.00 | 0.08 | 0.01 |
| N. Observations | 300 | 300 | 300 | 300 | 244 | 242 | 242 | 244 | 264 | 258 | 232 | 264 |

*Note.* The difference-in-differences regressions used to measure the effect of the tick size program on the average daily volume traded by agency firms as liquidity providers. The independent variables are as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses are calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

To summarise, this section indicated that the tick size pilot: (i) created a substitution effect that led market participants to move their order flow from time priority maker–taker venues to the inverted venues, (ii) encouraged proprietary traders to increase their liquidity provision while it compelled banks to use marketable orders and (iii) did not affect the overall liquidity provision of agency firms. The next section focuses on market participants during trade and waiting costs with a particular attention on non-proprietary trading companies.

### 4.3.3 Tick size pilot and market participant's trading costs

This section tests the third hypothesis by analysing the effect of the tick size pilot program on: (i) implicit trading costs and (ii) on waiting costs. The market structure changes introduced by the tick size pilot program should decrease the likelihood for a marketable order to walk through the books due to the increased NBBO quoted depth (Harris, 1996). The thicker price grid produced by the policy change increases the potential price impact of marketable orders. Moreover, a thicker tick size increases the length of the order queue at the NBBO, compelling liquidity traders to either enter limit orders with lower execution probability or to use marketable orders (Yao & Ye, 2018).

While other papers analyse the effect of tick size changes on transaction costs (Harris, 1996; Lin, Swan & Mollica, 2018), this chapter analyses how far the three different market participant groups trade from the end-of-day volume-weighted average price, which can be interpreted as the average transaction price paid in the market.

The summary statistics reported in Table 4.8 indicate that banks' average execution price was, on average, 1 basis point higher than the market volume-weighted average price on low quoted spread securities and up to 6.92 basis points higher on stocks with wider quoted spreads.

**Table 4.8: Pre-Pilot Average Daily Implicit Transaction Costs**

| Quoted spread group | Proprietary trading companies | Banks | Agency firms |
|---|---|---|---|
| Low quoted spread | –2.60 | 0.85 | –1.14 |
| | (28.92) | (16.90) | (32.37) |
| Medium quoted spread | –2.35 | 1.35 | –2.98 |
| | (45.47) | (29.63) | (45.92) |
| High quoted spread | –0.99 | 6.92 | –5.86 |
| | (67.09) | (59.57) | (67.11) |

*Note.* The implicit transaction costs in basis points per market participant group stock day from 1 April 2016 to 1 October 2016. The implicit transaction cost was calculated as the percentage difference between the transaction price and the end-of-day consolidated volume-weighted average price multiplied by 1 if the market participant buys the security and –1 if otherwise. Standard errors are reported in parentheses.

Further, Table 4.8 indicates that proprietary trading companies, on average, executed their orders at a lower price compared to other market participants on *low* and *medium quoted spread* securities. Similarly, agency firms exhibited negative implicit transaction costs. Consistent with previous findings, agency firms supplied more liquidity and executed their order at better prices compared to proprietary trading companies on high quoted spread securities. Consistent with the summary statistics, the difference-in-differences regressions reported in Table 4.9 suggest that the tick size pilot program only amplified the differences across market participant groups. First, it is important to highlight that both proprietary trading companies and agency firms experienced lower implicit transaction costs for *G2* and *G3* treatment securities with a pre-pilot quoted spread lower than $0.04. These effects dissipated across the other quoted spread groups as the tick size became a less binding constraint. Second, the policy change seemed to increase the implicit transaction costs for banks for *low* and *medium quoted spread* securities, while the trading performances seemed unchanged on *high quoted spread* stocks. Overall, these results suggest that non-proprietary trading companies were affected asymmetrically by the policy change as banks exhibited significantly higher transaction costs, while agency firms seemed to execute their orders at better prices compared to the rest of the market.

## Table 4.9: Difference-in-Differences Regression Analysis for the Implicit Transaction Costs

| | *Low quoted spread* | | | *Medium quoted spread* | | | *High quoted spread* | | |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Proprietary trading companies* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | –2.74 | –2.37 | –2.81 | –1.38 | –2.00 | –3.78 | 2.68 | 3.27 | –0.58 |
| | (5.38)*** | (4.68)*** | (5.55)*** | (1.17) | (2.75)*** | (3.89)*** | (1.18) | (0.95) | (0.49) |
| Group | –0.32 | –0.33 | 0.15 | –0.49 | –1.17 | 0.59 | –0.10 | –5.65 | –2.05 |
| | (0.31) | (0.43) | (0.21) | (0.37) | (1.08) | (0.36) | (0.02) | (1.45) | (0.76) |
| Pilot | –1.12 | –0.85 | –0.40 | –2.06 | –1.98 | –1.75 | –6.76 | –5.85 | –3.43 |
| | (1.38) | (1.00) | (0.54) | (1.49) | (2.03)** | (1.21) | (1.72)* | (1.36) | (1.52) |
| Group*Pilot | –2.38 | –2.34 | –7.21 | –3.40 | –2.44 | –5.99 | 2.68 | 1.73 | –3.39 |
| | (1.50) | (1.66)* | (4.8)*** | (1.71)* | (1.34) | (2.20)** | (0.42) | (0.35) | (0.81) |
| Adjusted $R^2$ | 0.04 | 0.05 | 0.19 | 0.07 | 0.05 | 0.06 | 0.00 | 0.02 | 0.02 |
| N. observations | 308 | 228 | 300 | 240 | 352 | 244 | 280 | 264 | 264 |
| *Panel B: Banks* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | 1.05 | 0.89 | 0.57 | 2.11 | 2.25 | 1.21 | 7.04 | 10.58 | 6.26 |
| | (4.81)*** | (3.70)*** | (2.94)*** | (3.40)*** | (3.00)*** | (2.49)*** | (3.00)*** | (4.39)*** | (4.82)*** |
| Group | 0.06 | –0.23 | 0.23 | –0.22 | –1.23 | –0.52 | 3.70 | –1.51 | 0.59 |
| | (0.18) | (0.67) | (0.66) | (0.24) | (1.41) | (0.63) | (1.16) | (0.44) | (0.30) |
| Pilot | 0.55 | 0.34 | 0.77 | 0.62 | –0.97 | 0.48 | 1.31 | –3.29 | 1.30 |
| | (1.23) | (1.03) | (2.49)*** | (0.68) | (1.17) | (0.63) | (0.40) | (1.15) | (0.64) |
| Group*Pilot | 2.30 | 2.93 | 4.36 | 1.14 | 5.44 | 5.80 | –4.49 | 3.43 | 0.83 |
| | (2.68)*** | (3.36)*** | (4.99)*** | (0.81) | (3.14)*** | (3.26)*** | (1.05) | (0.85) | (0.28) |
| Adjusted $R^2$ | 0.08 | 0.13 | 0.24 | 0.00 | 0.04 | 0.11 | 0.00 | –0.01 | 0.00 |
| N. observations | 308 | 228 | 300 | 240 | 352 | 244 | 280 | 264 | 264 |
| *Panel C: Agency firms* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | –1.01 | –1.04 | –0.11 | –4.38 | –3.08 | –2.94 | –6.90 | –10.14 | –7.19 |
| | (1.92)* | (2.22)** | (0.26) | (2.16)** | (3.55)*** | (3.08)*** | (3.69)*** | (4.48)*** | (3.86)*** |
| Group | –1.45 | 0.55 | –1.75 | 0.52 | –0.80 | 0.57 | –1.15 | 1.78 | 1.07 |
| | (1.93)* | (0.69) | (1.81)* | (0.22) | (0.62) | (0.38) | (0.38) | (0.49) | (0.42) |
| Pilot | 0.55 | 0.98 | –0.28 | 2.87 | 1.16 | 1.32 | –2.40 | 2.00 | –0.39 |
| | (0.77) | (1.39) | (0.43) | (1.25) | (1.02) | (1.05) | (0.70) | (0.64) | (0.15) |
| Group*Pilot | –1.38 | –2.82 | –2.61 | –1.50 | 0.35 | –4.28 | 4.33 | 1.11 | 0.87 |
| | (1.18) | (2.23)** | (1.88)* | (0.54) | (0.19) | (2.01)** | (0.93) | (0.25) | (0.24) |
| Adjusted $R^2$ | 0.04 | 0.02 | 0.08 | 0.00 | 0.00 | 0.01 | –0.01 | 0.00 | –0.01 |
| N. observations | 308 | 228 | 300 | 240 | 352 | 244 | 280 | 264 | 264 |

*Note.* The difference-in-differences regressions used to analyse the effect of a tick size consolidation on the implicit transaction cost in basis points per market participant group stock day. Implicit transaction costs were calculated as the percentage difference between the transaction price and the end-of-day consolidated volume-weighted average price multiplied by 1 if the market participant bought the security and –1 if otherwise. The independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses are calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Although implicit transaction costs play an important role in explaining market participants' trading performances, they are not the only relevant measure of institutional trading costs. Investors decide whether to use marketable or limit orders based on their need for immediacy. If a market participant needs to buy or sell a certain security quickly, he/she will use marketable orders. Conversely, patience investors can enter limit orders away from the NBBO to obtain better execution prices. This paragraph analyses the effect of the tick size pilot program on market participants' waiting costs. Waiting costs are difficult to examine as lower fills rate may be due to higher cancellation rates rather than lower execution probability. Because of this reason, this chapter analyses whether there are important variations in the proportion of fully executed and fully cancelled orders due to the policy change. If the execution rate increases and the cancellation rate decreases, then market participants are willingly keeping their orders on the book for longer. Conversely, if the execution rate increases, but the cancellation rate does not change, it means that market participants are experiencing marginally lower waiting costs as the limit order's likelihood of being executed is higher than before.

**Table 4.10: Pre-Pilot Average Daily Waiting Costs Summary Statistics**

| *Panel A: % executed orders* | *Proprietary trading companies* | *Banks* | *Agency firms* |
|---|---|---|---|
| Low quoted spread | 3.88% | 14.58% | 13.63% |
| | (0.04) | (0.08) | (0.08) |
| Medium quoted spread | 3.64% | 8.75% | 9.13% |
| | (0.07) | (0.08) | (0.08) |
| High quoted spread | 3.38% | 6.76% | 5.31% |
| | (0.09) | (0.09) | (0.09) |
| *Panel B: % cancelled orders* | *Proprietary trading companies* | *Banks* | *Agency firms* |
| Low quoted spread | 90.39% | 82.82% | 81.93% |
| | (0.07) | (0.09) | (0.12) |
| Medium quoted spread | 93.05% | 88.22% | 87.16% |
| | (0.11) | (0.09) | (0.12) |
| High quoted spread | 88.23% | 89.65% | 91.62% |
| | (0.21) | (0.11) | (0.12) |

*Note.* The two waiting cost proxy variables calculated from 1 April 2016 to 1 October 2016. For each order entered on BX, PSX and Nasdaq at the NBBO, I used the unique sequence number to track whether the order was only entered, fully executed, partially executed, fully cancelled, partially cancelled or repriced. Then, I calculated the average daily percentage of (fully) executed orders and the average daily percentage of (fully) cancelled orders for each market participant group. Standard deviations are reported in parentheses.

The summary statistics in Table 4.10 indicate that all market participants cancelled more than 80% of the orders they entered in the trading system, while they fully executed less than 15% of their submitted orders. Specifically, proprietary trading companies' execution rate was between 3% and 4% in the pre-pilot period while their cancellation rate was 90.39%, 93.05% and 88.23% for the *low*, *medium* and *high quoted spread* securities, respectively. Conversely, non-proprietary trading companies' execution rate was significantly higher for the *low quoted spread* group as the proportion of executed orders was 14.58% for banks and 13.63% for agency firms and lower for *high quoted spread* securities. Because of these asymmetries, the cancellation rate differed significantly between proprietary and non-proprietary trading companies for securities with a pre-pilot quoted spread lower than $0.11. Overall, Table 4.10 suggests that banks and agency firms tended to place a larger quantity of orders with the intention of executing them, while proprietary trading companies tactically cancelled most of their orders and only filled completely a minor portion of them, which is consistent across the quoted spread groups.

Consistent with previous results on liquidity provision, the difference-in-differences regressions on the waiting costs suggest that the tick pilot program encouraged proprietary trading companies to reduce their cancellation rate on all treatment securities. Conversely, the percentage of fully cancelled order for non-proprietary trading companies decreased for *medium quoted spread* securities. Specifically, banks reduced their cancellation rate by 3.81%, 2.84% and 3.01% for *G1*, *G2* and *G3*, respectively, while agency firms' cancellation rate decreased most significantly for *G2*. The intuition behind these empirical results is that in *low quoted spread* securities the pre-pilot bid-ask spread was already tight and banks didn't need to cancel and resubmit their orders very often as the price grid was fairly limited. Conversely, on *high quoted spread* securities there wasn't much trading activity going on reducing the banks' need for quote revision. *Medium quoted spread* securities exhibited a quite high dollar bid-ask spread and were actively traded in the pre-pilot period. Therefore banks, which were the main liquidity providers, reduced their cancellation rate on *medium quoted spread* treatment securities as the thicker tick size led to a thicker price grid. Table 4.11b indicates that proprietary trading companies' proportion of executed orders increased for stocks with a pre-pilot spread lower than $0.11 while banks were proportionally receiving a higher fill rate on securities with a pre-pilot spread higher than $0.04. Further, the execution rate for agency firms decreased on the *low quoted spread* group, while it increased on the other treatment securities.

## Table 4.11a: Difference-in-Differences Regression Analysis for the Percentage of (Fully) Cancelled Orders

| | *Low quoted spread* | | | *Medium quoted spread* | | | *High quoted spread* | | |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Proprietary trading companies* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | 90.73% | 90.43% | 90.57% | 93.02% | 92.85% | 92.32% | 88.96% | 86.36% | 88.29% |
| | (225.96)*** | (213.62)*** | (240.15)*** | (148.25)*** | (157.6)*** | (79.65)*** | (57.70)*** | (44.66)*** | (50.13)*** |
| Group | –0.11% | –0.74% | –0.42% | 0.64% | 1.18% | –0.22% | –0.45% | 1.08% | 1.46% |
| | (0.19) | (1.20) | (0.78) | (0.81) | (1.64) | (0.15) | (0.20) | (0.40) | (0.64) |
| Pilot | –0.68% | –0.19% | –0.68% | –0.45% | –0.13% | –0.83% | 1.43% | 1.32% | 1.61% |
| | (1.10) | (0.30) | (1.22) | (0.52) | (0.15) | (0.54) | (0.73) | (0.52) | (0.73) |
| Group*Pilot | –6.93% | –7.78% | –7.71% | –14.60% | –14.74% | –10.21% | –7.06% | –7.16% | –10.99% |
| | (6.44)*** | (7.54)*** | (8.76)*** | (8.84)*** | (11.11)*** | (5.32)*** | (2.52)*** | (2.08)** | (3.74)*** |
| Adjusted $R^2$ | 0.31 | 0.46 | 0.48 | 0.48 | 0.49 | 0.28 | 0.05 | 0.02 | 0.09 |
| N. observations | 308 | 228 | 300 | 240 | 352 | 244 | 280 | 264 | 264 |
| *Panel B: Banks* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | 83.43% | 82.40% | 83.31% | 87.94% | 87.78% | 88.26% | 89.56% | 90.05% | 89.67% |
| | (141.47)*** | (132.91)*** | (139.25)*** | (155.91)*** | (188.95)*** | (136.61)*** | (170.07)*** | (157.1)*** | (149.7)*** |
| Group | –1.39% | –0.05% | –0.12% | 0.17% | 0.76% | 0.46% | 0.08% | –0.38% | –0.36% |
| | (1.66)* | (0.05) | (0.15) | (0.21) | (1.14) | (0.53) | (0.10) | (0.45) | (0.43) |
| Pilot | –1.25% | –1.19% | –2.17% | –2.57% | –2.93% | –2.78% | –0.26% | –1.00% | –1.18% |
| | (1.52) | (1.46) | (2.55)*** | (3.34)*** | (4.29)*** | (3.02)*** | (0.34) | (1.16) | (1.27) |
| Group*Pilot | 0.64% | 0.49% | 0.58% | –3.81% | –2.84% | –3.01% | –1.01% | –1.65% | –0.84% |
| | (0.55) | (0.43) | (0.51) | (2.93)*** | (2.93)*** | (2.22)** | (0.89) | (1.19) | (0.69) |
| Adjusted $R^2$ | 0.01 | 0.00 | 0.03 | 0.20 | 0.20 | 0.15 | 0.00 | 0.03 | 0.02 |
| N. observations | 308 | 228 | 300 | 240 | 352 | 244 | 280 | 264 | 264 |
| *Panel C: Agency firms* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | 83.47% | 81.25% | 82.53% | 87.32% | 86.21% | 87.75% | 91.90% | 91.42% | 91.26% |
| | (109.55)*** | (87.86)*** | (116.42)*** | (118.81)*** | (126.01)*** | (107.01)*** | (208.07)*** | (172.68)*** | (190.55)*** |
| Group | –2.00% | –0.37% | –0.98% | –0.90% | 1.41% | 0.07% | 0.66% | –0.05% | –0.15% |
| | (1.48) | (0.29) | (0.83) | (0.83) | (1.53) | (0.06) | (1.14) | (0.07) | (0.22) |
| Pilot | 1.25% | 1.59% | 0.80% | 2.63% | 3.68% | 2.65% | 1.96% | 1.62% | 1.47% |
| | (1.26) | (1.05) | (0.72) | (2.90)*** | (4.41)*** | (2.55)*** | (3.48)*** | (2.29)** | (1.68)* |
| Group*Pilot | 2.06% | 1.47% | 1.30% | –1.97% | –4.66% | –2.63% | –2.88% | –1.63% | –0.52% |
| | (1.25) | (0.77) | (0.84) | (1.44) | (4.12)*** | (1.80)* | (3.43)*** | (1.57) | (0.46) |
| Adjusted $R^2$ | 0.02 | 0.02 | 0.00 | 0.05 | 0.06 | 0.03 | 0.05 | 0.02 | 0.01 |
| N. observations | 308 | 228 | 300 | 240 | 352 | 244 | 280 | 264 | 264 |

*Note.* The difference-in-differences regressions used to analyse the effect of a tick size consolidation on the average percentage of fully cancelled orders. Each order entered at the NBBO was classified as submitted, fully executed, partially executed, fully cancelled, partially cancelled and repriced based on its latest update in the matching engine. The dependent variable in these regression models was the percentage of fully cancelled orders per market participant group stock day. The independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

## Table 4.11b: Difference-in-Differences Regression Analysis for the Percentage of (Fully) Executed Orders

| | *Low quoted spread* | | | *Medium quoted spread* | | | *High quoted spread* | | |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Proprietary trading companies* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | 3.91% | 3.72% | 4.05% | 3.57% | 4.13% | 3.55% | 3.02% | 3.77% | 3.67% |
| | (18.91)*** | (20.02)*** | (18.00)*** | (14.16)*** | (13.01)*** | (11.14)*** | (11.9)*** | (8.21)*** | (7.91)*** |
| Group | –0.09% | 0.00% | –0.04% | –0.25% | –0.55% | –0.05% | 0.20% | –0.63% | –0.16% |
| | (0.29) | (0.01) | (0.13) | (0.67) | (1.37) | (0.11) | (0.54) | (1.13) | (0.27) |
| Pilot | 0.40% | 0.26% | 0.55% | 0.42% | 0.64% | 0.82% | 1.01% | 0.85% | 0.70% |
| | (1.09) | (0.80) | (1.46) | (1.14) | (1.29) | (1.58) | (2.06)** | (1.19) | (1.02) |
| Group*Pilot | 1.50% | 1.94% | 2.71% | 1.20% | 0.57% | 1.64% | –1.19% | –0.64% | 0.13% |
| | (3.23)*** | (4.43)*** | (5.71)*** | (2.34)** | (0.99) | (2.59)*** | (2.06)** | (0.79) | (0.16) |
| Adjusted $R^2$ | 0.11 | 0.23 | 0.29 | 0.08 | 0.02 | 0.13 | 0.02 | 0.02 | 0.00 |
| N. observations | 308 | 228 | 300 | 240 | 352 | 244 | 280 | 264 | 264 |
| *Panel B: Banks* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | 14.36% | 14.68% | 14.07% | 9.14% | 9.11% | 8.42% | 6.97% | 6.80% | 6.83% |
| | (24.25)*** | (25.21)*** | (24.00)*** | (17.89)*** | (26.69)*** | (17.69)*** | (17.95)*** | (18.21)*** | (17.92)*** |
| Group | 0.66% | 0.56% | 0.19% | –0.32% | –0.75% | 0.24% | –0.44% | –0.22% | 0.04% |
| | (0.79) | (0.68) | (0.26) | (0.44) | (1.44) | (0.36) | (0.85) | (0.41) | (0.08) |
| Pilot | –0.29% | –0.21% | 0.29% | 1.70% | 2.26% | 1.99% | 1.11% | 1.41% | 1.21% |
| | (0.40) | (0.29) | (0.41) | (2.64)*** | (4.25)*** | (2.83)*** | (2.08)** | (2.38)*** | (2.07)** |
| Group*Pilot | –0.48% | –0.58% | –0.72% | 2.83% | 2.31% | 2.50% | 1.60% | 2.20% | 2.04% |
| | (0.47) | (0.56) | (0.77) | (3.01)*** | (3.17)*** | (2.45)*** | (2.08)** | (2.62)*** | (2.50)*** |
| Adjusted $R^2$ | 0.00 | –0.01 | –0.01 | 0.19 | 0.21 | 0.17 | 0.09 | 0.14 | 0.13 |
| N. observations | 308 | 228 | 300 | 240 | 352 | 244 | 280 | 264 | 264 |
| *Panel C: Agency firms* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | 12.98% | 13.91% | 13.76% | 9.37% | 10.17% | 8.60% | 4.89% | 5.39% | 5.43% |
| | (25.52)*** | (26.53)*** | (27.71)*** | (16.4)*** | (20.78)*** | (14.59)*** | (16.80)*** | (14.42)*** | (14.92)*** |
| Group | 0.16% | 0.85% | –0.17% | –0.22% | –1.45% | –0.14% | 0.00% | 0.18% | 0.33% |
| | (0.23) | (1.04) | (0.26) | (0.27) | (2.32)** | (0.17) | (0.01) | (0.34) | (0.58) |
| Pilot | 1.03% | –0.09% | 0.50% | –0.06% | –0.78% | 0.23% | 0.64% | 0.47% | 0.57% |
| | (1.34) | (0.11) | (0.71) | (0.08) | (1.19) | (0.28) | (1.43) | (0.81) | (1.00) |
| Group*Pilot | –4.35% | –4.20% | –2.85% | 2.51% | 4.12% | 1.94% | 1.80% | 1.85% | 1.03% |
| | (4.50)*** | (3.82)*** | (3.18)*** | (2.27)** | (4.71)*** | (1.67)* | (2.57)*** | (2.10)** | (1.18) |
| Adjusted $R^2$ | 0.11 | 0.12 | 0.07 | 0.04 | 0.08 | 0.02 | 0.09 | 0.06 | 0.03 |
| N. observations | 308 | 228 | 300 | 240 | 352 | 244 | 280 | 264 | 264 |

*Note.* The difference-in-differences regressions used to analyse the effect of a tick size consolidation on the average percentage of fully executed orders. Each order entered at the NBBO was classified as submitted, fully executed, partially executed, fully cancelled, partially cancelled and repriced based on its latest update in the matching engine. The dependent variable in these regression models was the percentage of fully executed orders per market participant group stock day. The independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise; the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Overall, the empirical results suggested that both proprietary trading companies and banks were cancelling fewer orders while experiencing higher execution rates. Conversely, agency firms seemed to experience higher waiting costs on *low quoted spread* securities as their execution rate decreased by up to one-third, while their cancellation rate did not significantly change. This finding suggests that when the tick size was a binding constraint, banks used a larger portion of marketable orders while agency firms' waiting costs increased significantly. Therefore, the tick size pilot program affected all non-proprietary trading companies by either increasing their demand for immediacy or their waiting costs.

To summarise, the empirical evidence in this section suggested that the tick size pilot: (i) increased the differences among market participants' implicit trading costs, (ii) made it difficult for banks to trade at the VWAP, (iii) decreased cancellation rates and increased execution rates for banks and proprietary trading companies and (vi) increased agency firms' overall waiting costs. The following section analyses the effect of the policy change on proprietary trading companies' revenues.

### 4.3.4 Tick size pilot and proprietary trading companies' revenues

Finally this section tests the last hypothesis developed in this chapter by looking at whether the tick size pilot program increases proprietary trading companies' revenues in small and medium market capitalisation stocks.

The pre-pilot summary statistics indicate that, on average, each market participant earned between \$10.88 and \$19.86 on *low* and *medium quoted spread* securities and about \$12.52 on those stocks with a pre-pilot spread higher than \$0.11 (see Table 4.12). As the tick size pilot program so far encourages non-proprietary traders to either use a larger proportion of marketable orders or face higher trading costs, it appears plausible to expect that HFT are extracting higher revenues for treatment securities with a pre-pilot quoted spread lower than \$0.04.

**Table 4.12: Pre-Pilot Proprietary Trading Companies Profits**

| | *Proprietary trading companies' revenues* |
|---|---|
| Low quoted spread | \$10.88 |
| | (2,375.31) |
| Medium quoted spread | \$19.86 |
| | (927.25) |
| High quoted spread | \$12.52 |
| | (1,012.06) |

*Note.* The summary statistics of proprietary trading company profits from 1 April 2016 to 1 October 2016. Profitability was measured as the end-of-day volume-weighted average price difference between sell and buy transactions multiplied by the maximum between the sold and bought volume per MPID stock day. Standard errors are reported in parentheses.

Consistent with these expectations, Table 4.13 indicates that the policy change increased proprietary trading companies' revenues for *G2* and *G3 low quoted spread* securities by $18.87 and $30.98, respectively. The tick size pilot encouraged proprietary trading companies to provide liquidity on tick-constrained securities as the revenue per identifier was $18.87 higher on *G2* and $30.98 higher on *G3*. Further, it is important to highlight that proprietary trading companies extract almost three times more revenue on securities subject trade-at rule possibly due to the increased order flow coming from non-proprietary trading companies.

**Table 4.13: Difference-in-Differences Regression Analysis for Proprietary Traders' Revenues**

| | *Low quoted spread* | | | *Medium quoted spread* | | | *High quoted spread* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* | *G1* | *G2* | *G3* |
| Intercept | $15.00 | $27.31 | $15.04 | $22.41 | $16.92 | –$0.62 | $5.78 | $3.10 | $10.06 |
| | (6.37)*** | (4.15)*** | (5.16)*** | (7.73)*** | (3.87)*** | (0.05) | (0.96) | (0.54) | (1.12) |
| Group | –$24.33 | –$12.34 | $4.45 | –$6.49 | –$5.61 | $14.86 | –$22.13 | $0.30 | $7.16 |
| | (0.88) | (1.76)* | –0.9 | (1.38) | (1.16) | (1.26) | (1.42) | (0.02) | (0.68) |
| Pilot | $12.41 | –$0.38 | $8.73 | $3.26 | $20.58 | $34.10 | –$2.91 | –$2.07 | $9.62 |
| | (2.46)*** | (0.05) | (1.78)* | (0.35) | (2.99)*** | (2.68)*** | (0.17) | (0.15) | (0.79) |
| Group*Pilot | $25.43 | $18.87 | $30.98 | $5.73 | –$3.98 | –$8.18 | $21.55 | $51.11 | –$8.15 |
| | (0.91) | (2.14)** | (3.78)*** | (0.54) | (0.50) | (0.58) | (0.85) | (1.18) | (0.51) |
| Adjusted $R^2$ | 0.01 | 0.03 | 0.19 | 0.00 | 0.06 | 0.07 | 0.00 | 0.00 | –0.01 |
| N. Observations | 308 | 228 | 300 | 240 | 352 | 242 | 276 | 257 | 259 |

*Note.* The difference-in-differences regressions used to analyse the effect of a tick size consolidation on the average proprietary trading companies' profits. In line with Carrion (2013), profitability was measured as the end-of-day volume-weighted average price difference between sell and buy transactions multiplied by the maximum between the sold and bought volume per MPID stock day. The independent variables were as follows: the dummy *Group* equals 1 if the stock is subject to the policy change and 0 if otherwise, the variable *Pilot* equals 1 when the stock's tick size is $0.05 and 0 if otherwise and the interaction variables. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

In conclusion, the policy change increased proprietary trading company revenues on *low quoted spread* stocks, as predicted by Yao and Ye (2018) and Hagströmer and Norden (2013).

## 4.4 Conclusions

This chapter analysed the effect of the tick size pilot on market competition, liquidity provision, implicit transaction costs, waiting costs and proprietary trading companies' revenues across BX, PSX and Nasdaq. In line with Yao and Ye (2018), this empirical analysis focused on understanding whether different classes of non-proprietary trading companies were similarly affected by the policy change.

This study investigated whether the policy change affected the total number of MPIDs and the trading value distribution among the three market participants' groups. Overall, this section suggests that the tick size pilot program did not increase competition among market competition across the three markets, but it appeared to have a significant effect on BX, which is the time priority taker–maker stock market. The examination of the MPIDs indicates more agency firms' and proprietary trading companies' identifiers trading on treatment securities for the inverted market. This result is confirmed by the analysis of the HHI, which indicated that the total dollar trading volume was now more evenly distributed among the three market participant groups for treatment securities trading on BX. Nonetheless, the increased competition in BX is not representative of the whole US equity market.

H2 examined the effect of the policy change on proprietary trading companies' liquidity provision for treatment securities by analysing each market participant group's average daily trading volume and percentage of passive orders executed. The empirical results suggested that only agency firms significantly reduced their average daily volume for *G2* treatment securities with a pre-pilot spread lower than $0.04. Conversely, the policy change did not appear to strongly affect banks' and proprietary trading companies' average daily volume. When looking at market participants' average daily volume on each stock exchange, the tick size pilot program appeared to create a relevant substitution effect between the time-priority maker–taker market (Nasdaq) and the inverted market (BX) for treatment securities with a pre-pilot quoted spread lower than $0.04. The policy change appeared to encourage banks to significantly reduce their liquidity provision by 5% on all treatment stocks with a pre-pilot quoted spread lower than $0.11, while proprietary trading companies increased their liquidity provision by 5% on *low quoted spread* stocks affected by the market structure change. Moreover, the empirical results suggest that agency firms did not change their overall liquidity provision, but appeared to supply more liquidity on BX and PSX.

H3 examined the effect of the tick size pilot program on market participants' implicit transaction costs and waiting costs. The results of these two tests suggested that non-proprietary trading companies have different liquidity preferences. Agency firms' implicit transaction costs were mostly unaffected by the policy change due to their strategic use of both the inverted and the pro-rata execution system markets. Nonetheless, agency firms' orders execution rate decreased by 2% to 5%, suggesting that their overall waiting costs were now higher as it takes longer for an agency firm to fill a client's order. Conversely, banks' implicit transaction costs suggested that these market participants' average execution prices were now 4 basis points higher than the market volume-weighted average price for treatment securities with a pre-pilot quoted spread lower than $0.04. This result is statistically and economically significant considering that banks are the most active market participant group in the analysed markets. Concurrently, the waiting costs for banks on treatment securities were roughly the same as before the introduction of the market microstructure change. This analysis indicates that proprietary trading companies had a lower order cancellation rate, higher fill rates and lower implicit transaction costs.

Finally, this chapter examined the effects of the program on proprietary trading companies' revenues. According to the empirical findings, proprietary trading companies were earning up to $30 more on *low quoted spread* treatment stock. Further, the trade-at rule seemed to have a strong and positive effect on proprietary trading companies' revenues.

In conclusion, this research suggests that the tick size pilot program affected market participant groups differently based on their business model. Overall, the program does not foster competition among market participants, while it appears to transfer wealth from banks and agency firms to proprietary trading companies. Proprietary trading companies increased their liquidity provision and their trading revenues on treatment securities with a pre-pilot quoted spread lower than $0.04. Conversely, banks decreased their liquidity provision and experienced higher transaction costs for treatment securities, while agency firms only experienced higher waiting costs. These results suggest that banks tend to employ less patient algorithmic execution strategies compared to agency firms.

Chapter 5 analyses the effects of the tick size pilot program on market participants' abilities to set the NBBO price and on their intraday order aggressiveness patterns.

# Chapter 5: Tick Size Pilot and Market Participants' Intraday Trading Behaviour: Does Speed Still Matter?

This chapter is essentially a continuation of the topic developed in Chapter 4. The previous chapter analysed changes in market participants' trading behaviour on treatment stocks affected by the tick size pilot program. The empirical results suggested that the policy change led to an increase in proprietary trading companies' liquidity provision on BX while banks and agency firms experienced higher trading costs based on the market participants' needs for immediacy. Specifically, banks, which provide both direct market access and execution services to buy side institutions, are encouraged by the policy change to cross the spread more frequently for treatment securities, while agency firms reduced their average daily volume on tick-constrained *G2* securities as they faced higher waiting costs. Proprietary trading companies increased their trading revenues for *G2* and *G3* securities with a pre-pilot quoted spread lower than $0.04. These end-of-day results are in line with predictions from Yao and Ye (2018), who stated that tick size consolidations led to queue rationing and exacerbated the need for speed. Therefore, if speed is the key to explaining non-proprietary trading companies' increased implicit transaction costs for securities affected by the tick size pilot program, it is reasonable to expect that proprietary trading companies set NBBO prices more frequently compared to the other market participants for treatment stocks. The following analysis investigates whether the changes in order submission strategies are driven by market participants' intrinsic liquidity preferences or by differences in speed.

First, this chapter analyses whether proprietary trading companies are faster than banks and agency firms regarding queue speed (Baron, Brogaard, Hangströmer & Kirilenko, 2018). According to Yao and Ye (2018), tick size consolidations exacerbate the need for speed and compel slow traders to use marketable orders, as they are unable to establish time priority. However, their paper does not empirically test whether changes in tick size consolidation directly affect market participants' queue speed. This chapter fills the gap in the literature by testing the following hypothesis:

H5: Proprietary trading companies set prices more frequently compared to other market participants ex post tick pilot.

Second, I use the available data to examine banks' principal and agency activity. As suggested in Brogaard et al. (2015), principal orders can be either due to proprietary trading activity or to a bank's institutional order flow. In either case, banks' agency and proprietary technology may differ in speed and result in different NBBO price-setting behaviour for treatment securities affected by the tick size pilot program. I analyse whether banks switch between the two business models for treatment securities by testing the following hypothesis:

H6: The tick size consolidation causes banks to increase quote setting at the NBBO through principal trading orders.

Subsequently, this chapter examines the intraday order submission strategies of agency firms, banks and proprietary trading companies to better understand the nature of their business. Previous academic literature has suggested that the existence of different types of market participants creates well-known intraday volume and volatility patterns (Admati & Pfleiderer, 1988; Anand, Chakravarty & Martell 2005). These theoretical and empirical papers indicate that informed traders should enter more (less) marketable orders at the beginning (end) of the trading session while discretionary liquidity traders, as introduced by Admati and Pfleiderer (1988), use a larger portion of aggressive orders towards the end of the day as they must fill their clients' orders within the trading session. Hence, the seventh hypothesis tested is:

H7: Different types of market participants have different intraday order submission strategies.

Lastly, this chapter studies the effect of the tick size pilot on each market participant group's intraday order submission strategy and on the overall intraday implicit transaction costs. While the academic literature has suggested that tick size constraints constitute a limit to trading that investors juggle by increasing their trading activities outside stock exchanges (Foley & Putniņš, 2016; Kwan, Masulis & McInish, 2015), this thesis analyses the effects of a tick size consolidation on the intraday order submission strategies on stock exchanges. Looking at both the intraday order aggressiveness of banks and agency firms and intraday implicit transaction costs allows us to test how the policy change affects market participant responsiveness to the trade-off between waiting costs and the cost of crossing the bid-ask spread. Through this measure, I test the following hypothesis:

H8: The tick size consolidation affects market participants' intraday order submission strategies and their intraday implicit transaction costs.

## 5.1 Data Description and Sample Selection

### 5.1.1 Data overview

This research employs Nasdaq order submission, cancellation and execution data and SIP quote and trade data to study market participants' trading behaviour. I used the data regarding two price–time priority order-driven markets (BX and Nasdaq) to assess the relative importance of speed and the declared business models in explaining market participants' order submission strategies.

Each Nasdaq order record contains the reference date, stock symbol, order entry time expressed in nanoseconds, buy/sell indicator, accepted price of the order, order size, MPID, OUCH's capacity flag and BBO weight indicator. The capacity flag indicates whether a broker/dealer, entering an order in the trading system, is buying or selling a security on its own account (principal) or on its client's account (*agency*, *riskless*, *other*). This information is entered by the market participants on the trading system to comply with FINRA Rule 7440, which requires any FINRA member to *record the capacity in which the member executed the transaction (e.g., agency, principal or riskless principal*). The BBO Weight flag identifies how far the accepted price of an order is from the NBBO at the time it was entered. Each Nasdaq execution record is characterised by the reference date, stock symbol, execution time expressed in nanoseconds, buy/sell indicator, execution price, executed shares, the liquidity flag indicating who is the liquidity provider (taker) in the transaction and the MPID of counterparts of the transaction.

SIP quote messages contain the reference date, stock symbol, time expressed in microseconds, bid/ask price, bid/ask size, exchange identifier (PID) and quote condition. SIP trade messages cover the reference date, stock symbol, time expressed in microseconds, execution price, executed shares, exchange identifier (PID) and sale conditions. In this chapter, the NBBO midpoint prices are calculated from SIP NBBO quotes from 9:30 am to 4:00 pm by filtering out all messages in which the ask is higher than the bid price or in which the prices equal $0.01 or $199,999.99.

### 5.1.2 Sample selection

In the spirit of the pilot program, this analysis uses the treatment groups' classification to estimate the causal effect of the policy change on market participants' order submission strategies by considering all the Nasdaq-listed securities that are not excluded from the pilot program during the sample period. Each stock is also categorised using its pre-pilot average daily dollar quoted spread in one of the following three categories: (i) *very liquid*, which has a pre-pilot bid–ask spread lower than \$0.04; (ii) *liquid* securities with a pre-pilot bid–ask spread between \$0.04 and \$0.11; and (iii) *illiquid*, if otherwise. These first two categories represent the 33th and the 66th percentiles, respectively, of the distribution of the stocks' average daily dollar quoted spread from 1 April 2016 to 1 October 2016. This choice assures that each quoted spread group has the same stock count. Similar to Huang and Stoll (1996), each treatment stock $i$ is matched to a control stock $j$ within its pre-pilot quoted spread group such as it minimises the following score:

$$score_{ij} = \left[\frac{Price_i - Price_j}{(Price_i + Price_j) \times 0.5}\right]^2 + \left[\frac{Mkt\ Cap_i - Mkt\ Cap_j}{(Mkt\ Cap_i + Mkt\ Cap_j) \times 0.5}\right]^2$$

*Price* is the closing price and *Mkt Cap* is the market value of the securities on 1 April 2016. If two treatment securities are matched with the same control stock, the pair with the highest score is excluded from the sample as Smith and Todd (2005) suggest that matching with replacement would increase the average quality of our matches, but increase the variance of the estimator.

**Table 5.1: Pre-Pilot Summary Statistics**

| Panel A: Bid–ask spread <\$0.04 | Control | Treatment |
|---|---|---|
| Number of securities | 135 | 135 |
| Avg. market value | \$670,495,104 | \$675,358,325 |
| Avg. daily dollar volume | \$4,862,815 | \$5,444,449 |
| Avg. quoted spread (bps) | 37 | 37 |
| Avg. % Nasdaq lit market share | 57% | 57% |
| **Panel B: Bid–ask spread between \$0.04 and \$0.11** | **Control** | **Treatment** |
| Number of securities | 141 | 141 |
| Avg. market value | \$646,787,927 | \$642,108,744 |
| Avg. daily dollar volume | \$5,028,496 | \$4,969,889 |
| Avg. quoted spread (bps) | 78 | 81 |
| Avg. % Nasdaq lit market share | 59% | 59% |
| **Panel C: Bid–ask spread >\$0.11** | **Control** | **Treatment** |
| Number of securities | 131 | 131 |
| Avg. market value | \$452,212,768 | \$454,955,496 |
| Avg. daily dollar volume | \$2,624,063 | \$2,280,583 |
| Avg. quoted spread (bps) | 236 | 227 |
| Avg. % Nasdaq lit market share | 60% | 60% |

*Note*. The pre-pilot summary statistics of the matched securities used in this research. Each security is matched following the methodology outlined by Huang and Stoll (1996).

The summary statistics of the selected stocks are reported in Table 5.1; these indicate that the lit trading volume of the securities included in our matched samples is executed primarily on Nasdaq's exchanges. Interestingly, *very liquid* and *liquid* securities had similar average daily market values and dollar traded volume, but significantly different relative quoted spread, suggesting that these securities mainly differ in their average price levels. According to Yao and Ye (2018), the tick size consolidation should lead to queue rationing on securities with the same stock characteristics as our *very liquid* sample. Therefore, I focus most of my attention on the market participants' trading behaviour in these stocks. I*lliquid* securities are characterised by a significantly low average daily market value, low average daily dollar traded volume and high relative quoted spread.

As for the previous chapter, it is worth mentioning that the results of this analysis should be interpreted with caution. While I am confident that the findings hereby presented underestimate the true differences between the three market participant groups, our results cannot be used to assess the impact of the tick size pilot on market quality as Nasdaq data only cover 60% of the U.S. total lit trading activity.

## 5.2 Methodology

This section provides an in-depth overview of the methodology used to test the relevant hypotheses for this chapter. First, this section provides a brief description of the regression models used in this chapter; second, it presents the variables of interest used to test each hypothesis.

### 5.2.1 Econometric model

Because of the structure of the pilot program, the natural methodology to use to analyse the effect of the policy change on market participants' trading behaviour is the difference-in-differences analysis.

In line with Bertrand et al. (2004), the differences-in-differences methodology is used to test *H5*, *H6* and *H8* by collapsing the data into the pre- and post-period averages. I estimate a regression equation for each market participant, liquidity and tick pilot group, which can be mathematically expressed as:

$$\bar{y}_{it} = \alpha + \beta_1 Group_i + \beta_2 Pilot_t + \beta_3 Group_i \times Pilot_t + \varepsilon_{it} \tag{5.1}$$

*Y* is the average of the variable of interest for stock *i* during the trading period *t*, *Group* is a dummy variable that equals 1 if the security *i* belongs to the treatment group and 0 if otherwise, *Pilot* is a dummy variable indicating the pre- or post-pilot periods and the interaction variable is the so-called difference-in-differences coefficient.

The standard errors of these regressions are adjusted using White's methodology, which controls for potential heteroskedasticity issues.

*H7* tests the differences in intraday trading behaviour among market participants through a simple stock fixed effect model for the pre-pilot sample of data. For each liquidity and market participant group, I use the following equation:

$$\overline{\%\ aggressive}_{ib}^{l} = \varphi_b + \theta_i + \varepsilon_{ib} \tag{5.2}$$

The dependent variable is the average daily (difference in) proportion of aggressive orders entered by the (two) market participants' groups on stock *i* within the time bucket *b*. The independent variables in this regression are as follows: a dummy variable for each time bucket $\varphi$ and the stock's fixed effects $\theta$. Further, standard errors are adjusted using Newey–West standard errors (2 lags), which control for potential autocorrelation and heteroskedasticity issues.

### 5.2.2 Variables of interest

This section describes the variables of interest used to test the hypotheses developed in this chapter. The four hypotheses developed are tested by analysing the average percentage of price sets by each market participants group, the proportion of banks' agency orders setting the NBBO, the intraday average proportion of aggressive orders entered by market participant group and the intraday implicit trading cost. H5 is tested by analysing the effects of the policy change on the number of times a MPID undercuts the others by improving the national best bid or offer between 9:30 am and 4:00 pm. This behaviour, defined as price setting, is at the heart of Yao and Ye's (2018) argument; they suggested that proprietary traders use their speed advantage on *very liquid* securities to be at the front of the queue and to compel non-proprietary traders to submit more marketable orders. Consequently, this research empirically tests whether market participants belonging to a specific group increase or decrease the proportion of times they improve the NBBO as a consequence of the tick size pilot program. Mathematically the variable of interest is calculated as follows:

$$\%\ Price\ Set_{it}^{M} = \frac{1}{n}\sum_{f=1}^{n} \frac{number\ of\ orders\ setting\ a\ new\ NBBO_{it}^{M}}{total\ price\ setting\ orders_{it}} \tag{5.3}$$

*% Price Set* represents the total number of orders that improve the national best bid or the offer at the order's entry time on stock *i*, during the trading day *t* by each market participant's group *M* divided by the total number of orders that improved the NBBO on that security within the same day. These orders are identified on our dataset through the OUCH's BBO flag, which equals 'S' when the order entered by the market participant improves either the national best bid or offer.

H6 is tested by looking at changes in the proportion of agency orders entered by banks' identifiers that improve the NBBO throughout the trading day from 9:30 am and 4:00 pm. Our database allows us to calculate this using the following:

$$\%\ agency_{it} = \frac{agency_{it}}{agency_{it} + principal_{it} + riskless_{it} + other_{it}} \tag{5.4}$$

*Agency*, *principal*, *riskless* and *other* represent the number of price setting orders entered by the bank trading entity for security *i* during the trading day *t*.

The third variable of interest proxies the intention of a market participant to consume liquidity from 9:30 am to 4:00 pm of each trading day. Similar to Rule 605, each order entered by the MPID is categorised based on its type and its accepted order price relative to the NBBO midpoint price. In this analysis, fill or kill and immediate or cancel orders are considered very aggressive, as the intention of the market participants using these order types is clearly to remove liquidity from the market. Likewise, buy (sell) orders with an accepted order price higher (lower) than the NBBO midpoint price are categorised as aggressive. Orders with the reference price at the NBBO midpoint price are classified as at the midpoint and the remaining orders are considered non-aggressive. As suggested by Admati and Pfleiderer (1988), I test whether different market participants have different intraday order aggressiveness patterns and how these change because of the tick pilot. Therefore, the variable of interest for H7 and H8 is calculated as follows:

$$\%\ aggressive_{itb}^{M} = \frac{1}{n}\sum_{f=1}^{n} \frac{aggressive_{itbf} + very\ aggressive_{itbf}}{total\ orders_{itbf}} \tag{5.5}$$

This measures the average proportion of *aggressive* and *very aggressive* orders on stock *i* during the 30-minute time bucket *b* entered by each identifier *f* belonging to the market participants' group *M* on the day *t*.

The fourth variable used in this research to test *H8* is the implicit transaction cost, as defined in the previous chapter. This variable proxy is calculated as follows:

$$implicit\ transaction\ costs_{itb} = \sum_{j=1}^{m} \frac{side_{itbj} \times \left(Price_{itbj} - VWAP_{it}\right) \times volume_{itbj}}{volume_{itbj}} \tag{5.6}$$

*Implicit transaction costs* represent the volume weighted difference between the execution price (*Price*) of the transaction *j* on the Nasdaq books and the SIP end-of-day volume-weighted average price (*VWAP*) multiplied by +1 if the liquidity taker is buying the security and –1 if otherwise. The implicit transaction costs are calculated for each 30-minute time interval *b* on each stock *i*.

## 5.3 Empirical Findings

This section presents the empirical findings of the hypothesis tests conducted in this chapter.

### 5.3.1 Market participants' heterogeneity and price setting behaviour

Market participants must revise their quotes based on the state of the order book and the security's public information. In this process, the tick size plays a central role in determining order submission strategies as it represents the minimum price increment necessary to enforce time priority. Kwan et al. (2015) indicate that when the securities' quoted spread is equal to the tick size, investors move their order flow from stock exchanges to alternative trading systems to overcome the limit to trading. Consistent with this, Figure 2 indicates that, because of the pilot program, market participants faced a thicker price grid and were unable to frequently improve the NBBO in all but one of the treatment groups. The thicker price grid increased the value of the highest priority in the queue and encouraged market participants to fiercely compete to be the price setter.

Table 5.2 indicates strong differences in the price setting behaviour of the different market participants. On average, proprietary traders set prices more frequently for very liquid securities as these market participants improved the NBBO prices approximately 52% of the time. Banks were the main price setters on liquid and illiquid stocks in which their price improvement market share was as high as 40%. As expected, agency firms were never the main price setter in any of the analysed samples, regardless of its liquidity group. Nonetheless, agency firms, on average, set 34% of the prices on illiquid securities while it improved the NBBO less than 13% of the times on very liquid stocks, suggesting that they play an important role in the price discovery process on securities with a bid–ask spread higher than $0.11. Proprietary traders played a minor role on illiquid stocks as they only improved the NBBO approximately 14% of the time.

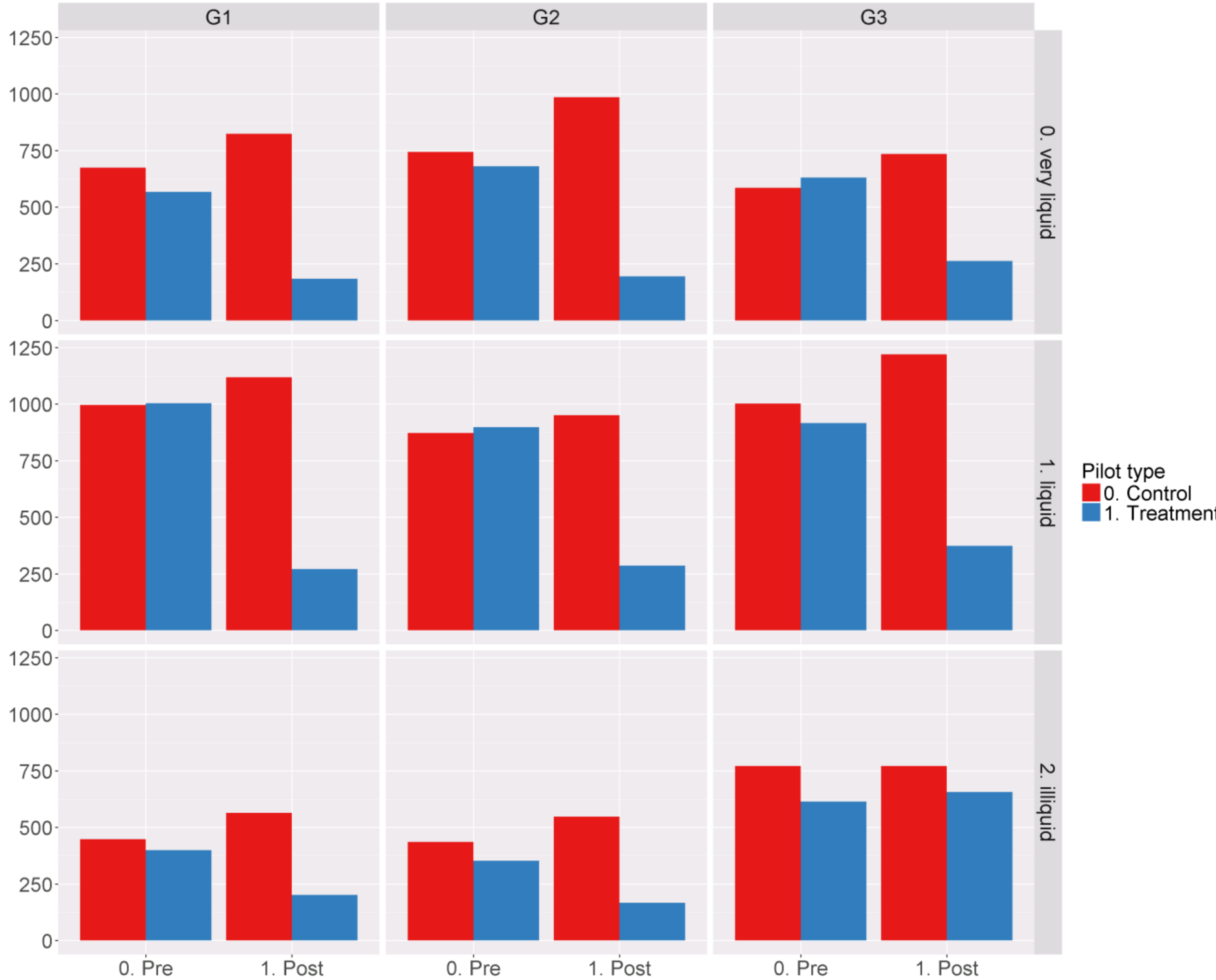


**Figure 2: Average daily number of NBBO price set per market participant identifier.**

*Note.* Orders that improved either the national best bid or the national best offer were observed in the Nasdaq data using the BBO flag, which equals 'S' when an order entered in the system set a new NBBO price. Summary statistics and difference-in-differences coefficients and t-statistics are reported in the appendix (see Tables A2a and A2b).

**Table 5.2: Pre-Pilot Summary Statistics for the Percentage of the NBBO Price Set**

| | *Treatment* | | | *Control* | | |
|---|---|---|---|---|---|---|
| *Table A: Very liquid* | Average | St. Deviation | N. Obs. | Average | St. Deviation | N. Obs. |
| Proprietary trading companies | 52.42% | 14.57% | 135 | 52.35% | 15.92% | 135 |
| Banks | 34.68% | 8.89% | 135 | 33.99% | 8.79% | 135 |
| Agency firms | 12.71% | 8.92% | 135 | 13.51% | 10.37% | 135 |
| *Table B: Liquid* | Average | St. Deviation | N. Obs. | Average | St. Deviation | N. Obs. |
| Proprietary trading companies | 30.73% | 15.88% | 141 | 29.18% | 16.47% | 141 |
| Banks | 40.51% | 8.53% | 141 | 40.17% | 8.22% | 141 |
| Agency firms | 28.21% | 14.17% | 141 | 30.36% | 14.62% | 141 |
| *Table C: Illiquid* | Average | St. Deviation | N. Obs. | Average | St. Deviation | N. Obs. |
| Proprietary trading companies | 14.40% | 7.78% | 131 | 14.06% | 9.10% | 131 |
| Banks | 47.52% | 12.46% | 131 | 48.17% | 13.89% | 131 |
| Agency firms | 34.38% | 15.09% | 131 | 34.74% | 15.78% | 131 |

*Note.* The table contains the percentage of times a proprietary trading company, bank or agency firm set a new national best bid or offer within a trading day between 9:30 am and 4:00 pm between 1 April 2016 and 1 October 2016.

The effects of the policy change on market participants' price setting behaviours are reported in Table 5.3; essentially, the gains of one group were the losses of the others, creating a zero-sum effect. The difference-in-differences coefficients indicated that the policy change encouraged banks to improve the NBBO more frequently on *very liquid* and *liquid* securities. These effects were particularly strong for *G3* securities with a pre-pilot bid–ask spread lower than $0.04 in which banks' price setting market share increased by 16.14% at the expenses of proprietary traders. Conversely, the tick size pilot program induced proprietary traders to become more active on *illiquid* securities in which their price setting market share increased by 6.16%, 7.65% and 7.23% for *G1*, *G2* and *G3* stocks, respectively, while agency firms were only marginally less at the front of the queue than before for treatment securities. The difference-in-differences coefficients associated with agency firms were statistically significant only for *liquid* stocks.

Overall, the policy change induced banks to increase their price setting market share on *very liquid* securities while proprietary trading companies were encouraged to set prices on *illiquid* stocks in which they were the least active during the pre-pilot period. In contrast with Yao and Ye (2018), these results indicate that both banks and proprietary trading company firms had access to the same technology as they are both capable of being at the front of the queue for securities with the quoted spread constrained by the tick size. In the next section, I analyse whether the pilot program changed the proportion of banks' orders setting a new NBBO price labelled as 'a*gent'*.

## Table 5.3: Difference-in-differences analysis on the average daily % NBBO price set

| | *Very liquid* | | | *Liquid* | | | *Illiquid* | | |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Proprietary trading companies* | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| Intercept | 54.35% | 52.11% | 51.80% | 30.86% | 27.24% | 30.12% | 12.46% | 14.07% | 14.78% |
| | (22.99)*** | (18.82)*** | (24.17)*** | (11.79)*** | (12.78)*** | (11.62)*** | (12.91)*** | (9.28)*** | (9.89)*** |
| Group | –3.89% | 3.65% | 2.16% | 0.99% | 2.85% | –1.71% | 1.20% | –2.82% | 0.20% |
| | (1.13) | (1.01) | (0.73) | (0.27) | (0.97) | (0.45) | (0.87) | (1.56) | (0.10) |
| Pilot | –7.89% | –10.74% | –5.98% | –0.94% | –2.45% | –4.82% | 5.42% | 4.50% | 2.69% |
| | (2.45)** | (3.06)*** | (2.04)** | (0.28) | (0.89) | (1.39) | (2.45)** | (1.93)* | (1.16) |
| Group* Pilot | –5.28% | –2.14% | –14.70% | 2.16% | 4.76% | 4.65% | 6.16% | 7.65% | 7.23% |
| | (1.16) | (0.46) | (3.86)*** | (0.47) | (1.29) | (0.99) | (2.05)** | (2.30)** | (2.26)** |
| Adjusted $R^2$ | 0.15 | 0.14 | 0.26 | 0.01 | 0.04 | 0.01 | 0.21 | 0.16 | 0.12 |
| N. Observations | 168 | 168 | 204 | 160 | 248 | 156 | 168 | 164 | 192 |
| *Panel B: Banks* | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| Intercept | 32.91% | 33.58% | 33.99% | 41.39% | 40.00% | 38.63% | 47.76% | 48.58% | 47.61% |
| | (20.87)*** | (25.68)*** | (29.18)*** | (34.14)*** | (39.35)*** | (26.44)*** | (20.28)*** | (20.33)*** | (28.07)*** |
| Group | 1.89% | –1.91% | –0.06% | –0.83% | –1.17% | 3.47% | 1.21% | –2.62% | –0.06% |
| | (0.91) | (1.02) | (0.03) | (0.42) | (0.81) | (1.68)* | (0.38) | (0.87) | (0.02) |
| Pilot | 9.78% | 10.35% | 7.73% | 6.47% | 7.06% | 7.47% | 0.79% | 0.71% | 2.81% |
| | (4.50)*** | (5.60)*** | (4.56)*** | (3.62)*** | (5.07)*** | (3.4)*** | (0.24) | (0.22) | (1.01) |
| Group* Pilot | 7.65% | 5.46% | 16.14% | 3.85% | 2.54% | 3.76% | –2.88% | –1.04% | –3.76% |
| | (2.30)** | (1.87)* | (6.03)*** | (1.47) | (1.15) | (1.18) | (0.66) | (0.25) | (1.00) |
| Adjusted $R^2$ | 0.33 | 0.33 | 0.51 | 0.22 | 0.19 | 0.23 | 0.00 | 0.01 | 0.01 |
| N. Observations | 168 | 168 | 204 | 160 | 248 | 156 | 168 | 164 | 192 |
| *Panel C: Agency firms* | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| Intercept | 12.74% | 14.07% | 14.00% | 27.53% | 32.38% | 30.97% | 37.34% | 34.15% | 33.98% |
| | (10.01)*** | (7.12)*** | (9.9)*** | (13.42)*** | (17.13)*** | (12.6)*** | (14.47)*** | (13.93)*** | (15.25)*** |
| Group | 1.83% | –1.55% | –1.92% | –0.14% | –1.88% | –2.21% | –3.81% | 5.29% | –0.71% |
| | (0.96) | (0.61) | (1.07) | (0.05) | (0.70) | (0.63) | (1.02) | (1.48) | (0.25) |
| Pilot | –1.91% | 0.47% | –1.63% | –5.35% | –4.35% | –2.53% | –5.20% | –3.38% | –4.77% |
| | (1.11) | (0.17) | (0.85) | (1.81)* | (1.63) | (0.73) | (1.58) | (0.96) | (1.53) |
| Group* Pilot | –4.01% | –5.16% | –2.98% | –7.42% | –8.39% | –8.73% | –3.89% | –8.46% | –3.09% |
| | (1.67)* | (1.54) | (1.31) | (1.87)* | (2.28)** | (1.92)* | (0.84) | (1.73)* | (0.78) |
| Adjusted $R^2$ | 0.07 | 0.06 | 0.08 | 0.15 | 0.13 | 0.12 | 0.09 | 0.07 | 0.06 |
| N. Observations | 168 | 168 | 204 | 160 | 248 | 156 | 168 | 164 | 192 |

*Note.* The effect of the tick pilot program on the average daily percentage of orders setting a new NBBO. In line with Bertrand et al. (2004), the observations were averaged over the pre-pilot and post-pilot period to minimise potential serial autocorrelation issues. The dependent variable was the average percentage of orders setting an NBBO per security period MPID group. The independent variables were as follows: a dummy variable that discriminates between the treatment and control group; *Post*, which is a dummy variable that distinguishes between the pre- and post-pilot period; and their interaction variable. To account for heteroskedasticity, the t-statistics reported in parentheses are calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

### 5.3.2 Tick size consolidation and banks' business model

Banks are often labelled as non-HFT companies by the academic literature because of the data structure and the dichotomy of their business model (Brogaard, Hendershott & Riordan, 2014; Carrion, 2013; Hirschey, 2013; Yao & Ye, 2018). This current research appears to be the first attempt to describe the trading behaviour of this class of market participants using Nasdaq data.

Our previous results indicate that banks and proprietary trading companies have access to the same trading technology and, when necessary, the former are capable of being at the front of the queue more frequently compared to all other market participants. Nonetheless, banks are characterised by several business units that provide financial services to institutional investors such as: (i) capital commitment, (ii) direct market access and (iii) algorithmic execution services. Banks may employ different technologies to provide these services to their clients; therefore, the changes in the percentage of price setting orders results observed in Section 5.2.1 may be driven by either their principal or agency execution business. In this section, I test whether the increased proportion of price setting orders is due to their agency or principal services. Therefore, an increased proportion of agency orders setting the NBBO would indicate that investors are capable of being at the front of the queue for treatment securities.

The capacity flag allows us to divide banks' orders into principal, riskless and agency. The pre-pilot proportion of agency orders within the group of banks in the analysed sample is displayed in Figure 3. Treatment samples are labelled 'G1', 'G2' or 'G3'while control samples are preceded by 'C'. Pre-pilot averages, standard deviations and number of observations split between control and treatment samples are provided in the appendix (see Table A3).

The average daily proportion of banks' agency orders improving the NBBO, as indicated in Figure 3, is strikingly similar across our sample, regardless of the stocks' liquidity group suggesting that more than 62% of the orders entered through banks' MPIDs were labelled as 'agent'.

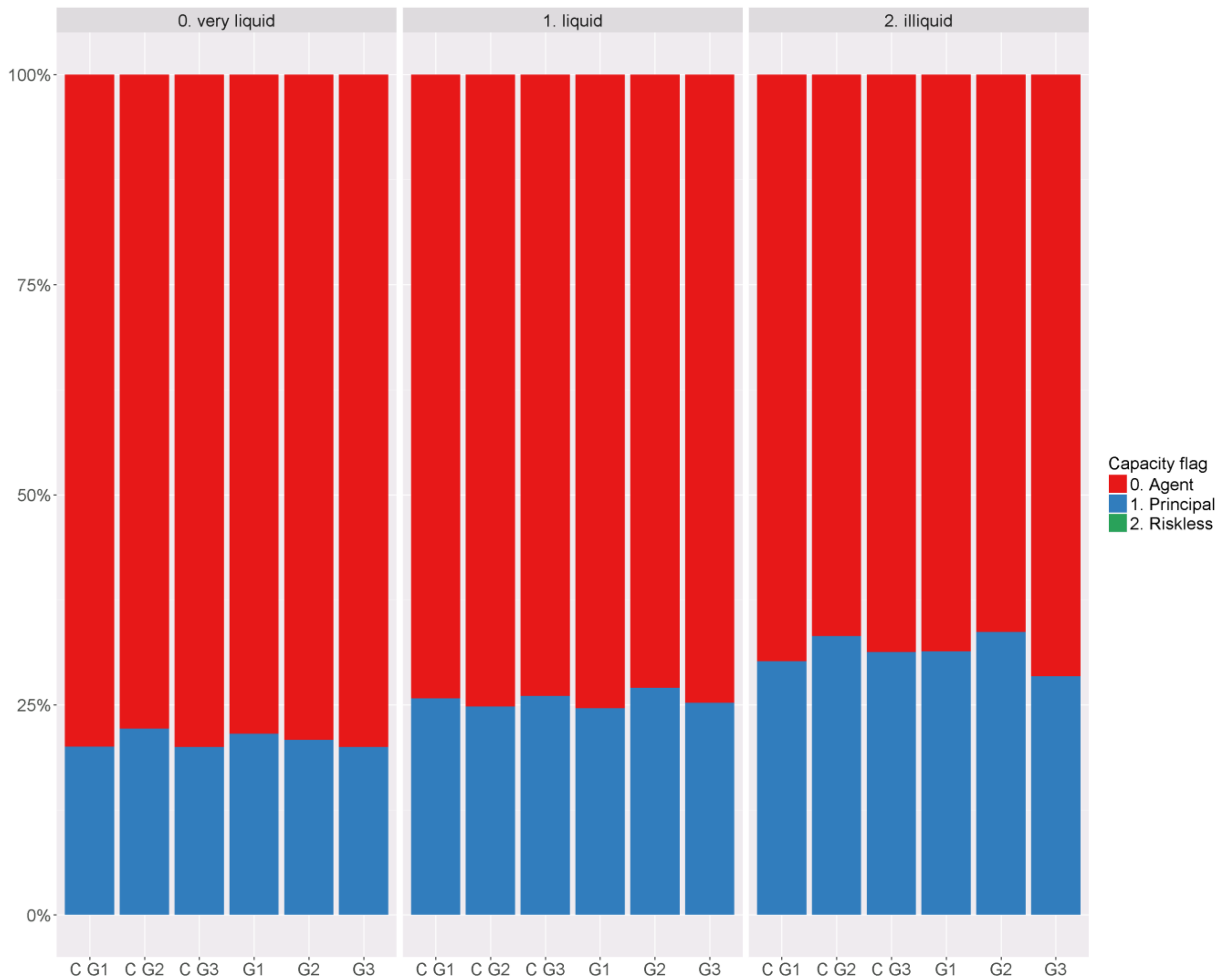


**Figure 3: Pre-pilot average percentage of banks' orders improving the NBBO labelled as 'agent'.**

The effects of the policy change on banks' proportion of agency and principal trading are outlined in Table 5.4, which reports the difference-in-differences regression outputs for the nine analysed samples. The difference-in-differences coefficients are positive across all samples, but are most strongly and consistently significant on very liquid securities.

These empirical findings suggest that investors had access to innovative technology, which allows them to compete in speed with proprietary trading companies. The next sections analyse the intraday order submission strategies of proprietary trading companies, agency firms and banks to infer whether market participants' trading strategies are fundamentally driven by their business model.

**Table 5.4: Difference-in-Differences Analysis for the Average Daily Percentage of Banks' Orders Setting the NBBO Labelled as 'Agent'**

| | *Very liquid* | | | *Liquid* | | | *Illiquid* | | |
|---|---|---|---|---|---|---|---|---|---|
| | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| Intercept | 80.69% | 77.70% | 80.91% | 73.78% | 76.03% | 72.45% | 66.12% | 62.61% | 65.64% |
| | (93.08)*** | (63.71)*** | (99.76)*** | (65.31)*** | (61.98)*** | (43.13)*** | (31.02)*** | (26.63)*** | (37.14)*** |
| Group | –3.09% | 1.53% | –0.62% | 0.71% | –4.82% | 1.22% | –1.69% | –0.93% | 3.49% |
| | (2.28)** | (0.98) | (0.58) | (0.40) | (2.91)*** | (0.56) | (0.57) | (0.26) | (1.40) |
| Pilot | 1.55% | 2.31% | 1.44% | 4.20% | 1.19% | 3.62% | –1.00% | 3.00% | 1.83% |
| | (1.27) | (1.46) | (1.22) | (2.83)*** | (0.77) | (1.82)* | (0.32) | (0.87) | (0.74) |
| Group*Pilot | 8.02% | 6.13% | 6.82% | 2.22% | 6.20% | 3.28% | 7.65% | 6.37% | 2.63% |
| | (4.32)*** | (2.86)*** | (4.48)*** | (0.94) | (2.67)*** | (1.24) | (1.79)* | (1.29) | (0.77) |
| Adjusted $R^2$ | 0.25 | 0.24 | 0.27 | 0.13 | 0.08 | 0.12 | 0.03 | 0.05 | 0.06 |
| N. Obs. | 168 | 168 | 204 | 160 | 248 | 156 | 168 | 164 | 192 |

Note. The effect of the tick pilot on the average daily percentage of banks' agency orders improving the NBBO. In line with Bertrand et al. (2004), the observations were averaged over the pre-pilot and post-pilot period to minimise potential serial autocorrelation issues. The dependent variable was the average percentage of banks' orders setting a new NBBO labelled as '*Agent*' per security period bank trading entity. The independent variables were as follows: a dummy variable that discriminated between the treatment and control groups; *Pilot*, which is a dummy variable that distinguishes between the pre- and post-pilot period; and their interaction variable. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

### 5.3.3 The cross-section of market participants' order aggressiveness

The analysis of the market participants' order submission strategies is not novel in the academic literature as other authors have extensively studied the so-called order aggressiveness of heterogeneous agents throughout the trading day. Biais et al. (1995) used the order messages to indicate that the conditional probability of investors placing limit orders was higher when quoted spreads were large. Similarly, Hangströmer, Nordén and Dong (2014) studied the order aggressiveness of market maker HFT, opportunistic HFT and non-HFT and indicated that fast traders tended to consider the trade-off between the waiting cost and the cost of crossing the bid–ask spread when they submitted their orders. This current research differs from the previous papers as we use time bucket dummy variables to test for systematic differences among market participants' groups in their intraday order submission strategies. In line with McInish and Wood (1992), the significance of the time dummy variables represent, in this perspective, the market participants' time-to-date preferences between entering a limit or an aggressive order (see Section 5.1.3). The decision to slice our sample into 30-minute intervals was derived from Heston, Korajczyk and Sadka (2010), who discovered striking price return patterns at 30-minute intervals. Here, they tested whether persistent price returns patterns existed within the trading day; they used both 5- and 30-minute intervals, and concluded that half-hour return intervals were sufficient to faithfully characterise high-frequency returns (Heston et al., 2010).

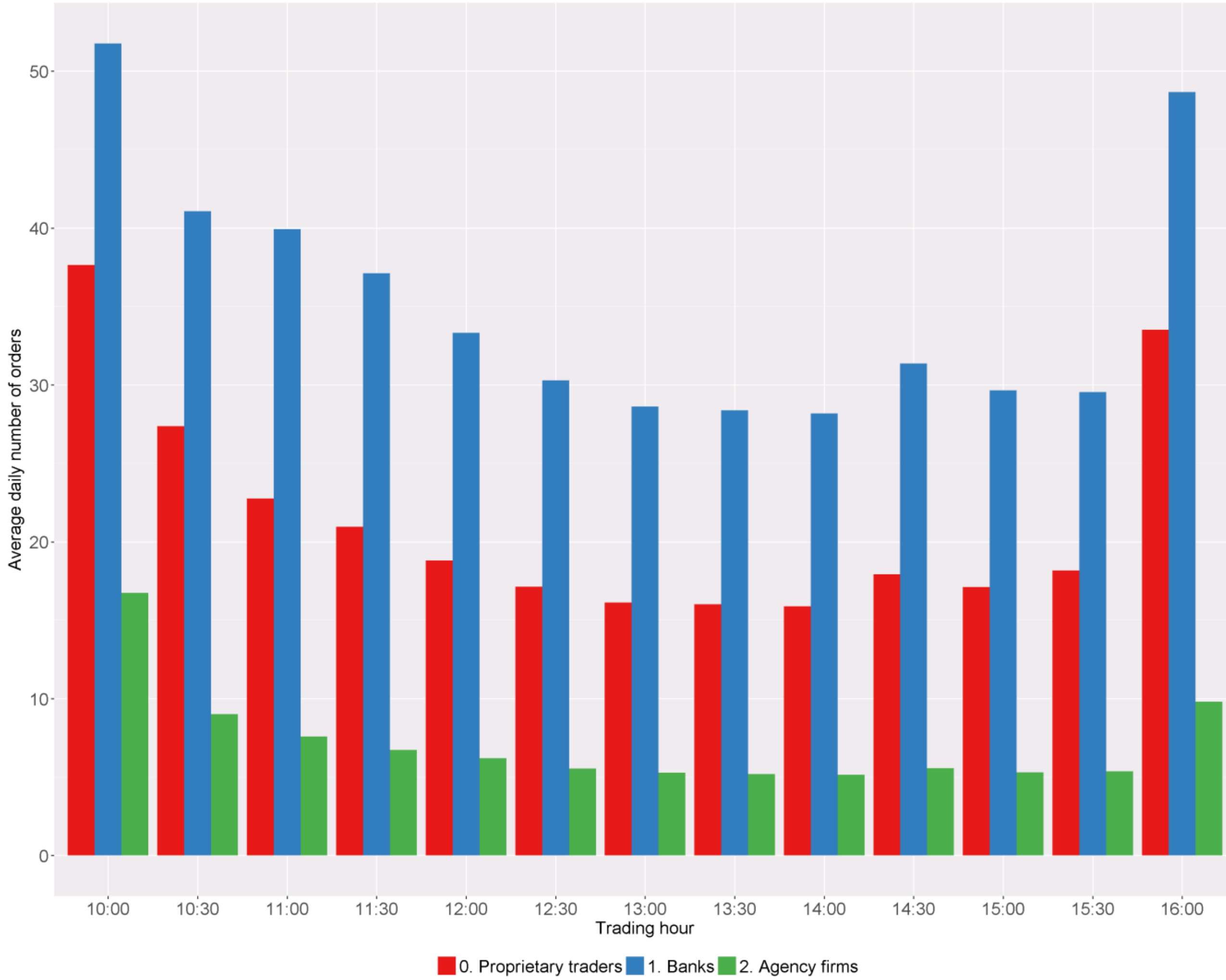


**Figure 4: Pre-pilot average daily number of orders per market participant identifier.**

In contrast with the methodologies of other papers, I do not use trading volume, quoted spreads or volatility as control variables in the regression models as the estimated equations would otherwise be strongly subject to both multicollinearity and endogeneity issues. The average order aggressiveness of the market participants generated the market quality patterns observed in the data and not the other way around. Further, I am only interested in capturing the different intraday order aggressiveness of proprietary traders, banks and agency firms, as the purpose of this analysis is to assess whether different business models are associated with different intraday order submission strategies.

Figure 4 indicates the average daily number of orders entered by each trading entity during the trading day. Interestingly, bank identifiers, on average, enter more orders than all other market participants, suggesting that these market participants behave similarly to the market marker HFT described by Hangströmer and Nordén (2013). Further, the chart indicates that all market participants, regardless of their business model, decreased the amount of orders they submitted between 10:00 am and 1:00 pm.

**Table 5.5a: Panel Regression for the Pre-Pilot Average Daily Order Aggressiveness of Very Liquid Securities**

| Very liquid | Proprietary trading companies (1) | Banks (2) | Agency firms (3) | (1) – (2) | (1) – (3) | (2) – (3) |
|---|---|---|---|---|---|---|
| 10:30 | 14.25% | 4.03% | 9.74% | 10.22% | 4.51% | –5.71% |
| | (42.68)*** | (31.31)*** | (50.67)*** | (27.43)*** | (13.57)*** | (24.46)*** |
| 11:00 | 15.66% | 4.22% | 11.81% | 11.44% | 3.86% | –7.59% |
| | (42.34)*** | (28.35)*** | (54.27)*** | (27.62)*** | (10.81)*** | (28.13)*** |
| 11:30 | 16.18% | 4.23% | 11.90% | 11.95% | 4.28% | –7.67% |
| | (43.25)*** | (28.45)*** | (54.04)*** | (28.90)*** | (12.11)*** | (28.02)*** |
| 12:00 | 16.13% | 3.75% | 11.33% | 12.38% | 4.80% | –7.58% |
| | (43.05)*** | (25.54)*** | (53.02)*** | (30.06)*** | (13.76)*** | (28.28)*** |
| 12:30 | 15.98% | 3.68% | 11.84% | 12.30% | 4.13% | –8.17% |
| | (42.56)*** | (24.20)*** | (56.04)*** | (29.78)*** | (11.89)*** | (29.98)*** |
| 13:00 | 16.03% | 3.31% | 11.59% | 12.72% | 4.44% | –8.28% |
| | (42.28)*** | (22.77)*** | (55.56)*** | (30.60)*** | (12.33)*** | (31.09)*** |
| 13:30 | 16.03% | 3.37% | 11.36% | 12.66% | 4.66% | –7.99% |
| | (42.5)*** | (23.09)*** | (55.37)*** | (30.67)*** | (13.28)*** | (30.73)*** |
| 14:00 | 16.27% | 3.70% | 11.63% | 12.57% | 4.64% | –7.93% |
| | (43.38)*** | (25.32)*** | (55.58)*** | (30.41)*** | (13.38)*** | (29.39)*** |
| 14:30 | 16.86% | 3.86% | 11.84% | 13.00% | 5.03% | –7.97% |
| | (44.60)*** | (26.33)*** | (56.15)*** | (31.23)*** | (14.31)*** | (29.36)*** |
| 15:00 | 16.94% | 4.49% | 13.15% | 12.46% | 3.80% | –8.66% |
| | (44.28)*** | (30.43)*** | (60.93)*** | (29.67)*** | (10.69)*** | (31.96)*** |
| 15:30 | 17.34% | 4.89% | 12.20% | 12.46% | 5.15% | –7.31% |
| | (44.49)*** | (32.04)*** | (52.58)*** | (29.21)*** | (14.56)*** | (26.12)*** |
| 16:00 | 14.00% | 6.34% | 15.70% | 7.66% | –1.70% | –9.36% |
| | (29.64)*** | (31.29)*** | (54.98)*** | (16.05)*** | (4.06)*** | (29.68)*** |
| Stock Fixed Effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.69 | 0.48 | 0.70 | 0.56 | 0.28 | 0.44 |
| N. Observations | 3,510 | 3,510 | 3,510 | 3,510 | 3,510 | 3,510 |

*Note*. The panel regression model calculated on the pre-pilot intraday average market participants' order aggressiveness on securities with a pre-pilot quoted spread lower than $0.04. The dependent variable of this regression was the average percentage of the total buy (sell) orders with a limit price higher (lower) than the NBBO midpoint price and IOC and FOK orders entered by each market participant group per stock time bucket. The independent variables reported in the table were time dummy variables associated with each 30-minute time bucket. Newey–West standard errors are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

During this period, the average daily number of orders for bank identifiers decreased from 50 to 20, proprietary trading companies reduced their order submission by 18 units and agency firms' average number of orders shrunk from 13 to 5. All market participants submitted a larger number of orders during the last 30 minutes of the trading session. However, the average aggressiveness of these orders was not constant throughout the trading day and varied by market participant group.

**Table 5.5b: Panel Regression for the Pre-Pilot Average Daily Order Aggressiveness of Liquid Securities**

| Liquid | Proprietary trading companies (1) | Banks (2) | Agency firms (3) | (1) – (2) | (1) – (3) | (2) – (3) |
|---|---|---|---|---|---|---|
| 10:30 | 11.33% | 3.65% | 6.51% | 7.68% | 4.82% | –2.86% |
| | (41.36)*** | (21.70)*** | (38.33)*** | (22.18)*** | (16.88)*** | (12.13)*** |
| 11:00 | 14.78% | 4.11% | 7.67% | 10.68% | 7.11% | –3.56% |
| | (49.84)*** | (21.20)*** | (43.76)*** | (27.81)*** | (22.72)*** | (14.17)*** |
| 11:30 | 15.66% | 4.25% | 7.80% | 11.40% | 7.86% | –3.54% |
| | (53.86)*** | (21.14)*** | (43.41)*** | (29.57)*** | (25.26)*** | (13.44)*** |
| 12:00 | 16.01% | 4.36% | 6.92% | 11.64% | 9.09% | –2.56% |
| | (56.16)*** | (20.96)*** | (35.95)*** | (30.01)*** | (29.67)*** | (9.20)*** |
| 12:30 | 16.62% | 4.71% | 7.11% | 11.91% | 9.51% | –2.39% |
| | (57.60)*** | (22.89)*** | (40.22)*** | (30.69)*** | (32.23)*** | (9.04)*** |
| 13:00 | 16.90% | 4.41% | 7.30% | 12.49% | 9.61% | –2.89% |
| | (58.70)*** | (21.30)*** | (41.44)*** | (32.43)*** | (31.92)*** | (11.05)*** |
| 13:30 | 17.28% | 4.36% | 7.29% | 12.92% | 9.99% | –2.93% |
| | (59.29)*** | (21.64)*** | (39.71)*** | (33.51)*** | (32.46)*** | (11.28)*** |
| 14:00 | 18.09% | 4.78% | 8.12% | 13.31% | 9.97% | –3.34% |
| | (60.59)*** | (23.07)*** | (38.51)*** | (33.72)*** | (30.93)*** | (11.65)*** |
| 14:30 | 19.28% | 5.07% | 8.39% | 14.21% | 10.90% | –3.32% |
| | (65.07)*** | (24.48)*** | (47.14)*** | (36.15)*** | (34.12)*** | (12.38)*** |
| 15:00 | 19.52% | 5.38% | 9.55% | 14.14% | 9.97% | –4.17% |
| | (67.45)*** | (25.35)*** | (52.2)*** | (35.8)*** | (32.09)*** | (15.54)*** |
| 15:30 | 20.18% | 5.59% | 9.48% | 14.58% | 10.70% | –3.89% |
| | (67.68)*** | (27.61)*** | (50.27)*** | (36.99)*** | (33.97)*** | (14.36)*** |
| 16:00 | 17.05% | 7.97% | 15.59% | 9.08% | 1.46% | –7.62% |
| | (47.70)*** | (32.09)*** | (55.86)*** | (20.17)*** | (3.81)*** | (21.82)*** |
| Stock Fixed Effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.78 | 0.40 | 0.66 | 0.56 | 0.52 | 0.20 |
| N. Observations | 3,666 | 3,666 | 3,666 | 3,666 | 3,666 | 3,666 |

*Note*. The panel regression model calculated on the pre-pilot intraday average market participants' order aggressiveness on securities with a pre-pilot quoted spread higher than $0.04 but lower than $0.11. The dependent variable for this regression was the average percentage of the total buy (sell) orders with a limit price higher (lower) than the NBBO midpoint price and IOC and FOK orders entered by each market participant group per stock time bucket. The independent variables were time dummy variables associated with each 30-minute time bucket. Newey–West standard errors are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

The results of the panel regressions reported in Tables 5.5a, 5.5b and 5.5c suggest that non-proprietary trading companies tended to increase their use of marketable orders as they approached the end of the trading day, while proprietary trading companies displayed the opposite behaviour. Agency firms entered 3.50%, 6.11% and 4.26% more aggressive orders on *very liquid*, *liquid* and *illiquid* securities, respectively, in the last 30 minutes of the trading session. Banks exhibited a similar order submission strategy as the agency firms, while proprietary traders demonstrated the opposite trading behaviour; their order aggressiveness between 3:30 pm and 4:00 pm diminished by 3.34%, 3.13% and 1.20% across the three stock liquidity groups, respectively[4]. Proprietary trading

[4] The results are statistically significant and formally tested in the appendix (Table A4a-A4c).

companies were always more aggressive than the other market participants from 10:30 am to 3:30 pm across all the samples. Conversely, banks appeared to be the main liquidity providers for securities with a pre-pilot quoted spread lower than $0.11 as most of their limit orders were not aggressive. The differences in order aggressiveness between banks and agency firms were smaller and sometimes not significant for securities with a pre-pilot bid–ask spread higher than $0.11, suggesting that agency firms play a key role on the least liquid securities.

**Table 5.5c: Panel Regression for the Pre-Pilot Average Daily Order Aggressiveness of Illiquid Securities**

| Illiquid | Proprietary trading companies (1) | Banks (2) | Agency firms (3) | (1) – (2) | (1) – (3) | (2) – (3) |
|---|---|---|---|---|---|---|
| 10:30 | 6.41% | 4.61% | 3.73% | 1.80% | 2.68% | 0.88% |
| | (21.79)*** | (18.58)*** | (19.52)*** | (4.43)*** | (8.38)*** | (2.99)*** |
| 11:00 | 8.66% | 4.36% | 5.05% | 4.31% | 3.61% | –0.69% |
| | (27.74)*** | (15.79)*** | (24.53)*** | (10.2)*** | (10.05)*** | (2.36)** |
| 11:30 | 10.03% | 4.20% | 5.18% | 5.84% | 4.85% | –0.98% |
| | (29.63)*** | (13.72)*** | (22.54)*** | (12.49)*** | (11.75)*** | (2.92)*** |
| 12:00 | 10.08% | 4.35% | 5.48% | 5.73% | 4.60% | –1.13% |
| | (27.19)*** | (14.45)*** | (23.33)*** | (11.62)*** | (10.7)*** | (3.32)*** |
| 12:30 | 10.31% | 7.14% | 5.58% | 3.18% | 4.73% | 1.55% |
| | (29.13)*** | (22.64)*** | (23.61)*** | (6.86)*** | (11.43)*** | (4.39)*** |
| 13:00 | 10.78% | 6.82% | 5.05% | 4.01% | 5.74% | 1.76% |
| | (29.55)*** | (21.21)*** | (22.59)*** | (8.34)*** | (14.14)*** | (4.92)*** |
| 13:30 | 10.82% | 7.16% | 5.70% | 3.66% | 5.12% | 1.46% |
| | (31.52)*** | (22.03)*** | (23.7)*** | (7.48)*** | (13.12)*** | (4.21)*** |
| 14:00 | 11.34% | 7.26% | 6.92% | 4.08% | 4.42% | 0.34% |
| | (32.85)*** | (22.44)*** | (24.82)*** | (8.29)*** | (10.41)*** | (0.95) |
| 14:30 | 13.22% | 7.20% | 7.00% | 6.02% | 6.22% | 0.20% |
| | (35.95)*** | (22.6)*** | (27.81)*** | (12.22)*** | (14.33)*** | (0.59) |
| 15:00 | 12.95% | 7.39% | 5.95% | 5.57% | 7.01% | 1.44% |
| | (36.10)*** | (23.47)*** | (24.74)*** | (10.99)*** | (18.18)*** | (3.89)*** |
| 15:30 | 13.12% | 5.30% | 7.29% | 7.82% | 5.84% | –1.98% |
| | (39.63)*** | (16.79)*** | (28.05)*** | (17.39)*** | (14.16)*** | (4.97)*** |
| 16:00 | 11.92% | 7.10% | 11.55% | 4.82% | 0.38% | –4.44% |
| | (29.08)*** | (18.93)*** | (30.85)*** | (10.17)*** | (0.81) | (10.76)*** |
| Stock Fixed Effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.39 | 0.21 | 0.35 | 0.06 | 0.09 | 0.08 |
| N. Observations | 3,404 | 3,406 | 3,406 | 3,404 | 3,404 | 3,406 |

*Note*. The panel regression model calculated on the pre-pilot intraday average market participants' order aggressiveness on securities with a pre-pilot quoted spread higher than $0.11. The dependent variable for this regression was the average percentage of the total buy (sell) orders with a limit price higher (lower) than the NBBO midpoint price and IOC and FOK orders entered by each market participant group per stock time bucket. The independent variables reported were time dummy variables associated with each 30-minute time bucket. Newey–West standard errors are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Consistent with the previous literature (Admati & Pfleiderer, 1998; Anand, Chakravarty & Martell, 2005), these empirical findings suggest that proprietary trading companies behaved as informed traders as they provided liquidity at the end of the day while they used more marketable orders during the trading day. Conversely, bank and agency firm identifiers submitted more aggressive orders towards the end of the trading session, suggesting that these market participants were essentially discretionary liquidity traders.

In Section 5.2.4, I test whether the tick size pilot program changes asymmetrically the order submission strategies of the three market participants groups.

### 5.3.4 Tick size consolidation and order submission strategies

This section analyses the effect of the policy change on the order submission strategies of the three market participant groups. As suggested by Yao and Ye (2018), the thicker price grid imposed by the tick size consolidation makes it expensive for market participants to step in front of standing limit orders and reduces the possible order placement strategies adopted by both liquidity providers and consumers. In this section, I test whether this exogenous event affects differently the order submission strategies of the three market participant groups. Agency firms, which are less sensitive to waiting costs and are less often price setters, should place more orders away from the NBBO on treatment securities. Conversely, banks, which are very sensitive to waiting costs, should place a higher amount of marketable orders as they approach the end of the trading session.

Tables 5.6a, 5.6b and 5.6c, which report the interaction variables of the difference-in-differences regressions, indicate that the policy change only marginally affected the intraday order aggressiveness of the market participants on *illiquid* securities, suggesting that the tick size consolidation imposed by the program did not affect treatment stocks across these samples.

Conversely, the tick size pilot program induced agency firms to reduce the proportion of aggressive orders used within the trading day (see Table 5.6a). Specifically, these market participants were submitting up to 9% more non-aggressive order in the last 30 minutes of the trading day, indicating that the policy change encouraged agency firms to execute their orders through passive strategies.

Likewise, Table 5.6b indicates that proprietary traders were using more non-aggressive orders on very liquid treatment securities. Interestingly, this behavioural change was statistically significant both at the beginning and towards the end of the trading day, when banks and agency firms sought more liquidity (Hirschey, 2013). This empirical finding suggests that proprietary traders provided more liquidity when it was mostly needed, while they tended to be very aggressive between 11:30 am and 2:00 pm. Instead, banks increased their order aggressiveness by about 2% from 11:30 am to 3:00 pm on *very liquid* securities. This important result suggests that bank identifiers are ultimately high-speed liquidity traders that need to fill their clients' orders by the end of the trading day. The inefficiency generated by the tick size change implicitly increased waiting costs and induced banks to take more liquidity, regardless of their speed.

Finally, it is important to highlight that, while agency firms consistently reduced their order aggressiveness throughout the trading day, banks and proprietary trading companies changed their behaviours during certain specific periods. These patterns can be explained by analysing the effect of the pilot program on the intraday implicit transaction costs patterns (see Table 5.7).

The difference-in-differences regressions show that the tick size consolidation increases implicit transaction costs by up to 12 basis points at the beginning and towards the end of the trading session, when impatience traders are most likely to submit marketable orders. Therefore, Tables 5.6b, 5.6c and 5.7 outline that proprietary traders and banks adapted their order submission strategies to maximise their pay-off conditional to their business model by considering the trade-off between waiting cost and the cost of crossing the bid–ask spread, as suggested by Hangströmer and Nordén (2013). Further, Table 5.6b indicates that proprietary trading companies tended to increase their liquidity provision when liquidity traders were willing to pay the most to have it, while Table 5.6c indicates that banks became more aggressive during the trading day to minimize their implicit transaction costs.

**Table 5.6a: Difference-in-Differences Analysis for the Average Daily Percentage of Aggressive Orders Per Agency Firm**

| | *Very liquid* | | | *Liquid* | | | *Illiquid* | | |
|---|---|---|---|---|---|---|---|---|---|
| *Hours* | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| 10:00 | –1.65% | –2.42% | –3.21% | –0.99% | 0.63% | –0.28% | –0.87% | –0.30% | –1.83% |
| | (1.13) | (1.77)* | (2.20)** | (0.65) | (0.57) | (0.20) | (0.82) | (0.25) | (1.44) |
| 10:30 | –3.40% | –3.10% | –3.95% | 0.95% | 0.04% | 0.75% | 0.66% | 1.58% | 0.29% |
| | (2.47)** | (2.46)** | (2.88)*** | (0.60) | (0.04) | (0.44) | (0.51) | (1.09) | (0.19) |
| 11:00 | –3.59% | –4.29% | –5.22% | 1.00% | 0.12% | 0.42% | 1.55% | 0.92% | 1.31% |
| | (2.52)** | (3.23)*** | (3.78)*** | (0.62) | (0.1) | (0.24) | (1.15) | (0.62) | (0.85) |
| 11:30 | –4.05% | –4.60% | –5.63% | 1.49% | 0.17% | 0.71% | 0.73% | 1.28% | 0.94% |
| | (2.90)*** | (3.25)*** | (4.14)*** | (0.94) | (0.14) | (0.43) | (0.51) | (0.82) | (0.53) |
| 12:00 | –4.13% | –4.76% | –5.90% | 1.58% | 0.94% | 0.95% | 0.88% | 1.52% | 1.25% |
| | (2.78)*** | (3.36)*** | (4.32)*** | (0.95) | (0.79) | (0.57) | (0.62) | (0.92) | (0.68) |
| 12:30 | –3.00% | –4.19% | –5.53% | 2.83% | 1.26% | 0.94% | 0.93% | 2.35% | 1.43% |
| | (2.09)** | (2.93)*** | (4.09)*** | (1.78)* | (1.09) | (0.55) | (0.56) | (1.34) | (0.73) |
| 13:00 | –4.14% | –5.32% | –5.70% | 2.41% | 0.65% | 1.21% | 2.05% | 3.09% | 1.88% |
| | (2.86)*** | (3.65)*** | (4.16)*** | (1.48) | (0.55) | (0.73) | (1.32) | (1.78)* | (1.04) |
| 13:30 | –3.93% | –4.24% | –5.52% | 2.80% | 1.05% | 1.25% | 1.56% | 3.11% | 1.62% |
| | (2.72)*** | (2.78)*** | (4.02)*** | (1.72)* | (0.91) | (0.78) | (1.08) | (1.96)* | (0.90) |
| 14:00 | –4.91% | –5.10% | –5.62% | 2.17% | 0.88% | 0.66% | 0.74% | 2.43% | 1.48% |
| | (3.32)*** | (3.52)*** | (4.13)*** | (1.29) | (0.75) | (0.40) | (0.43) | (1.44) | (0.87) |
| 14:30 | –4.26% | –5.25% | –5.58% | 2.19% | 0.70% | 0.90% | 1.77% | 2.75% | 2.12% |
| | (2.83)*** | (3.71)*** | (4.25)*** | (1.37) | (0.58) | (0.56) | (1.20) | (1.90)* | (1.09) |
| 15:00 | –4.95% | –5.26% | –6.16% | 1.36% | 0.50% | 0.60% | 1.13% | 2.46% | 1.62% |
| | (3.24)*** | (3.69)*** | (4.74)*** | (0.80) | (0.43) | (0.35) | (0.75) | (1.52) | (0.88) |
| 15:30 | –6.28% | –6.75% | –6.68% | 0.28% | 0.44% | –0.67% | 1.32% | 1.85% | 1.92% |
| | (4.19)*** | (4.52)*** | (5.18)*** | (0.16) | (0.36) | (0.40) | (0.79) | (1.07) | (1.03) |
| 16:00 | –7.09% | –8.92% | –7.58% | –4.54% | –4.18% | –3.64% | –0.93% | 0.20% | 0.47% |
| | (5.46)*** | (6.93)*** | (6.21)*** | (3.26)*** | (4.27)*** | (2.71)*** | (0.76) | (0.14) | (0.32) |

*Note*. The difference-in-differences coefficients for the average percentage of liquidity taking orders per agency firm's MPID during the trading day. An order was classified as aggressive if it was an IOC or FOK or if the limit price of a buy (sell) limit order was higher (lower) than the midpoint price. Standard errors adjusted by heteroskedasticity are reported within parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

**Table 5.6b: Difference-in-Differences Analysis for the Average Percentage of Aggressive Orders Per Proprietary Trading Company**

| | *Very liquid* | | | *Liquid* | | | *Illiquid* | | |
|---|---|---|---|---|---|---|---|---|---|
| *Hours* | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| 10:00 | –3.28% | –2.07% | –5.61% | –4.39% | –1.53% | –1.53% | –0.84% | –0.78% | –2.07% |
| | (1.98)** | (1.18) | (3.18)*** | (2.72)*** | (1.27) | (0.86) | (0.71) | (0.72) | (2.00)** |
| 10:30 | –0.87% | –1.25% | –3.96% | –1.19% | –0.61% | 1.17% | –0.61% | –0.51% | 1.19% |
| | (0.47) | (0.66) | (2.08)** | (0.60) | (0.48) | (0.61) | (0.42) | (0.31) | (0.86) |
| 11:00 | –0.04% | –1.72% | –3.92% | –2.27% | –1.39% | –0.50% | –1.13% | –0.71% | –1.13% |
| | (0.02) | (0.90) | (2.06)** | (1.21) | (1.03) | (0.25) | (0.69) | (0.42) | (0.62) |
| 11:30 | –0.99% | –1.74% | –2.69% | –1.11% | –1.39% | 1.92% | –1.48% | –0.20% | –0.16% |
| | (0.50) | (0.86) | (1.40) | (0.59) | (1.09) | (1.01) | (0.94) | (0.12) | (0.09) |
| 12:00 | –0.64% | –1.99% | –2.78% | –1.39% | –0.89% | 2.25% | –1.93% | –0.27% | 0.45% |
| | (0.33) | (0.98) | (1.40) | (0.70) | (0.68) | (1.08) | (1.33) | (0.16) | (0.27) |
| 12:30 | –1.11% | –2.07% | –2.99% | –0.84% | –0.32% | 1.09% | –0.72% | 0.19% | 2.16% |
| | (0.58) | (1.01) | (1.50) | (0.42) | (0.24) | (0.58) | (0.43) | (0.11) | (1.37) |
| 13:00 | –0.67% | –2.55% | –3.16% | –1.09% | –0.82% | 1.99% | 0.25% | 0.41% | 1.45% |
| | (0.34) | (1.25) | (1.62) | (0.57) | (0.64) | (1.02) | (0.16) | (0.24) | (1.04) |
| 13:30 | –0.61% | –2.48% | –3.18% | –0.69% | –0.61% | 1.84% | –0.64% | –0.45% | 1.68% |
| | (0.31) | (1.21) | (1.61) | (0.35) | (0.47) | (0.94) | (0.41) | (0.25) | (1.11) |
| 14:00 | –0.84% | –2.39% | –3.82% | –1.46% | –1.58% | 0.66% | –1.90% | –0.44% | 2.30% |
| | (0.44) | (1.21) | (1.95)* | (0.75) | (1.21) | (0.35) | (1.25) | (0.26) | (1.48) |
| 14:30 | –1.26% | –3.59% | –3.98% | –2.77% | –2.52% | –1.72% | –1.59% | –0.09% | 1.21% |
| | (0.66) | (1.75)* | (2.05)** | (1.44) | (1.99)** | (0.88) | (1.04) | (0.05) | (0.83) |
| 15:00 | –1.64% | –3.35% | –4.11% | –2.97% | –2.29% | –1.05% | –2.52% | –1.07% | –0.84% |
| | (0.84) | (1.65)* | (2.17)** | (1.55) | (1.83)* | (0.57) | (1.44) | (0.63) | (0.45) |
| 15:30 | –1.91% | –3.97% | –4.80% | –3.39% | –2.95% | –1.95% | –1.56% | –1.45% | –0.01% |
| | (1.00) | (2.02)** | (2.52)** | (1.69)* | (2.39)** | (1.02) | (1.01) | (0.88) | (0.01) |
| 16:00 | –2.61% | –5.43% | –4.93% | –2.67% | –4.50% | –2.11% | –3.20% | –3.19% | 0.76% |
| | (1.50) | (3.12)*** | (2.78)*** | (1.43) | (3.92)*** | (1.12) | (2.26)** | (1.73)* | (0.58) |

*Note*. The difference-in-differences coefficients for the average percentage of liquidity taking orders per proprietary trading company's MPID during the trading day. An order was classified as potentially liquidity taking if it was an IOC or FOK or if the limit price of a buy (sell) limit order was higher (lower) than the midpoint price. T-statistics based on standard errors adjusted by heteroskedasticity are reported within parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

**Table 5.6c: Difference-in-Differences Analysis for the Average Percentage of Aggressive Orders Per Bank**

| | *Very liquid* | | | *Liquid* | | | *Illiquid* | | |
|---|---|---|---|---|---|---|---|---|---|
| *Hours* | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| 10:00 | –0.34% | –0.51% | –1.06% | –1.56% | –0.71% | –0.35% | –1.48% | –1.11% | –2.03% |
| | (0.37) | (0.62) | (1.27) | (1.75)* | (0.99) | (0.36) | (1.39) | (1.12) | (2.21)** |
| 10:30 | 1.47% | 1.13% | 1.46% | 0.87% | 0.69% | 1.69% | 2.41% | 0.82% | –0.10% |
| | (1.42) | (1.19) | (1.64) | (0.91) | (0.99) | (1.58) | (1.90)* | (0.59) | (0.10) |
| 11:00 | 1.16% | 1.43% | 1.99% | 0.55% | 0.39% | 1.80% | 2.33% | 1.56% | 0.63% |
| | (1.14) | (1.60) | (2.29)** | (0.54) | (0.55) | (1.72)* | (1.93)* | (1.16) | (0.57) |
| 11:30 | 1.53% | 1.53% | 2.13% | 1.18% | 0.31% | 2.23% | 2.02% | 2.17% | 0.66% |
| | (1.48) | (1.71)* | (2.49)** | (1.11) | (0.43) | (1.95)* | (1.52) | (1.54) | (0.63) |
| 12:00 | 2.11% | 1.84% | 2.66% | 1.16% | 1.18% | 1.90% | 1.85% | 2.23% | 1.33% |
| | (2.06)** | (2.02)** | (3.05)*** | (1.19) | (1.63) | (1.68)* | (1.48) | (1.54) | (1.21) |
| 12:30 | 2.59% | 1.97% | 2.79% | 1.11% | 0.78% | 1.89% | 1.42% | 1.97% | 0.59% |
| | (2.45)** | (2.15)** | (3.19)*** | (1.06) | (1.03) | (1.65)* | (1.06) | (1.26) | (0.55) |
| 13:00 | 2.37% | 1.87% | 2.75% | 1.23% | 1.20% | 1.88% | 0.78% | 2.02% | 1.66% |
| | (2.29)** | (2.03)** | (3.26)*** | (1.23) | (1.62) | (1.62) | (0.59) | (1.30) | (1.49) |
| 13:30 | 2.62% | 1.88% | 2.64% | 1.11% | 1.12% | 1.80% | 1.74% | 2.76% | 1.03% |
| | (2.71)*** | (2.01)** | (3.03)*** | (1.17) | (1.54) | (1.6) | (1.44) | (1.71)* | (0.85) |
| 14:00 | 2.77% | 1.68% | 2.52% | 1.65% | 1.29% | 1.75% | 1.79% | 1.62% | 1.98% |
| | (2.63)*** | (1.82)* | (2.86)*** | (1.57) | (1.79)* | (1.59) | (1.43) | (0.96) | (1.58) |
| 14:30 | 2.42% | 1.86% | 2.81% | 1.72% | 1.16% | 1.96% | 2.03% | 2.83% | 2.59% |
| | (2.34)** | (2.11)** | (3.29)*** | (1.65)* | (1.56) | (1.72)* | (1.56) | (1.78)* | (2.13)** |
| 15:00 | 1.67% | 1.20% | 2.06% | 1.65% | 1.14% | 2.12% | 1.94% | 2.17% | 2.09% |
| | (1.68)* | (1.37) | (2.42)** | (1.65)* | (1.59) | (1.94)* | (1.65)* | (1.36) | (1.76)* |
| 15:30 | 1.47% | 0.83% | 1.75% | 0.95% | –0.11% | 1.04% | 2.61% | 2.55% | 0.88% |
| | (1.51) | (0.94) | (2.12)** | (0.96) | (0.16) | (1.01) | (2.02)** | (1.80)* | (0.78) |
| 16:00 | –0.89% | –1.19% | 0.33% | –0.14% | –0.73% | 0.44% | 0.47% | 2.63% | 3.50% |
| | (0.96) | (1.46) | (0.42) | (0.15) | (1.10) | (0.45) | (0.40) | (1.91)* | (3.32)*** |

*Note*. The difference-in-differences coefficients for the average percentage of liquidity taking orders per bank's MPID during the trading day. An order was classified as potentially liquidity taking if it was an IOC or FOK or if the limit price of a buy (sell) limit order was higher (lower) than the midpoint price. T-statistics based on standard errors adjusted by heteroskedasticity are reported within parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

**Table 5.7: Difference-in-Differences Analysis of the Average Implicit Transaction Cost**

| | *Very Liquid* | | | *Liquid* | | | *Illiquid* | | |
|---|---|---|---|---|---|---|---|---|---|
| *Hours* | G1 | G2 | G3 | G1 | G2 | G3 | G1 | G2 | G3 |
| 10:00 | 5.33 | 9.23 | 8.82 | –2.70 | 5.64 | 8.50 | –25.35 | 4.59 | 7.20 |
| | (1.95)* | (2.98)*** | (3.83)*** | (0.60) | (1.04) | (1.93)* | (1.83)* | (0.33) | (0.79) |
| 10:30 | –0.86 | –0.31 | 3.63 | 1.75 | –3.64 | –1.84 | 5.73 | –0.43 | –5.47 |
| | (0.30) | (0.10) | (1.43) | (0.43) | (0.85) | (0.41) | (0.41) | (0.04) | (0.62) |
| 11:00 | 1.78 | 0.68 | 3.78 | 2.48 | –4.11 | 0.43 | 16.16 | 8.50 | –7.36 |
| | (0.67) | (0.18) | (1.25) | (0.61) | (0.91) | (0.11) | (1.20) | (0.89) | (0.75) |
| 11:30 | 2.91 | 0.45 | 4.03 | 4.29 | 0.12 | 3.37 | 33.96 | 1.71 | –12.91 |
| | (0.87) | (0.11) | (1.34) | (0.97) | (0.03) | (0.79) | (2.22)** | (0.17) | (1.36) |
| 12:00 | 2.09 | –1.38 | 3.39 | 1.12 | 0.77 | –2.24 | 41.54 | 16.72 | –10.35 |
| | (0.61) | (0.50) | (1.21) | (0.25) | (0.18) | (0.61) | (1.06) | (1.87)* | (1.19) |
| 12:30 | –0.27 | –1.73 | 4.04 | 2.30 | –2.70 | 1.87 | –7.45 | –5.22 | –4.80 |
| | (0.11) | (0.66) | (1.40) | (0.59) | (0.58) | (0.49) | (0.42) | (0.45) | (0.51) |
| 13:00 | 2.85 | 2.23 | 2.77 | 8.74 | –4.38 | –0.73 | 3.35 | 3.34 | –17.18 |
| | (1.21) | (0.64) | (1.13) | (2.03)** | (1.02) | (0.17) | (0.22) | (0.36) | (1.98)** |
| 13:30 | 0.35 | 4.96 | 4.87 | 5.04 | 3.79 | –2.41 | 4.60 | 5.94 | –16.16 |
| | (0.14) | (1.41) | (1.75)* | (1.06) | (0.64) | (0.53) | (0.31) | (0.67) | (1.91)* |
| 14:00 | 1.77 | 0.14 | 4.68 | 8.55 | –4.15 | 2.96 | –0.79 | 3.88 | –8.90 |
| | (0.66) | (0.04) | (1.67)* | (1.97)** | (0.80) | (0.80) | (0.05) | (0.45) | (1.11) |
| 14:30 | 2.97 | 1.89 | 4.34 | 8.56 | 1.76 | 0.43 | 15.38 | 2.22 | –6.87 |
| | (1.01) | (0.63) | (1.67)* | (1.83)* | (0.40) | (0.11) | (1.33) | (0.16) | (0.85) |
| 15:00 | 3.51 | –1.47 | 2.98 | 7.45 | –1.75 | 2.40 | 20.06 | 6.82 | –12.40 |
| | (1.25) | (0.55) | (1.16) | (1.68)* | (0.43) | (0.55) | (1.42) | (0.78) | (1.08) |
| 15:30 | 3.70 | 4.51 | 7.13 | 8.74 | –1.76 | –3.55 | 4.40 | 12.28 | –10.34 |
| | (1.36) | (0.85) | (2.38)** | (2.01)** | (0.44) | (0.82) | (0.17) | (1.27) | (1.21) |
| 16:00 | 8.83 | 8.54 | 12.22 | 13.02 | 3.44 | 3.28 | 10.68 | 4.65 | –10.91 |
| | (2.37)** | (1.76)* | (3.81)*** | (2.58)*** | (0.81) | (0.80) | (0.88) | (0.52) | (1.43) |

*Note*. The difference-in-differences coefficients for the average implicit transaction costs by stock-period MPIDs during the trading day. The implicit transaction cost was calculated as the percentage difference between the transaction price and the end-of-day consolidated volume-weighted average price multiplied by 1 if the market participant bought the security and –1 if otherwise. T-statistics based on standard errors adjusted by heteroskedasticity are reported within parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Overall these results suggest that speed played a relatively minor role in determining market participants' order submission strategies while the market participants' business models appear very important in explaining traders' heterogeneous behaviour.

### 5.3.5 Conclusions

This study used an exogenous event, the tick size pilot program, to analyse the effects of speed and business models on market participants' trading and quoting behaviour.

Prior research supports the notion that the different business models of market participants generate intraday trading patterns by analysing the interaction of market markers, liquidity and informed traders. According to Anand et al. (2005), liquidity traders tended to use limit orders within the trading day and were compelled to use marketable orders close to the realisation of their demand. Conversely, informed traders took liquidity during the trading session and added liquidity towards the end of the day.

More recent papers focused on the effects of speed on market participants' trading behaviour by indicating that fast traders can use their speed advantage either opportunistically or to engage into market making strategies. In the former case, these market participants played an important role in ensuring the securities' price efficiency. In the latter case, fast traders improved market quality by narrowing the bid–ask spread. This current research fills the gap between these two streams of literature by analysing whether market participants' business models or their speed play a central role in explaining the order submission strategies of proprietary trading companies, banks and agency firms.

First, this analysis tested Yao and Ye's (2018) speculation by analysing whether a tick size consolidation encouraged proprietary traders to be at the front of the queue by setting the NBBO prices more frequently than the other market participants (H5). The results of this empirical analysis suggest that banks identifiers tended to increase by up to 16% the number of times they set a new NBBO price on securities with a pre-pilot bid–ask spread lower than $0.04 as the tick size consolidated.

Second, I tested H6 by examining whether banks' changes in price setting behaviour was associated with an increased proportion of their principal trading orders. The empirical evidence demonstrated that these market participants traded 70% of the time on behalf of their clients and their changed price setting behaviour was driven by the banks' agency business, suggesting that investors have access to the same innovative technology as proprietary trading companies.

Third, I focused on the market participant' groups intraday average order aggressiveness to understand whether proprietary trading companies, banks and agency firms acted as liquidity traders or informed traders as explained in H7. The results of this section indicated that bank and agency firm identifiers tended to submit a larger portion of aggressive orders towards the end of the day, regardless of the stocks' liquidity groups. However, proprietary trading companies tended to submit very aggressive orders within the trading day, while using more limit orders at the end of the trading session. These patterns suggest that both banks and agency firms behave as liquidity traders, while proprietary trading companies' order submission strategies recall the behaviour of informed traders (Anand, Chakravarty & Martell, 2005). Further, the differences in non-proprietary companies' order aggressiveness tended to shrink for securities with a pre-pilot spread higher than $0.11, suggesting that agency firms play a key role in illiquid securities.

Fourth, the difference-in-differences analysis of the market participants' intraday order aggressiveness for *very liquid* securities suggested that, because of the tick size pilot program, proprietary traders entered more limit orders at the beginning and end of the day, banks placed more aggressive orders during the trading session to minimise their execution costs and agency firms reduced their order aggressiveness regardless of the time of the day.

These results suggest that while banks had the same speed as proprietary traders, the policy change induced this type of non-proprietary trading company to take more liquidity throughout the trading day. Conversely, proprietary traders used their innovative technology to add liquidity when other market participants needed it. Therefore, Chapter 5's results encourage future researchers to care less about the effects of speed on market quality and to focus their future efforts in understanding the economics of the trading industry by segregating market participants based on their business models.

# Chapter 6: Tick Size Pilot and Heterogeneous High-Frequency Traders

This chapter examines whether different types of proprietary trading companies leverage their comparative advantages to maximise their trading revenues. As suggested by both the theoretical and empirical literature, I identify two classes of proprietary trading companies: (i) those who prevalently use marketable orders to opportunistically take liquidity and (ii) market makers. According to the current academic literature, opportunistic traders are specialised in processing information concerning the security's value, while market makers use its superior speed to be at the front of the queue, manage their inventory risk and reduce their adverse selection costs. The theoretical model developed by Li et al. (2018) introduces a homogeneous group of proprietary trading companies that decide whether to prevalently use marketable or limit orders based on the stock's characteristics and on the liquidity trader's arrival rate. In this framework, proprietary trading companies' willingness to supply or demand liquidity, also known as make–take spread, is highly sensitive to changes in relative tick size (Yao & Ye, 2018). However, this theoretical model does not account for market participants' heterogeneity. Our investigation adds new insights to the current academic literature by examining whether both opportunistic traders and market makers increased their liquidity provision on treatment securities since the beginning of the pilot program. The first hypothesis tested in this chapter is as follows:

H9: Both opportunistic and market maker high-frequency traders provide more liquidity on tick pilot stocks ex post consolidation.

The remaining hypotheses focus on understanding whether opportunistic and market making proprietary trading companies use different channels to maximise their expected pay-off given the exogenous change in tick size. The academic community has long established that proprietary trading companies improve price efficiency by opportunistically using marketable orders. This empirical evidence suggested that proprietary trading companies act as informed traders and maximise their trading profit by using their informational advantage over all other market participants. Baron et al. (2018) indicate that differences in speed explain the cross-sectional differences of proprietary trading companies' ability to trade on short-lived information and manage adverse selection risk. In this chapter, I hypothesise that opportunistic traders maximise their revenues by specialising either in avoiding informed traders or in taking advantage of short-term price movements. This is formalised in the following hypotheses:

H10: Opportunistic proprietary traders have higher per-share price impact than market makers for liquidity demanding orders ex post consolidation.

H11: Opportunistic proprietary traders have higher per-share realised spreads than market makers for liquidity supplying orders ex post consolidation.

Empirical research focused on the behaviour of fast market makers indicated that proprietary trading companies use their speed to reduce their inventory constraints, better manage their adverse selection costs and provide liquidity more aggressively (Brogaard, Hagströmer, Nordén & Riordan, 2015). Other theoretical and empirical papers portray them as rent extractors that try to capture the spread as many times as possible using their speed to crowd out non-proprietary trading companies (Ait-Sahalia & Sağlam, 2013; Li, Wang & Ye, 2018; Yao & Ye, 2018). The analysis conducted in this current study differs as it tests whether market makers specialise in capturing the spread more often than opportunistic proprietary traders on stocks with the bid–ask spread constrained by the minimum tick size ex post consolidation. Hence, the next hypotheses tested in this study are as follows:

H12: Market makers increase the number of times they capture the spread for tick pilot stocks with a large relative tick size ex post consolidation.

H13: Market makers set the NBBO more often than opportunistic proprietary traders *for* tick pilot securities with a large relative size ex post consolidation.

Finally, I examine the effects of competition among opportunistic and market maker proprietary trading companies on their trading revenues. The increased tick size should increase both realised spread on liquidity supplying orders and the price impact of marketable orders. Conversely, the increased competition among fast market participants may reduce the revenue per dollar traded. The academic literature thus far suggests that proprietary traders, in particular DMMs and SLPs, should increase their trading revenues on securities with the bid–ask spread constrained by the minimum tick size; however, this literature does not draw any conclusions regarding opportunistic proprietary traders (Li, Wang & Ye, 2018; O'Hara et al., in press; Yao & Ye, 2018). Therefore, the last hypothesis tested is:

H14: Both market makers *and* opportunistic proprietary trading companies increase their revenue per dollar traded *for* tick pilot securities ex post consolidation.

## 6.1 Data Description and Sample Selection

### 6.1.1 Data overview

This research uses both proprietary and publicly available data to examine HFT changes in trading behaviour caused by the tick size pilot program. The public data used for this research are derived from the SIP's NBBO quotes and trades information. Each quote message provides information about the following: the reference day, the stock ticker, timestamp, quote condition and the national best bid and ask prices. Each trade message contains the following: reference day, stock ticker, execution price, number of share executed, sale conditions and timestamp (Nasdaq Market Technology, 2018). Whenever manipulating the NBBO quotes, we consider messages that are active between 9:30 am and 4:00 pm and filter out those producing negative bid–ask spread values or with bid (ask) price equal to \$0.01 (\$199,999.99).

The proprietary data comprises all the exchange-level order submission, cancellation and execution messages generated on BX, PSX and Nasdaq from 1 April 2016 to 30 April 2017. The order submission and cancellation messages contain: the reference day, stock ticker, timestamp, buy–sell indicator, MPID, price, number of shares, the day-unique order reference number and the BBO weight indicator tracking whether a quote sets a new NBBO price. The execution messages provide information about the reference day, stock ticker, timestamp, buy–sell indicator, the MPID of the company that initiated the trade and the liquidity supplier's identity, the day-unique order reference number, the number of executed shares and the execution price (Nasdaq Trader, 2018). Further, I have access to information regarding the stock's total number of outstanding shares.

### 6.1.2 Sample selection

In line with the spirit of the pilot program, this study creates three samples of securities used to identify the changes in HFT trading behaviours for treatment securities. Following the recent literature on proprietary traders' activity regarding securities with a large relative tick size, I divide the 2319 securities into three classes: (i) securities with an average daily quoted spread lower than \$0.04 (*low quoted spread* group), (ii) securities with an average daily bid–ask spread higher than \$0.11 (*large quoted spread* group) and (iii) remaining stocks (*medium quoted spread* group). Similar to Huang and Stoll (1996), each treatment stock $i$ is matched to a control stock $j$ within its quoted spread group such as it minimises the following score:

$$score_{ij} = \left[\frac{Price_i - Price_j}{(Price_i + Price_j) \times 0.5}\right]^2 + \left[\frac{Mkt\ Cap_i - Mkt\ Cap_j}{(Mkt\ Cap_i + Mkt\ Cap_j) \times 0.5}\right]^2$$

*Price* is the closing price and *Mkt Cap* is the market value of the securities on 1 April 2016. If two treatment securities are matched with the same control stock, the pair with the highest score is excluded from the sample. Smith and Todd (2005) suggest that matching with replacement would increase the average quality of our matches, but increase the variance of the estimator.

Table 6.1 outlines that the lit trading volume of the securities included in our matched sample was executed mostly on Nasdaq's exchanges, suggesting that this analysis captures most of the lit activity on these stocks. Interestingly, securities in the *lo*w and *medium quoted spread* groups had similar market capitalisation and average daily consolidated dollar volume, but differed regarding the stock's price level. Therefore, I focus most of my attention on *low quoted spread* securities, as the new tick size regime is lower than the natural bid–ask spread, exacerbating the liquidity provider's need for speed (Yao & Ye, 2018). M*edium* and *high quoted spread* securities are used as robustness tests to ascertain whether the effects decreased with lower liquid securities.

**Table 6.1: Pre-Pilot Summary Statistics**

| Panel A: Bid–ask spread <$0.04 | Control | Treatment |
|---|---|---|
| Number of securities | 135 | 135 |
| Avg. market value | $670,495,104 | $675,358,325 |
| Avg. daily dollar volume | $4,862,815 | $5,444,449 |
| Avg. quoted spread (bps) | 37 | 37 |
| Avg. % Nasdaq lit market share | 57% | 57% |
| **Panel B: Bid–ask spread between $0.04 and $0.11** | **Control** | **Treatment** |
| Number of securities | 141 | 141 |
| Avg. market value | $646,787,927 | $642,108,744 |
| Avg. daily dollar volume | $5,028,496 | $4,969,889 |
| Avg. quoted spread (bps) | 78 | 81 |
| Avg. % Nasdaq lit market share | 59% | 59% |
| **Panel C: Bid–ask spread >$0.11** | **Control** | **Treatment** |
| Number of securities | 131 | 131 |
| Avg. market value | $452,212,768 | $454,955,496 |
| Avg. daily dollar volume | $2,624,063 | $2,280,583 |
| Avg. quoted spread (bps) | 236 | 227 |
| Avg. % Nasdaq lit market share | 60% | 60% |

*Note*. The pre-pilot summary statistics of the matched securities used in this research. Each security was matched using the methodology described in Huang and Stoll (1996).

As for the previous chapters, it is worth mentioning that the results of this analysis should be interpreted with caution. While I am confident that the findings hereby presented underestimate the true differences between the two market participant groups, our results cannot be used to assess the impact of the tick size pilot on market quality as Nasdaq data only cover 60% of the U.S. total lit trading activity.

### 6.1.3 Proprietary traders' description

The MPIDs attached to each message in the proprietary data are critical in this analysis as they are identified with certainty HFT trading activity. Similar to Baron et al.'s (2018) methodology, each high-frequency trader is classified based on their declared business model reported in the FOCUS filings available on the SEC's website. Consistent with the SEC's (2010) description of a proprietary trader, all companies that claim to strictly '*trade on their own account*' in their FOCUS report are classified as HFT. After retrieving the SEC reports for the 48 most active MPIDs—which represent 92.14% of the total traded volume on these three trading venues from 1 April 2016 to 31 April 2017)—I categorised 15 MPIDs as proprietary trading companies.

The empirical literature analysing the biodiversity of market participants further differentiates proprietary traders based on their trading statistics. The case study provided by Menkveld (2013) demonstrated that GETCO executes 70% (83%) of its trades through passive orders on Euronext (Chi-X), suggesting that this high-frequency trader acts commonly as a market maker. Likewise, Hangströmer and Nordén (2013) split high-frequency trading companies based on their percentage of liquidity supplied and the percentage of time that a proprietary trader is displaying both the best bid and the best offer. Benos and Sagade (2016) used market participants' median percentage of liquidity demanding trades on the LSE to split HFT into aggressive, neutral and passive.

In line with the previous empirical literature, the identified proprietary traders are classified as market makers if their pre-pilot median daily percentage of passive volume executed is higher than 80%.

**Table 6.2: Proprietary Traders' Distributions for the Average Daily Percentage of Passive Volume Execution**

| Class | Spread group | Average | St. Dev. | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|---|
| Market maker | Low | 74.30% | 30.51% | 0.00% | 60.00% | 85.07% | 100.00% | 100.00% |
| Market maker | Medium | 74.92% | 34.34% | 0.00% | 54.95% | 96.31% | 100.00% | 100.00% |
| Market maker | High | 80.09% | 31.39% | 0.00% | 71.82% | 100.00% | 100.00% | 100.00% |
| Opportunistic | Low | 41.43% | 34.76% | 0.00% | 7.25% | 35.98% | 69.98% | 100.00% |
| Opportunistic | Medium | 36.55% | 34.13% | 0.00% | 1.88% | 28.60% | 61.50% | 100.00% |
| Opportunistic | High | 37.63% | 36.83% | 0.00% | 0.00% | 27.80% | 67.35% | 100.00% |

*Note*. Distribution of the percentage of shares executed as liquidity suppliers per stock day MPID from 1 April 2016 to 1 October 2016.

Table 6.2 indicates that those MPIDs classified as market makers in this research resembled those described by Menkveld (2013), as their median daily percentage of shares executed passively never went below 80%, regardless of the stock quoted spread group. The summary statistics also suggest that opportunistic proprietary traders tended to passively execute their orders more frequently on *low quoted spread* securities, while their liquidity provision did not appear to be significantly different for the *medium* and *high quoted spread* groups. Conversely, market makers exhibited lower percentages of daily passively volume on securities with low bid–ask spread, while the ratio seemed higher for *high quoted spread* securities.

## 6.2 Methodology

This section presents the methodology used to examine the effects of the pilot changes on proprietary trading companies' trading strategies. This analysis uses a natural experiment, the tick size pilot program, and the access to Nasdaq databases to first examine the pre-pilot cross-sectional differences between opportunistic and market maker high-frequency traders and then examine on the effects of the program on the market participants across our samples. The remainder of this section is structured as follows: first, the econometrics models used to describe HFT and to test our hypothesis; second, an in-depth description of the variables of interest used to analyse market participants' trading behaviour.

### 6.2.1 Econometric model

This section discusses the econometric models used to analyse HFT behaviour. The pre-pilot cross-sectional differences between opportunistic and market maker proprietary trading companies are examined through fixed effects panel regression models. Logistic regressions are used on discretised variables strictly between zero and one. Mathematically, the models are as follows:

$$\bar{y}_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it} \tag{6.1}$$

$$\bar{y}_{it}^{mm} - \bar{y}_{it}^{op} = \alpha_i + \beta X_{it} + \varepsilon_{it} \tag{6.2}$$

$$d_i = \begin{cases} 1 \; if \; \bar{y}_i > 0.5 \\ 0 \; if \; \bar{y}_i \leq 0.5 \end{cases} \qquad d_i = \frac{e^{\beta \bar{X}_i + \varepsilon_i}}{1 + e^{\beta \bar{X}_i + \varepsilon_i}} \tag{6.3}$$

Equation 6.1 uses the groups' averages as a dependent variable calculated on each stock *i* for each trading day *t*, while Equation 6.2 measures the differences between market makers' and opportunistic traders' average trading performances. The dependent variable in Equation 6.3

represents a discretisation of daily average fractional data. The independent variables used in these models are as follows: the stock's fixed effects $a_i$, the natural logarithm of the trading volume, closing price and high–low volatility. The $\beta$s in the models effectively provide a means to examine the sensitivity of HFT strategies in relation to stock characteristics.

The correlation matrix between stocks' trading characteristics in Table 6.3 suggests that the three control variables used to examine market participant's trading strategies were not strongly correlated. Therefore, the regression analyses should not be affected by multicollinearity problems (Greene, 2010).

**Table 6.3: Correlation Matrix of the Stock Characteristics**

| | Ln(Volume+1) | Ln(Last Price) | Ln($ Quoted spread) | Ln(High Low volatility+1) |
|---|---|---|---|---|
| Ln(Volume+1) | 1.000 | 0.123 | –0.567 | 0.252 |
| Ln(Last Price) | 0.123 | 1.000 | 0.422 | –0.312 |
| Ln($ Quoted spread) | –0.567 | 0.422 | 1.000 | –0.101 |
| Ln(High Low volatility+1) | 0.252 | –0.312 | –0.101 | 1.000 |

*Note*. This correlation matrix is computed using stock's volume, dollar quoted spread, last sale price and high–low volatility from 1 April 2016 to 30 April 2017. Since the analysis employs the natural logarithm for most of the variables, we implicitly excluded all observations in which the trading volume was zero.

The natural experiment provided by the SEC is designed to clearly establish a causal link between the incentives introduced by the pilot program and changes in market participants' trading strategies by testing the hypotheses through difference-in-differences analysis. Mathematically, this econometric model is structured as follows:

$$\bar{y}_{it} = \alpha_i + \beta_1 Post_t + \beta_2 (Post_t \times Group) + \varepsilon_{it} \tag{6.4}$$

$$\bar{y}_{it}^{op} - \bar{y}_{it}^{mm} = \alpha_i + \beta_1 Post_t + \beta_2 (Post_t \times Group) + \varepsilon_{it} \tag{6.5}$$

Equation 6.4 analyses the average of the variable of interest *y* calculated on each stock *i* for each trading day *t*, while Equation 6.5 measures the differences between opportunistic traders' and market makers' average trading performances. Further, the control variables of this regression model are as follows: the stock's fixed effects $a_i$, a dummy variable $Post_t$ that equals 1 if the securities start trading in nickels and 0 if otherwise, and the dummy variable *Group* that equals 1 for treatment securities and 0 if otherwise. The interaction variable between time and group dummies ascertains the causal effect of the increased tick size on the analysed measures.

Consistent with Petersen (2009) and Thompson (2011), all standard errors for the linear models are double clustered by stock and reference day.

### 6.2.2 Variables of interest

This section describes and discusses the variables used to test the six hypotheses formulated in the previous sections.

The first hypothesis tested in this research involves the definition of voluntary market making. Hangströmer and Nordén (2013) appeared to provide the first empirical analysis to distinguish HFT between market makers and non-market makers. Their work analysed the 30 largest stocks trading on the Nasdaq OMX Stockholm between 2011 and 2012, and suggested that voluntary market making can be detected by looking at the market participant's presence at both sides of the book and at its liquidity supply. Further, theoretical papers indicated that the value of market making came primarily from their intermediation services towards impatience liquidity traders (Ait-Sahalia & Sağlam, 2013; Grossman & Miller 1988; Jovanovic & Menkveld, 2016). Following these speculations, the first hypothesis is as follows:

$$Liquidity\ Supply_{mit} = \frac{Passive\ volume_{mit}}{Total\ volume_{mit}} \tag{6.5}$$

$$\%\ BBO\ presence_{mit} = \frac{\sum_{b=1}^{13} Displaying\ NBBO_{mibt}}{13} \tag{6.6}$$

$$Intermediation_{mit} = \frac{Passive\ volume\ with\ non\ HFT_{mit}}{Total\ volume_{it}} \tag{6.7}$$

Equation 6.5 uses only the execution data to measure the percentage of passive volume executed by each market participant *m* on stock *i* during the trading day *t*. Instead, *the % BBO presence* is calculated by matching *b* snapshots taken every 30 minutes for all available displayed orders in the three order books with the official NBBO displayed on SIP during the same time period. If the proprietary trading company is quoting at both the national best bid and at the national best offer, the dummy variable *Displaying NBBO* equals 1. The market participant's presence is defined as the average of the number of times that the market participant *m* is displaying the NBBO within a trading day. Compared to Hangströmer and Nordén (2013), Equation 6.6 uses a smaller number of snapshots on a larger sample size for number of securities and time frame. Hence, it should provide an effective market making proxy. The last variable of interest used to test H9 is the percentage of liquidity supplying shares executed by each proprietary trading company against non-high-frequency trading companies on stock *i* during the trading day *t*. Based on the theoretical literature, the tick size consolidation should affect the so-called make–take spread (Li, Wang & Ye, 2018), incentivising both opportunistic and market maker HFT to increase their liquidity supply and their presence on top of the book.

H10 and H11 test whether opportunistic proprietary traders are better at predicting short-term price movements and at managing adverse selection risk than market makers. These two channels, according to Baron et al. (2018), can be measured with the following two equations:

$$Price\ impact = \sum \frac{volume\ \times side \times \frac{(midpoint_{t+i} - midpoint_t)}{midpoint_t}}{volume} \tag{6.8}$$

$$Realized\ spread = \sum \frac{volume\ \times side \times \frac{(price_t - midpoint_{t+i})}{midpoint_t}}{volume} \tag{6.9}$$

Most of the indexes are suppressed in the above equations to facilitate the reader's understanding of the two metrics. Equation 6.8 measures the volume-weighted change in midpoint price *i* seconds after each transaction initiated by a proprietary trading company within a trading day. The indicator *side* equals 1 if the buy–sell indicator signals a buy order and –1 if otherwise. If a high-frequency trader can (cannot) predict short-term price movements, its average price impact should be positive (negative). Similarly, Equation 6.9 measures the volume-weighted difference between the order's execution price and the midpoint price *i* seconds after each liquidity supplying transaction within a trading day. If a proprietary trader can (cannot) effectively manage the adverse selection risk, its average realised spread should be positive (negative). The measures reported in Equations 6.8 and 6.9 are calculated for each market participant group, security and trading day using both SIP NBBO prices and the execution prices reported in Nasdaq's proprietary data. Price impacts and realised spreads higher than 5% and those stock day combinations in which it is not possible to observe these measures for both market makers and opportunistic traders were excluded from the sample. The theoretical models suggest that opportunistic HFT order flow was positively correlated with news, while marker makers optimally set their quotes to gain a positive profit for supplying liquidity. Thus, opportunistic traders should be better at predicting short-term price movements, but not at handling adverse selection costs.

Inspired by Ait-Sahalia and Sağlam (2013), H12 and H13 ascertain whether market making HFT use their speed to set the NBBO to capture the bid–ask spread as much as possible. The key measures necessary to test those hypotheses are the total number of shares executed and the so-called queue speed, which is mathematically expressed as:

$$\text{queue speed}_{\text{mit}}^{\text{G}} = \frac{\text{\# NBBO set updates}_{\text{mit}}^{\text{G}}}{\text{\# NBBO set updates}_{\text{it}}} \tag{6.10}$$

This measures the number of times the NBBO is set by the market participant *m* belonging to the proprietary trading group *G* relative to the total number of NBBO set by any high-frequency trading company on stock *i* over the trading day *t*. Based on the theoretical model, the tick size pilot program should induce market making proprietary traders to be at the front of the queue more frequently for low quoted spread securities and capture more the bid–ask spread more frequently.

Lastly, O'Hara et al. (in press) suggest that an increased tick size should be mostly beneficial for DMMs and SLPs, and detrimental for quantitative traders and agency firms. However, the reported analysis does not consider that some of the quantitative traders (opportunistic traders) may switch from consuming liquidity to providing it, as suggested by Li et al. (2018), Hence, H14 examines whether both classes of HFT increase their revenues on treatment securities. In line with Carrion (2013), the revenue per dollar traded for each group is calculated as follows:

$$Revenues_{git} = \frac{\left(Sell\,VWAP_{git} - Buy\,VWAP_{git}\right) \times max\left(Sell\,volume_{git}, Buy\,volume_{git}\right.}{dollar\,volume_{git}} \tag{6.11}$$

*VWAP* stands for volume-weighted average price. By assuming that each proprietary trading company group *g* executes the difference between the buy and sell volume on other exchanges, the revenue can be decomposed into the difference between sell and buy volume-weighted average price and the volume of business on stock *i* during the trading day *t* divided by the total value traded. All observations in which either the buy or sell volume was equal to zero were removed from the sample. If competition among liquidity suppliers increased on the tick pilot stocks, market makers or opportunistic traders may have lower revenues from trading those securities. Conversely, if non-proprietary trading companies are crowded out from posting liquidity, HFT revenues per dollar traded should increase.

The next section presents the results of this paper's empirical investigation and outlines the trading behaviour of different classes of market participants.

## 6.3 Empirical Findings

This section presents the empirical findings of this chapter. Each group of hypotheses is presented in its own subparagraph, providing summary statistics, pre-pilot cross-sectional analysis and difference-in-differences analysis for each variable of interest.

### 6.3.1 Proprietary trading companies and market making

This section empirically tests H9. According to Li et al. (2018), a thicker tick size affects proprietary traders' make–take spread, which is the price difference between their willingness to supply liquidity and their willingness to demand liquidity, incentivising them to use their speed to be at the front of the queue to earn the spread.

Table 6.4 reports the pre-pilot summary statistics of the variables of interests that are used to proxy for market maker behaviour. The summary statistics indicate that market makers' liquidity supplied in this sample represented less than 0.5% of the total trading volume. They almost never quoted at both the national best bid and the national best offer, but they still executed more than 70% of their orders through passive orders, regardless of the stocks' quoted spread group. Conversely, opportunistic proprietary trading companies represented approximately 5% of the total liquidity supplied to liquidity traders across the three samples. They tended to quote at the NBBO more frequently on low quoted spread securities while they seemed to avoid the high quoted spread and used only 40% of passive orders to execute their trading strategies.

**Table 6.4: Pre-Pilot Summary Statistics: Market Making Variables**

| | Low quoted spread | | Medium quoted spread | | High quoted spread | |
|---|---|---|---|---|---|---|
| | Market makers | Opportunistic | Market makers | Opportunistic | Market makers | Opportunistic |
| % Passive volume | 73.29% | 42.92% | 73.70% | 39.79% | 79.35% | 42.02% |
| | (0.25) | (0.17) | (0.30) | (0.21) | (0.28) | (0.28) |
| % BBO presence | 0.11% | 1.39% | 0.01% | 0.18% | 0.00% | 0.20% |
| | (0.01) | (0.02) | (0.00) | (0.00) | (0.00) | (0.01) |
| % Intermediation | 0.46% | 6.94% | 0.16% | 5.00% | 0.06% | 4.76% |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

*Note*. The pre-pilot sample daily averages of the market making proxies used to test *H1. The variable % Passive volume* was the proportion of passive shares executed by each proprietary trading company, *% BBO presence* measured the percentage of times a high-frequency trader displayed both the national best bid and the national best offer and *% Intermediation* represented the percentage of passive volume traded against non-proprietary traders over the total number of shares traded by all market participants. Standard deviations are reported in parentheses.

**Table 6.5a: Logistic Regression for the Percentage of Passive Volume Per Market Participant Identifier**

| | Market makers | | Opportunistic proprietary traders | |
|---|---|---|---|---|
| | Coefficients | Marginal effects | Coefficients | Marginal effects |
| Intercept | –14.92 | | 7.32 | |
| | (3.03)*** | | (1.51)*** | |
| Ln(volume+1) | 1.87 | 0.14 | –0.44 | –0.06 |
| | (0.26)*** | (0.02)*** | (0.08)*** | (0.01)*** |
| Ln(price) | 0.38 | 0.03 | –1.86 | –0.24 |
| | (0.19)** | (0.02)* | (0.20)*** | (0.02)*** |
| Ln(high–low volatility+1) | 1.79 | 0.14 | –0.23 | –0.03 |
| | (0.43)*** | (0.03)*** | (0.29) | (0.04) |
| Loglikelihood | –182.48 | | –318.15 | |
| Obs. | 597 | | 814 | |

*Note*. The results of the logistic regression analysis on the discretised percentage of passive volume. The dependent variable equalled 1 if the pre-pilot average daily proportion of passive orders per proprietary trader group was higher than 0.5 and 0 if otherwise. The independent variables were as follows: the average daily volume, the average last sale price and the average high–low volatility from 1 April 2016 to 1 October 2016. White's standard errors are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

A cross-sectional examination of the two groups suggests that their liquidity provision strategies were strongly sensitive to a stock's characteristics. Table 5a indicates that the likelihood for a proprietary trading company of being a net liquidity supplier was strongly influenced by the stock's average daily volume, last sale price and high–low volatility. Consistent with Hangströmer and Nordén (2013), market makers appeared to be net liquidity suppliers on high volume and high volatility securities as those tended to have higher profitability and lower adverse selection costs. Opportunistic HFT tended to be net liquidity suppliers for low volume and low price securities. The magnitude of the marginal effect of the last sale price (–0.24) suggests that stock price level strongly influenced opportunistic traders' liquidity provisions, as previously suggested by Yao and Ye (2018).

Table 6.5b indicates that market makers' and opportunistic traders' *% BBO presence* and *% intermediation* sensitivities to stock characteristics had the same signs, but differed in magnitude. Proprietary trading companies appeared to quote at the NBBO and supply liquidity to non-high-frequency trading companies for high volume securities, while they tended to reduce their presence for volatile and high-priced stocks. Nonetheless, the differences between the two groups of proprietary traders appeared to be high on low volume, high price and volatile securities, while they appeared to be low on high volume and low price stocks.

**Table 6.5b: Panel Regressions Analysis of Proprietary Trading Companies' Market Making Proxies**

| | *Ln(% BBO presence+1)* | | | *Ln(% intermediation+1)* | | |
|---|---|---|---|---|---|---|
| | Market makers (1) | Opportunistic (2) | Difference (2)-(1) | Market makers (1) | Opportunistic (2) | Difference (2)-(1) |
| Ln(volume+1) | 0.0004 | 0.0031 | 0.0027 | 0.0013 | 0.0050 | 0.0037 |
| | (0.0001)*** | (0.0004)*** | (0.0003)*** | (0.0001)*** | (0.0004)*** | (0.0004)*** |
| Ln(last price) | –0.0004 | –0.0042 | –0.0038 | –0.0003 | –0.0107 | –0.0104 |
| | (0.0002)** | (0.0007)*** | (0.0006)*** | (0.0001)*** | (0.0008)*** | (0.0008)*** |
| Ln(Volatility+1) | –0.0152 | –0.1040 | –0.0887 | –0.0262 | –0.0581 | –0.0318 |
| | (0.0056)*** | (0.0164)*** | (0.0127)*** | (0.0030)*** | (0.0170)*** | (0.0160)** |
| Fixed effects | Stocks | Stocks | Stocks | Stocks | Stocks | Stocks |
| Adjusted $R^2$ | 0.0227 | 0.1285 | 0.1174 | 0.2019 | 0.0499 | 0.0399 |
| N. Observations | 100,079 | 100,079 | 100,079 | 98,925 | 98,925 | 98,925 |

*Note*. The results of six panel regressions for two market making proxies: the *% BBO presence* and the *% intermediation*. The former represented the average number of times a MPID quoted at the NBBO. The latter measured the percentage of passive volume executed against non-proprietary trading companies. The control variables were as follows: the total traded volume, last sale price and the high–low volatility. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively. All metrics were calculated from 1 April 2016 to 1 October 2016.

Overall, the summary statistics and the cross-sectional analysis of the HFT indicated that market makers tended to be more active on liquid securities while opportunistic traders provided liquidity on low priced securities. The difference-in-differences analysis enables us to test the dynamic behaviour of these two classes of market participants when facing a market microstructure change.

As Table 6.6a indicates, both market makers and opportunistic proprietary trading companies increased their liquidity supply on liquid tick pilot stocks. Conversely, their trading behaviour tended to diverge on *high quoted spread* securities. Market makers consistently increased their liquidity provision, while opportunistic traders did not change their order submission strategies on tick pilot stocks.

Further, market makers increased their liquidity provision for *low quoted spread* securities by 11.1%, 14.0% and 12.5% for *G1*, *G2* and *G3*, respectively, while the opportunistic traders increased their liquidity supply only by 5.6%, 4.8% and 12.3% for the same sample groups, respectively. These results suggest that the tick size increase per se has a stronger effect on market makers, whereas the trade-at rule, which induces more order flow to move from the dark to the lit market (Lin, Swan & Mollica, 2018), represents a stronger incentive to post liquidity for opportunistic traders.

**Table 6.6a: Difference-in-Differences Analysis for the Proportion of Passive Orders Used by Proprietary Traders**

| *Panel A: Low quoted spread* | Market makers | | | Opportunistic traders | | |
|---|---|---|---|---|---|---|
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | –0.022 | –0.033 | –0.017 | 0.046 | 0.032 | 0.048 |
| | (0.011)*** | (0.012)*** | (0.014) | (0.01)*** | (0.01)*** | (0.008)*** |
| Post X Group | 0.111 | 0.140 | 0.125 | 0.056 | 0.048 | 0.123 |
| | (0.018)*** | (0.017)*** | (0.021)*** | (0.013)*** | (0.012)*** | (0.011)*** |
| Fixed effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.01 | 0.03 | 0.02 | 0.07 | 0.04 | 0.17 |
| Observations | 17,521 | 18,063 | 21,261 | 22,736 | 22,544 | 27,581 |
| *Panel B: Medium quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | –0.036 | –0.070 | –0.029 | 0.047 | 0.063 | 0.058 |
| | (0.017)*** | (0.020)*** | (0.027) | (0.007)*** | (0.006)*** | (0.008)*** |
| Post X Group | 0.147 | 0.169 | 0.137 | 0.043 | 0.034 | 0.085 |
| | (0.026)*** | (0.027)*** | (0.037)*** | (0.010)*** | (0.010)*** | (0.012)*** |
| Fixed effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.02 | 0.02 | 0.01 | 0.04 | 0.04 | 0.08 |
| Observations | 12,578 | 15,945 | 10,257 | 21,218 | 32,183 | 20,176 |
| *Panel C: High quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | –0.079 | –0.054 | –0.024 | 0.048 | 0.060 | 0.054 |
| | (0.031)*** | (0.033)*** | (0.025) | (0.009)*** | (0.009)*** | (0.008)*** |
| Post X Group | 0.222 | 0.130 | 0.063 | 0.005 | –0.023 | 0.007 |
| | (0.057)*** | (0.044)*** | (0.036)* | (0.015) | (0.014)* | (0.014) |
| Fixed effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| Observations | 4,216 | 4,119 | 6,528 | 16,582 | 16,110 | 19,621 |

*Note*. The results of the difference-in-differences regression model on proprietary traders' proportions of passive orders. The dependent variable measured the average liquidity supplying shares executed divided by the total MPID volume. The dependent variables were as follows: a dummy variable *Post* equals 1 if the securities start trading in nickels and 0 if otherwise and the dummy variable *Group* equals 1 for treatment securities and 0 if otherwise. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Similar results are provided in Table 6.6b, in which the tick size pilot program homogeneously increased the market makers' BBO presence across all treatment securities. Regarding the pre-pilot presence on these securities, the 1.5% increase represented a strong and significant increase in presence for market makers to provide liquidity on all securities affected by the program. Opportunistic traders quoted at the NBBO more frequently only on *low quoted spread* securities in which the yield on market making strategies increased the most and on the securities subject to the trade-at rule.

## Table 6.6b: Difference-in-Differences Analysis for Proprietary Traders' Percentage of BBO Presence

| *Panel A: Low quoted spread* | Market makers | | | Opportunistic traders | | |
|---|---|---|---|---|---|---|
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.000 | 0.001 | 0.001 | –0.002 | –0.002 | 0.004 |
| | (0.000) | (0.001)*** | (0.001) | (0.003) | (0.002)*** | (0.002)*** |
| Post X Group | 0.018 | 0.025 | 0.014 | 0.030 | 0.032 | 0.043 |
| | (0.002)*** | (0.002)*** | (0.002)*** | (0.005)*** | (0.003)*** | (0.004)*** |
| Fixed effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.15 | 0.18 | 0.09 | 0.17 | 0.21 | 0.29 |
| Observations | 22,848 | 22,848 | 27,744 | 22,848 | 22,848 | 27,744 |
| *Panel B: Medium quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 | 0.001 |
| | (0.000) | (0.000) | (0.000) | (0.000)*** | (0.000)*** | (0.000)*** |
| Post X Group | 0.012 | 0.011 | 0.009 | 0.015 | 0.014 | 0.013 |
| | (0.002)*** | (0.001)*** | (0.002)*** | (0.002)*** | (0.001)*** | (0.002)*** |
| Fixed effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.10 | 0.11 | 0.09 | 0.22 | 0.22 | 0.20 |
| Observations | 21,760 | 33,728 | 21,216 | 21,760 | 33,728 | 21,216 |
| *Panel C: High quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.000 | 0.000 | 0.000 | 0.002 | 0.001 | 0.001 |
| | (0.000) | (0.000) | (0.000) | (0.000)*** | (0.000)*** | (0.000)*** |
| Post X Group | 0.003 | 0.002 | 0.002 | 0.003 | 0.003 | 0.005 |
| | (0.001)*** | (0.000)*** | (0.000)*** | (0.001)*** | (0.001)*** | (0.001)*** |
| Fixed effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.03 | 0.02 | 0.03 | 0.05 | 0.03 | 0.06 |
| Observations | 22,848 | 22,304 | 26,112 | 22,848 | 22,304 | 26,112 |

*Note*. The results of the difference-in-differences regression model on proprietary traders' proportion of passive orders. The dependent variable measured the average liquidity supplying shares executed divided by the total MPID volume. The dependent variables were as follows: a dummy variable *Post* equals 1 if the securities start trading in nickels and 0 if otherwise and the dummy variable *Group* equals 1 for treatment securities and 0 if otherwise. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

With the previous results in mind, it is easy to ascertain that the percentage of liquidity supplied to non-HFT increases for both market makers and opportunistic traders on *low quoted spread* securities as these market participants are quoting more frequently at the NBBO and supplying more liquidity. Table 6.6c confirms that the tick size pilot induced market makers to intermediate greater volume with non-proprietary trading companies on all treatment groups, while opportunistic traders increased their share of passive volume executed with liquidity traders only on *low quoted spread* stocks with an emphasis on *Group 3* equities.

**Table 6.6c: Difference-in-Differences Analysis for the Proprietary Traders' Percentage Intermediation**

| *Panel A: Low quoted spread* | Market makers | | | Opportunistic traders | | |
|---|---|---|---|---|---|---|
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.000 | 0.000 | 0.000 | –0.001 | –0.003 | 0.005 |
| | (0.000) | 0.000 | (0.001) | (0.003) | (0.003) | (0.002)*** |
| Post X Group | 0.016 | 0.018 | 0.010 | 0.010 | 0.006 | 0.020 |
| | (0.001)*** | (0.001)*** | (0.002)*** | (0.004)*** | (0.004)*** | (0.003)*** |
| Fixed effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.23 | 0.27 | 0.13 | 0.00 | 0.00 | 0.05 |
| Observations | 22,839 | 22,811 | 27,739 | 22,839 | 22,811 | 27,739 |
| *Panel B: Medium quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.000 | 0.000 | 0.000 | 0.010 | 0.011 | 0.008 |
| | (0.000)*** | (0.000)*** | (0.000) | (0.002)*** | (0.002)*** | (0.002)*** |
| Post X Group | 0.017 | 0.017 | 0.017 | 0.001 | –0.001 | 0.009 |
| | (0.001)*** | (0.001)*** | (0.002)*** | (0.003) | (0.003) | (0.003)*** |
| Fixed effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.22 | 0.20 | 0.22 | 0.01 | 0.01 | 0.01 |
| Observations | 21,681 | 33,403 | 20,884 | 21,681 | 33,403 | 20,884 |
| *Panel C: High quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.000 | 0.000 | 0.000 | 0.015 | 0.014 | 0.010 |
| | (0.000)*** | (0.000)*** | (0.000) | (0.002)*** | (0.003)*** | (0.002)*** |
| Post X Group | 0.010 | 0.009 | 0.009 | –0.004 | –0.007 | –0.002 |
| | (0.001)*** | (0.001)*** | (0.001)*** | (0.004) | (0.004)* | (0.003) |
| Fixed effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.06 | 0.05 | 0.09 | 0.00 | 0.00 | 0.00 |
| Observations | 19,997 | 19,733 | 23,339 | 19,997 | 19,733 | 23,339 |

*Note*. The results of the difference-in-differences regression model for proprietary traders' percentage of volume traded against non-HFT. The dependent variable measured the average liquidity supplying shares executed against non-proprietary trading companies divided by the total traded volume. The independent variables were as follows: a dummy variable *Post* equals 1 if the securities start trading in nickels and 0 if otherwise and the dummy variable *Group* equals 1 for treatment securities and 0 if otherwise. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Overall, these results suggest that changes in market structure, which incentivise voluntary market making, led all types of HFT to supply more liquidity for *low quoted spread* securities. Only proprietary traders specialised in market making tended to increase their liquidity provision on all treatment stocks regardless of their quoted spread group. The next sections focus on whether opportunistic traders and market makers are specialised in certain types of trading strategies and use their competitive advantages to maximise their expected profits from market making.

### 6.3.2 Tick size pilot and opportunistic traders

Inspired by the recent literature regarding informed HFT, this section analyses whether opportunistic traders are, on average, better at processing information compared to market makers (Foucault, Hombert & Rosu, 2016; Foucault, Kohzan & Tham, 2017; Menkveld & Zoiacan, 2017). In line with

Baron et al. (2018), price impact and realised spread are used as proxies for information processing. The price impact of liquidity taking orders measured the ability of a proprietary trading company to predict short-term price movements. The realised spread of liquidity supplying orders measured the ability of a market participant to provide liquidity when needed. Market making is profitable if the effective spread earned by the liquidity supplier is higher than the price impact of liquidity taking orders, which generates a positive realised spread.

These two measures can vary based on the chosen time horizon, which may lead to different conclusions based on this discretionary choice. As robustness tests, both price impact and realised spread are calculated using available NBBO midpoint prices 1, 5 and 10 seconds after each transaction that is executed by both types of proprietary trading companies.

Table 6.7 indicates that the average pre-pilot 5-second price impact was negatively correlated with the quoted spread for market makers as it equalled 4.40, 2.88 and 1.67 basis points for *low*, *medium* and *high quoted spread* stocks, respectively. Similarly, opportunistic traders' average 5-second price impact was 11.54 basis points for the *low quoted spread* group and equalled approximately 8.70 basis points across the remaining liquidity groups. The average pre-pilot 5-second realised spread tended to increase with the security's dollar quoted spread for opportunistic proprietary traders as they earned 0.53, 2.38 and 3.91 basis points on *low*, *medium* and *high quoted spread* securities, respectively. Market makers tended to earn more than 2 basis points per share for the low and high quoted spread groups, while their 5-second realised spread tended to be only 1.82 basis points on *medium quoted spread* stocks. As the *low* and *medium quoted spread* groups had similar market capitalisations and differed by price levels, this result implies that the yield of liquidity supplying strategies is low on high priced stocks and high on low priced stocks, as documented by Lepone and Wong (2017).

Further, Table 6.7 indicates that, by construction, price impacts tended to grow with the time horizon chosen, while realised spreads tended to decrease. The effects of the time horizon seem inconsistent only when measuring the average market makers' price impact on high quoted spread securities. Nonetheless, this inconsistency is irrelevant when testing H10 and H11, as the difference in price impacts and realised spreads among the two proprietary trader groups were consistent across all our samples.

**Table 6.7: Pre-Pilot Summary Statistics: Price impact and Realised Spread (bps)**

| | Low quoted spread | | Medium quoted spread | | High quoted spread | |
|---|---|---|---|---|---|---|
| | Market maker | Opportunistic | Market maker | Opportunistic | Market maker | Opportunistic |
| One second price impact | 4.20 | 10.81 | 2.52 | 7.77 | 1.80 | 7.79 |
| | (9.94) | (8.82) | (11.31) | (7.54) | (12.57) | (7.23) |
| Five seconds price impact | 4.40 | 11.54 | 2.88 | 8.63 | 1.67 | 8.77 |
| | (11.03) | (9.61) | (14.22) | (8.75) | (13.27) | (7.91) |
| Ten seconds price impact | 4.53 | 11.97 | 2.94 | 9.09 | 1.75 | 9.25 |
| | (11.87) | (10.1) | (15.4) | (9.07) | (14.35) | (7.90) |
| One second realised spread | 2.49 | 1.02 | 2.21 | 3.14 | 3.31 | 4.72 |
| | (10.52) | (7.00) | (16.6) | (8.15) | (17.24) | (8.31) |
| Five seconds realised spread | 2.34 | 0.53 | 1.82 | 2.38 | 2.74 | 3.91 |
| | (11.21) | (7.26) | (18.27) | (9.69) | (17.42) | (8.47) |
| Ten seconds realised spread | 2.23 | 0.26 | 1.57 | 1.89 | 2.32 | 3.37 |
| | (12.01) | (7.38) | (18.5) | (10.18) | (19.10) | (9.03) |

*Note*. The pre-pilot sample daily averages *price impacts* and *realised spreads* used to test *H2* and *H3*. *Price impact* represented the volume-weighted difference between the midpoint price immediately before and 1, 5 and 10 seconds after each trade multiplied by 1 if the market participant was buying the security and –1 if otherwise. *Realised spread* was the volume-weighted difference between the transaction price and the midpoint price 1, 5 and 10 seconds after each trade multiplied by 1 if the market participant was buying the security and –1 if otherwise. Both measures are relative to the pre-trade midpoint price and are expressed in basis points. *Price impacts* were calculated from the perspective of the liquidity consumer, while *realised spreads* were computed on liquidity supplying orders. Standard deviations are reported in parentheses.

Overall, Table 6.7 indicates that opportunistic traders were, on average, better at predicting short-term price movements and managing adverse selection costs in most of the samples, while market makers exhibited higher pre-pilot realised spreads on low quoted spread securities.

The cross-sectional analysis demonstrated that stock characteristics affect market makers' and opportunistic traders' 5-second priced in the same way. Indeed, the coefficients for both groups were associated negatively with the stock's trading volume and price, while the estimated effect of volatility on price impact was positive. These results are consistent with the idea that proprietary trading companies tend to predict or create strong short-term price changes for low price or low volume securities, while the opposite is true for heavily traded or pricy stocks.

Table 6.8 also indicates that the magnitude of each coefficient greatly differed among the two market participant groups and it was consistently larger in absolute value for the opportunistic traders. This result is possibly due to the differences in the distribution of the 5-second price impact among the two market participants groups, as this measure's average and standard deviations were consistently higher for opportunistic traders.

**Table 6.8: Panel Regressions for the 5-Second Price impacts and Realised Spreads**

| | Volume-weighted 5 seconds price impact (bps) | | | Volume-weighted 5 seconds realised spread (bps) | | |
|---|---|---|---|---|---|---|
| | Market makers (1) | Opportunistic (2) | Difference (2)–(1) | Market makers (1) | Opportunistic (2) | Difference (2)–(1) |
| Ln(volume+1) | –0.990 | –2.172 | –1.182 | –2.966 | –2.347 | 0.619 |
| | (0.184)*** | (0.193)*** | (0.206)*** | (0.278)*** | (0.165)*** | (0.212)*** |
| Ln(last price) | –2.446 | –4.723 | –2.277 | –1.810 | 0.273 | 2.085 |
| | (0.155)*** | (0.262)*** | (0.241)*** | (0.195)*** | (0.119)*** | (0.178)*** |
| Ln(Volatility+1) | 75.559 | 134.946 | 59.387 | 53.917 | 5.700 | –48.196 |
| | (9.411)*** | (6.837)*** | (10.886)*** | (12.344)*** | (7.196)*** | (11.412)*** |
| Fixed Effects | Stock | Stock | Stock | Stock | Stock | Stock |
| Adjusted $R^2$ | 0.061 | 0.389 | 0.038 | 0.042 | 0.052 | 0.023 |
| N. Observations | 31,916 | 31,916 | 31,916 | 40,709 | 40,709 | 40,709 |

*Note*. The results of six panel regressions for two information processing proxies: the *5-second price impact* and the *5-second realised spread*. *Price impact* represented the volume-weighted difference between the midpoint price immediately before and 5 seconds after each trade. *Realised spread* was the volume-weighted difference between the transaction price and the midpoint price 5 seconds after each trade. Both measures are relative to the pre-trade midpoint price and are expressed in basis points. *Price impacts* were calculated from the perspective of the liquidity consumer, while *realised spreads* were computed for liquidity supplying orders. The control variables were as follows: the traded volume, last sale price and the high–low volatility. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively. All metrics were calculated from 1 April 2016 to 1 October 2016.

Conversely, the panel regressions suggest that the sensitivity of the realised spreads to the stock price differed among the two types of proprietary trading companies. Consistent with Table 6.7, market makers tended to extract a high (low) per share yield from low (high) priced stocks, while the opposite was true for opportunistic traders. Therefore, the coefficient estimated on the last sale price was negative (–1.810) for market makers and positive (0.273) for opportunistic traders. Conversely, both groups extracted high (low) realised spreads on stocks with either low (high) trading volume or high (low) high–low volatility. Regarding the price impact, the differences in variability among the two groups' realised spreads observed in the summary statistics explains the difference in magnitude of the coefficients associated with the stock characteristics.

Table 6.9 examines the effects of the tick size pilot program on the differences between opportunistic traders' and market makers' information processing skills. First, the positive signs of the interaction variables in Panel A suggest that the differences in information processing pay-off between opportunistic traders and market makers are now significantly higher than before. Interestingly, opportunistic traders' advantage in price impact increases with the stock's regulatory constraints. The differences between the two groups were 5, 7 and 12 basis points higher for G1, G2 and G3, respectively. The differences in realised spreads surged by 3 basis points for all treatment stocks. As the average pre-pilot difference in the realised spread is approximately –2 basis points, these results suggest that opportunistic traders are now capable of extracting at least the same yield on liquidity supplying strategies as market markers. Panel B demonstrates that the effect of the tick size consolidation strongly affected the price impact as the difference-in-differences coefficients were positive and statistically significant. The results regarding the differences in realised spreads among the proprietary trading companies groups for the medium quoted spread securities were not consistent nor were strongly significant, suggesting that the yield on liquidity supplying strategies changes only on tick-constrained securities. These patterns are confirmed in Panel C, as the differences in pay-offs for high quoted spread securities did not change significantly across the three treatment groups.

**Table 6.9: Difference-in-Differences Regressions for the Difference Between Opportunistic Traders' and Market Makers' Price impact and Realised Spread**

| *Panel A: Low quoted spread* | Volume-weighted price impact (bps) | | | Volume-weighted realised spread (bps) | | |
|---|---|---|---|---|---|---|
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.644 | 0.557 | 0.666 | 0.273 | 0.808 | 1.043 |
| | (0.654) | (0.384) | (0.554) | (0.500) | (0.366)** | (0.581)* |
| Post X Group | 5.055 | 7.468 | 12.765 | 3.324 | 3.069 | 3.185 |
| | (1.246)*** | (1.380)*** | (1.454)*** | (1.352)*** | (0.852)*** | (0.984)*** |
| Fixed effects | Stocks | Stocks | Stocks | Stocks | Stocks | Stocks |
| Adj. $R^2$ | 0.004 | 0.020 | 0.042 | –0.001 | 0.002 | 0.002 |
| Observations | 14,297 | 15,128 | 16,928 | 17,066 | 17,680 | 20,744 |
| *Panel B: Medium quoted* spread | Volume-weighted price impact (bps) | | | Volume-weighted realised spread (bps) | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.099 | –0.046 | 0.117 | –0.834 | –0.435 | –0.132 |
| | (0.590) | (0.511) | (0.702) | (0.668) | (0.468) | (0.616) |
| Post X Group | 4.412 | 3.594 | 2.048 | 0.694 | 0.337 | –1.622 |
| | (1.128)*** | (1.020)*** | (0.871)*** | (1.708) | (0.951) | (0.951)* |
| Fixed effects | Stocks | Stocks | Stocks | Stocks | Stocks | Stocks |
| Adj. $R^2$ | –0.004 | –0.006 | –0.010 | –0.006 | –0.007 | –0.007 |
| Observations | 8,042 | 10,495 | 6,487 | 11,974 | 15,280 | 9,781 |
| *Panel C: High quoted spread* | Volume-weighted price impact (bps) | | | Volume-weighted realised spread (bps) | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.138 | –0.150 | –1.968 | 1.015 | –0.028 | –2.396 |
| | (1.212) | (0.711) | (1.260) | (1.680) | (0.727) | (1.415)* |
| Post X Group | 1.639 | 0.944 | 2.645 | 0.181 | –2.870 | –0.072 |
| | (1.696) | (1.754) | (1.353)* | (3.227) | (1.380)** | (1.600) |
| Fixed effects | Stocks | Stocks | Stocks | Stocks | Stocks | Stocks |
| Adj. $R^2$ | –0.028 | –0.024 | –0.015 | –0.013 | –0.011 | –0.007 |
| Observations | 1,742 | 1,877 | 3,269 | 3,956 | 3,793 | 6,310 |

*Note*. The results of the linear regressions on the difference between opportunistic traders' and market makers' *price impact* and *realised spread*. *Price impact* represented the volume-weighted difference between the midpoint price immediately before and 5 seconds after each trade. *Realised spread* was the volume-weighted difference between the transaction price and the midpoint price 5 seconds after each trade. Both measures are relative to the pre-trade midpoint price and are expressed in basis points. *Price impacts* were calculated from the perspective of the liquidity consumer, while *realised spreads* were computed on liquidity supplying orders. The independent variables were as follows: a dummy variable *Post* equals 1 if the securities start trading in nickels and 0 if otherwise and the dummy variable *Group* equals 1 for treatment securities and 0 if otherwise. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Overall, these results suggest that opportunistic traders used their technology to take advantage of the pilot program to increase their pay-off relative to the market makers from both providing liquidity and predicting short-term price movements. This empirical evidence indicates that overall opportunistic traders are equal or better at managing adverse selection risk and predict short-term price movements than market makers.

### 6.3.3 Tick size pilot and market makers

This section tests whether market makers have a technological advantage over opportunistic traders, which allows them to capture more often the bid–ask spread on treatment securities as suggested by the academic literature (Ait-Sahalia & Sağlam, 2013; Li, Wang & Ye, 2018; Yao & Ye, 2018). The two measures used to capture this difference among the two market participant groups were the queue speed and the average volume per MPIDs. According to Yao and Ye (2018), a tick size consolidation exacerbates the need for speed and encourages fast traders to use their technological advantage to be at the front of the queue and to earn the quoted spread. Therefore, an increased queue speed for market makers on treatment stocks indicates a speed advantage over opportunistic traders. Further, if market makers are at the front of the queue more frequently than before, their total trading volume should soar significantly on those stocks affected by the pilot program.

**Table 6.10: Pre-Pilot Average Queue Speed and Traded Volume Per Market Participant Identifier Stock Day**

| | Low quoted spread | | Medium quoted spread | | High quoted spread | |
|---|---|---|---|---|---|---|
| | Market makers | Opportunistic | Market makers | Opportunistic | Market makers | Opportunistic |
| Queue speed | 0.834% | 8.788% | 0.331% | 8.971% | 0.231% | 9.007% |
| | (0.021) | (0.008) | (0.017) | (0.006) | (0.014) | (0.005) |
| Ln(MPID volume+1) | 4.505 | 7.501 | 2.445 | 6.086 | 0.733 | 3.592 |
| | (3.117) | (1.651) | (3.080) | (2.198) | (1.965) | (2.775) |

*Note*. The table contains the pre-pilot average *queue speed* and *volume* per MPID stock day. Queue speed measured the percentage of times a proprietary trading company belonging to one of the two groups set the national best bid or the national best offer within a trading day. Standard deviations are reported in parentheses.

From the pre-pilot summary statistics presented in Table 6.10, it appears that market makers did not have a speed advantage over opportunistic traders. The average market making company was a price setter for 0.834%, 0.331% and 0.231% of the times for *low*, *medium* and *high quoted spread* securities, respectively. Conversely, the average opportunistic trader set 8.788%, 8.971% and 9.007% of the times for the NBBO over the same dollar quoted groups, respectively. These significant differences in queue speed are reflected in the average traded volume per MPIDs.

**Table 6.11: Panel Regression for the Pre-Pilot Queue Speed and Market Participant Identifier Volume**

| | Queue speed x 100 | | | Ln(MPID volume+1) | | |
|---|---|---|---|---|---|---|
| | Market makers (1) | Opportunistic (2) | (2)–(1) | Market makers (1) | Opportunistic (2) | (2)–(1) |
| Ln(Volume+1) | 0.162 | –0.059 | –0.220 | 1.321 | 1.317 | –0.004 |
| | (0.024)*** | (0.009)*** | (0.033)*** | (0.032)*** | (0.008)*** | (0.032) |
| Ln(Last price) | –0.184 | 0.067 | 0.250 | 0.434 | 0.348 | –0.086 |
| | (0.051)*** | (0.019)*** | (0.070)*** | (0.059)*** | (0.015)*** | (0.060) |
| Ln(Volatility+1) | –1.530 | 0.557 | 2.087 | –14.507 | –1.180 | 13.327 |
| | (1.231) | (0.448) | (1.679) | (1.255)*** | (0.338)*** | (1.226)*** |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.032 | 0.032 | 0.032 | 0.367 | 0.743 | 0.076 |
| N. Observations | 88,738 | 88,738 | 88,738 | 104,192 | 104,192 | 104,192 |

*Note*. The results of six panel regressions on two market making proxies: *average queue speed* and *average market participant traded volume*. *Queue speed* measured the percentage of times a proprietary trading company belonging to one of the two groups set the national best bid or the national best offer within a trading day. The control variables were as follows: traded *volume*, *last sale price* and high–low *volatility*. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively. All metrics were calculated from 1 April 2016 to 1 October 2016.

The pre-pilot cross-sectional analysis indicated that, by construction, the sensitivities of proprietary traders' queue speed had opposite signs for the two market participant groups. This result indicates that the gains for market makers were the opportunistic traders' losses in terms of queue speed. It is interesting, therefore, to analyse the differences in price setting behaviour among these two groups. These differences tended to decrease on heavily traded securities, while they tended to increase on volatile and pricy stocks. Conversely, Table 6.11 indicates that the sensitivities of the average market participant's trading volume to stock characteristics had the same sign for both proprietary trading groups. The differences between market makers' and opportunistic traders' coefficients related to the security's total traded volume and last sale price were not statistically significant. Conversely, the coefficient associated with the stock's high–low volatility was significantly lower for market makers, suggesting that these market participants were more sensitive to volatility compared to opportunistic traders.

**Table 6.12a: Difference-in-Differences Regression for the Proprietary Traders' Queue Speed x 100**

| *Panel A: Low quoted spread* | Market makers | | | Opportunistic traders | | |
|---|---|---|---|---|---|---|
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.389 | 0.256 | 0.552 | –0.141 | –0.093 | –0.201 |
| | (0.190)** | (0.214) | (0.217)** | (0.069)** | (0.078) | (0.079)** |
| Post X Group | 8.319 | 8.503 | 3.429 | –3.025 | –3.092 | –1.247 |
| | (0.789)*** | (0.647)*** | (0.648)*** | (0.287)*** | (0.235)*** | (0.236)*** |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.317 | 0.354 | 0.124 | 0.317 | 0.354 | 0.124 |
| Observations | 22,171 | 21,945 | 26,958 | 22,171 | 21,945 | 26,958 |
| *Panel B: Medium quoted* spread | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.027 | –0.067 | 0.371 | –0.010 | 0.024 | –0.135 |
| | (0.197) | (0.028)** | (0.236) | (0.072) | (0.010)** | (0.086) |
| Post X Group | 7.148 | 7.344 | 6.563 | –2.599 | –2.671 | –2.386 |
| | (0.625)*** | (0.521)*** | (0.701)*** | (0.227)*** | (0.189)*** | (0.255)*** |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.257 | 0.287 | 0.245 | 0.257 | 0.287 | 0.245 |
| Observations | 20,099 | 30,699 | 19,234 | 20,099 | 30,699 | 19,234 |
| *Panel C: High quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.067 | –0.059 | 0.175 | –0.024 | 0.022 | –0.064 |
| | (0.080) | (0.052) | (0.263) | (0.029) | (0.019) | (0.095) |
| Post X Group | 7.129 | 7.186 | 5.595 | –2.592 | –2.613 | –2.035 |
| | (0.886)*** | (0.949)*** | (0.925)*** | (0.322)*** | (0.345)*** | (0.336)*** |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.258 | 0.238 | 0.197 | 0.258 | 0.238 | 0.197 |
| Observations | 16,817 | 16,128 | 18,955 | 16,817 | 16,128 | 18,955 |

*Note*. The results of the difference-in-differences regressions on opportunistic traders' and market makers' *queue speed*. *Queue speed* measured the percentage of times a proprietary trading company belonging to one of the two groups set the national best bid or the national best offer within a trading day. *Queue spread* was the queue speed multiplied by 100. The independent variables were as follows: a dummy variable *Post* equals 1 if the securities start trading in nickels and 0 if otherwise and the dummy variable *Group* equals 1 for treatment securities and 0 if otherwise. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Overall, Table 6.10 and 6.11 demonstrate that it is not possible to infer whether market makers had a speed advantage on opportunistic traders. Instead, the difference-in-differences analysis presented in Table 6.12a indicates that, as the pilot program began, the average market makers significantly increased his/her NBBO queue speed, while the opposite was true for opportunistic traders. As suggested by Yao and Ye (2018), securities belonging to the *low quoted spread* group were the most affected by the increased tick size as liquidity supplying strategies became significantly more profitable for these stocks. This incentive encourages market makers to use their technological advantage to post their limit orders at the front of the queue as much as possible. As a consequence, the average queue speed for pre-pilot market makers increased by 8% for *G1* and *G2* stock and by 3% for *G3* stock. Conversely, opportunistic traders' queue speed decreased by 3% for *G1* and *G2* securities and by 1% for *G3* securities. These patterns are also valid for the *medium* and *high quoted* *spread* groups. Nonetheless, the magnitudes of the difference-in-differences estimators are significantly lower for securities subject to the trade-at rule for both proprietary trading groups. Considering the increased volume market share of lit trading venues for *G3* stocks (Lin, Swan & Mollica, 2018), it is possible to infer that non-proprietary traders compete to be at the front of the queue for this securities, which decreases the per MPID likelihood of being a price setter. Nevertheless, Table 6.12a suggests that the average market maker is now setting the NBBO more frequently than the average opportunistic trader for treatment stocks, indicating that there are differences in queue speed among these two market participant groups.

The difference-in-differences analysis of the average volume per MPID indicated that variations in the price setting behaviour do not necessarily affect the total number of shares traded by the market participants. Indeed, Table 6.12b suggests that the average volume for each opportunistic trader only decreased significantly for *G1* and *G2* stocks belonging to the *medium quoted spread* group. Conversely, average volume per MPID for market makers increased across all pilot and quoted spread groups. For both sets of proprietary trading companies, the changes in the average volume per MPID were the strongest for medium quoted spread securities. This result is possibly due to this group representing liquid and expensive securities that experienced a proportionally higher increase in trading volume compared to those stocks belonging to the low quoted spread group.

In line with Ait-Sahalia and Sağlam (2013), these analyses suggest that market makers do have a speed advantage over opportunistic traders and use their comparative advantage to capture the bid–ask spread as frequently as possible.

**Table 6.12b: Difference-in-Differences Analysis for the Natural Logarithm of Market Participant Identifier Volume Plus One**

| *Panel A: Low quoted spread* | Market makers | | | Opportunistic traders | | |
|---|---|---|---|---|---|---|
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.403 | 0.043 | 0.349 | 0.157 | 0.162 | 0.221 |
| | (0.136)*** | (0.146) | (0.127)*** | (0.080)* | (0.090)* | (0.069)*** |
| Post X Group | 1.382 | 1.231 | 0.973 | –0.023 | –0.115 | 0.012 |
| | (0.335)*** | (0.257)*** | (0.271)*** | (0.121) | (0.107) | (0.100) |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.127 | 0.071 | 0.072 | 0.004 | 0.001 | 0.016 |
| Observations | 22,848 | 22,848 | 27,744 | 22,848 | 22,848 | 27,744 |
| *Panel B: Medium quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.212 | –0.126 | 0.033 | 0.538 | 0.404 | 0.385 |
| | (0.154) | (0.095) | (0.119) | (0.107)*** | (0.093)*** | (0.096)*** |
| Post X Group | 1.774 | 2.546 | 2.286 | –0.415 | –0.253 | 0.186 |
| | (0.281)*** | (0.242)*** | (0.299)*** | (0.140)*** | (0.116)** | (0.141) |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.133 | 0.192 | 0.187 | 0.031 | 0.016 | 0.044 |
| Observations | 21,760 | 33,728 | 21,216 | 21,760 | 33,728 | 21,216 |
| *Panel C: High quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | –0.049 | –0.048 | –0.085 | 0.410 | 0.485 | 0.364 |
| | (0.100) | (0.046) | (0.088) | (0.092)*** | (0.094)*** | (0.087)*** |
| Post X Group | 1.696 | 1.393 | 1.465 | –0.041 | –0.062 | 0.064 |
| | (0.273)*** | (0.239)*** | (0.256)*** | (0.113) | (0.131) | (0.126) |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | 0.176 | 0.148 | 0.141 | 0.019 | 0.022 | 0.017 |
| Observations | 22,848 | 22,304 | 26,112 | 22,848 | 22,304 | 26,112 |

*Note*. The results of the difference-in-differences regressions on opportunistic traders' and market makers' *average trading volume*. The dependent variable was a natural logarithm for the *average traded volume* per MPID + 1. The independent variables were as follows: a dummy variable Post equals 1 if the securities start trading in nickels and 0 if otherwise and the dummy variable Group equals 1 for treatment securities and 0 if otherwise. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

### 6.3.4 Heterogeneous proprietary trading companies, tick pilot and trading revenues

The previous sections indicated that opportunistic traders provided and consumed liquidity opportunistically by placing marketable orders when prices were trending and limiting orders when there was little adverse selection risk. Conversely, market makers tended to place their limit orders at the inside to capture the quoted spread as often as possible. This section examines whether the policy change increased the revenue per dollar traded for both groups. An increase in tick size and the trade-at rule should increase HFT potential pay-off from their trading activity. Conversely, the increased competition among proprietary trading companies and the increased similarities of the trading strategies may diminish the overall revenue per dollar traded.

**Table 6.13: Pre-Pilot Revenue Per Dollar Traded in Basis Points**

| | Low quoted spread | | Medium quoted spread | | High quoted spread | |
|---|---|---|---|---|---|---|
| | Market makers | Opportunistic | Market makers | Opportunistic | Market makers | Opportunistic |
| Revenue | 2.266 | 4.842 | 2.911 | 4.542 | 3.360 | 2.711 |
| | (42.089) | (36.422) | (58.999) | (57.420) | (47.410) | (69.656) |

*Note*. The table contains the pre-pilot average *revenues per dollar traded*. In line with Carrion (2013), *Revenues* measures the difference in volume-weighted average price between the sell and buy transactions multiplied by the maximum between the purchased and the sold volume per dollar traded. This measure is expressed in basis points and was calculated from 1 April 2016 to 1 October 2016. Standard deviations are reported in parentheses.

**Table 6.14: Panel Regression for the Revenues Per Dollar Traded (Basis Points)**

| | Revenues per dollar traded (basis points) | | |
|---|---|---|---|
| | Market makers (1) | Opportunistic (2) | (2) – (1) |
| Ln(Volume+1) | –2.174 | –0.788 | 1.339 |
| | (0.454)*** | (0.304)*** | (0.585)** |
| Ln(Last price) | –0.617 | –3.382 | –1.393 |
| | (0.394) | (0.347)*** | (0.442)*** |
| Ln(Volatility+1) | 32.035 | 51.733 | 41.074 |
| | (36.882) | (30.793)* | (40.868) |
| Fixed effect | Stocks | Stocks | Stocks |
| Adj. $R^2$ | 0.002 | 0.003 | 0.002 |
| N. Observations | 36,101 | 85,313 | 36,087 |

*Note*. The results of three panel regressions on the *revenues per dollar traded*. The dependent variable was the difference in volume-weighted average price between sell and buy transactions multiplied by the maximum between the purchased and the sold volume per dollar traded. The control variables were as follows: traded *volume*, *last sale price* and high–low *volatility*. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively. All metrics were calculated from 1 April 2016 to 1 October 2016.

In a regular environment, the average revenue per dollar traded was positive, but highly volatile for both proprietary trading groups (see Table 6.13). Consistent with their business model, market makers' revenues were positively correlated to the stock's dollar quoted spread, while the opposite was true for opportunistic traders. Nonetheless, opportunistic traders tended to earn 2.57 and 1.63 basis points more than market makers on low and medium quoted spread securities, respectively. The performances of these two market participant groups were quite similar for high quoted spread securities as the differences in revenues were approximately 0.65 basis points.

Table 6.14 indicates that these differences in revenue may derive from differences in sensitivity for their strategies in relation to the stock's characteristics. On average, market makers tend to have lower revenues per dollar traded than opportunistic traders for heavily traded securities. Conversely, opportunistic traders' revenues are more sensitive to a stock price level than market makers, suggesting that the yield on information processing strategies is lower on securities with a small relative tick size.

**Table 6.15: Difference-in-Differences Analysis for the Revenues Per Dollar Traded (Basis Points)**

| *Panel A: Low quoted spread* | Market makers | | | Opportunistic traders | | |
|---|---|---|---|---|---|---|
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 0.810 | –2.960 | –1.631 | 2.018 | 1.462 | 0.642 |
| | (1.193) | (1.393)** | (1.153) | (1.129)* | (0.829)* | (0.743) |
| Post X Group | 4.447 | 3.672 | 12.998 | 1.078 | 2.781 | 5.455 |
| | (2.497)* | (1.781)** | (3.038)*** | (1.497) | (1.199)** | (1.158)*** |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | –0.004 | –0.004 | 0.001 | –0.003 | –0.002 | 0.000 |
| Observations | 15,580 | 16,515 | 19,356 | 22,447 | 22,119 | 27,287 |
| *Panel B: Medium quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | –1.961 | 3.029 | –2.166 | –0.175 | 3.467 | 2.189 |
| | (1.085)* | (1.668)* | (2.759) | (0.794) | (1.201)*** | (1.218)* |
| Post X Group | 4.002 | –5.351 | 4.913 | 6.317 | 0.410 | 2.572 |
| | (1.883)** | (2.607)** | (3.581) | (1.944)*** | (1.962) | (1.724) |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | –0.007 | –0.008 | –0.008 | –0.002 | –0.003 | –0.003 |
| Observations | 10,348 | 13,273 | 8,870 | 20,236 | 30,547 | 19,079 |
| *Panel C: High quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | 1.462 | –2.756 | –1.417 | 0.911 | 5.265 | 3.438 |
| | (3.915) | (2.445) | (2.179) | (1.766) | (2.601)** | (1.363)** |
| Post X Group | 3.377 | 3.795 | 2.750 | 2.145 | –5.663 | 2.237 |
| | (6.296) | (4.193) | (2.784) | (2.907) | (3.186)* | (2.426) |
| Fixed effect | Stock | Stock | Stock | Stock | Stock | Stock |
| Adj. $R^2$ | –0.015 | –0.015 | –0.009 | –0.006 | –0.006 | –0.005 |
| Observations | 3,111 | 2,905 | 5,678 | 14,060 | 13,022 | 16,502 |

*Note*. The results of the difference-in-differences regressions on opportunistic traders' and market makers' *revenues per dollar traded*. The dependent variable was the difference in volume-weighted average price between the sell and buy transactions multiplied by the maximum between the purchased and the sold volume per dollar traded. The independent variables were as follows: a dummy variable *Post* equals 1 if the securities start trading in nickels and 0 if otherwise and the dummy variable *Group* equals 1 for treatment securities and 0 if otherwise. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

The policy change consistently increased the revenue per dollar traded on *low quoted spread* treatment stocks for both market makers and opportunistic traders. Market makers experienced the highest increase in revenue per dollar traded as they now earn 13 basis points more for *G3* securities, while opportunistic traders' revenue increased by 5.45 basis points for the same group of stock. Instead, the results on all other regressions do not seem to be reliable as the adjusted $R^2$ of these regressions are negative. Furthermore, the analysis of the total revenues in Table A7 (appendix) show that only the estimates are positive and statistically significant only for opportunistic traders on *G2* and *G3 low quoted spread* securities, consistently with the results in chapter 4.

Overall, these results corroborate the existing literature on the relationship between tick size and proprietary trading companies' revenues (Yao & Ye, 2018). Nevertheless, this research demonstrates that a tick size consolidation do not necessarily benefit market makers, but they mostly benefit proprietary traders specialised in processing information.

## 6.4 Conclusions

Most of the current academic literature regarding high-frequency trading focuses on examining the relationship between fast trading and market quality. Some theoretical papers examine the effect of either fast informed traders or fast market makers on either liquidity traders' order submission strategies or on market quality (Ait-Sahalia & Sağlam, 2013; Cartea & Penalva, 2012; Foucault, Hombert & Rosu 2016; Foucault, Kohzan & Tham, 2017), while the latest theoretical and empirical research has examined the joint effect of tick size changes on the behaviour of fast proprietary trading companies and market quality (Li, Wang & Ye, 2018; O'Hara et al., in press; Yao & Ye, 2018). Nonetheless, the literature has not yet studied the channels proprietary traders use to take advantage of market making incentives. This research fills the gap in the literature by analysing changes in the trading behaviour of two different types of HFT when facing the same market making incentive structure.

First, our analysis provided evidence that both opportunistic traders and market makers increased their liquidity provision by more than 5% on *low* and *medium quoted spread* treatment stocks using a higher proportion of limit orders and increasing their NBBO presence. Nevertheless, only market makers appeared to increase their liquidity provision on the least liquid securities.

Second, the empirical evidence suggested that opportunistic traders had an informational advantage over market makers as they tended to trade ahead of large price movement and supplied liquidity when there was low adverse selection risk. As the SEC enforces the pilot program, opportunistic traders' realised spread is 3 basis points higher than the one obtained by market makers for tick-constrained securities.

Third, the tick size consolidation encouraged market makers to set the NBBO 8% more frequently than opportunistic traders and to trade more frequently any treatment security, confirming the hypotheses developed by Ait-Sahalia and Sağlam (2013). Overall, this section demonstrated that market makers appear to have a technological advantage over opportunistic traders, which allows them to capture the bid–ask spread as much as possible.

Finally, both market makers and opportunistic traders experienced an increase in revenues per dollar traded on *low quoted spread* treatment securities. Interestingly, HFT experienced the largest increase in revenue on stocks affected by the trade-at rule as non-proprietary trading companies are now obligated to trade more often on the lit exchanges. This empirical result suggests that proprietary traders' revenues are affected the most by changes in liquidity traders' activity rather than by changes in tick size. Overall, this research demonstrates that, regardless of their specialisation, HFT react similarly to the same incentives by leveraging their comparative advantage to increase their revenues per dollar traded. I believe that future research should focus on understanding whether it is necessary to subsidise liquidity to improve market quality for investors.

# Chapter 7: Summary and Future Research

This current research used an exogenous event, the tick size pilot program, to study the biodiversity of market participants trading on three Nasdaq exchanges. Using Nasdaq proprietary data and the SEC's FOCUS report, I examined the trading behaviour of three groups of market participants trading small–medium market capitalisation stocks that were affected by the tick size pilot program (1 April 2016 to 30 April 2017). The 48 classified MPIDs, which represent more than 90% of the total trading activity on the Nasdaq exchanges, were categorised based on their declared nature of business into proprietary trading companies, banks and agency firms.

The analysis can be divided in three parts: (i) an analysis of the effects of the policy change on market participants' competition for order flow, liquidity provision and transaction costs; (ii) an examination of the order submission strategies employed by the three groups, focusing on banks' trading behaviour; and (iii) an overview of how proprietary trading companies leverage their specific technological advantages to maximise their trading revenues.

The results outlined Chapter 4 indicated that the tick size pilot program did not increase market participants' competition across the three Nasdaq exchanges. Nonetheless, the policy change encouraged proprietary trading companies to increase their liquidity provision to maximise their trading revenues. Conversely, banks, which are the major liquidity providers for small–medium market capitalisation securities, reduced their liquidity supply, experienced higher implicit transaction costs and moved their order flow from Nasdaq to BX. Agency firms did not change their liquidity provision nor experienced an increase in the implicit transaction costs. Nevertheless, the tick size pilot program increased an agency firm's waiting costs and reduced their total trading volume for *G2* treatment securities with a pre-pilot quoted spread lower than \$0.04. These empirical findings indicate that proprietary trading companies are the main beneficiaries of the policy change, as suggested by O'Hara et al. (in press) and Yao and Ye (2018), and that banks and agency firms have different liquidity preferences. Overall, banks cross the spread more frequently for treatment securities, while agency firms are subject to higher waiting costs.

Chapter 5 provided an in-depth analysis of market participants intraday order submission strategies and the NBBO price setting behaviour of proprietary trading companies, banks and agency firms on securities affected by the tick size pilot program. According to Yao and Ye (2018), large relative tick size exacerbates the need for speed, allowing proprietary trading companies to dominate the liquidity provision for these securities due to their superior technological advantage. This mechanism compels non-proprietary trading companies to use marketable order to execute their orders. Nonetheless, the empirical findings in Chapter 5 demonstrated that this theory is not entirely true as banks tend to be at the front of the queue as often as proprietary trading companies for treatment securities with a pre-pilot quoted spread lower than \$0.04. Further, I indicated that this increase in the percentage of times that banks set the NBBO price was associated with an increase of the proportion of the banks' agency business, suggesting that investors ultimately have access to the same innovative technology as proprietary trading companies. Nevertheless, the analysis of the intraday order submission strategies of the three market participant groups suggests that banks and agency firms are ultimately liquidity traders that use increasingly more marketable orders as they approach the end of the trading day to satisfy their clients' liquidity needs. These results indicate that the tick size pilot program increases waiting costs and compels impatient market participants to enter a larger portion of aggressive orders during the trading day when the transaction costs are the lowest. The empirical evidence supports the idea that emerged in Chapter 4 that the results are mainly driven by differences in business models rather than differences in trading technology.

The final part of the study examined the behaviour of proprietary trading companies when facing a market making incentive. As suggested by Hangströmer and Nordén (2013), proprietary trading companies are divided in two categories: (i) those who opportunistically use marketable orders to take advantage of price inefficiencies and (ii) market makers. The analysis demonstrated that the tick size pilot program induced both types of proprietary trading companies to engage in market making strategies as they increased their presence at the NBBO and their liquidity provision to banks and agency firms. However, opportunistic traders leveraged their superior capacity to process information to increase their trading revenues, while market makers exploited their speed advantage to be at the front of the queue and increase their total trading volume. This important finding suggests that subsidising liquidity leads both groups to act as market makers on securities with a pre-pilot quoted spread lower than \$0.04. Conversely, only market makers increased their liquidity provision across all treatment stocks regardless of their quoted spread group as they can exploit their superior technology.

In conclusion, this study demonstrated that a multitude of non-proprietary trading companies in the market are characterised by different business models and these play a key role in small–medium market capitalisation companies. Banks are sophisticated liquidity traders with access to innovative technologies that are sensitive to waiting costs. The study results suggested that banks are as fast as proprietary trading companies for tick-constrained treatment securities, but cross the spread more frequently. Conversely, agency firms are willing to wait longer to execute their orders as they try to minimise their implicit transaction costs. Finally, this study demonstrated that proprietary trading companies exploit different channels to take advantage of the market making incentive created by the tick size pilot. Nonetheless, only market makers increased their liquidity provision for the most illiquid securities in this current sample.

Therefore, scope exists for future researcher to focus their attention on the biodiversity of non-proprietary trading companies to understand the role they play in ensuring market quality and price efficiency. Further, based on the empirical evidence provided in this dissertation, regulators worldwide should consider the biodiversity of market participants and their business models when analysing the wealth effects created by market microstructure changes such as the tick size consolidation or the trade-at rule.

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# Appendix

**Table A1: Rebate *S*tructure**

| Liquidity Codes | Panel A: Fee Structure | | | Panel B: % Exchange Volume | | |
|---|---|---|---|---|---|---|
| | BX | PSX | Nasdaq | BX | PSX | Nasdaq |
| 0 | $0.0000 | $0.0000 | $0.0017 | 0.00% | 0.00% | 0.06% |
| 7 | –$0.0020 | $0.0000 | $0.0028 | 1.05% | 0.00% | 4.13% |
| 8 | –$0.0020 | $0.0000 | $0.0028 | 13.68% | 0.00% | 2.18% |
| A | –$0.0020 | $0.0025 | $0.0056 | 25.60% | 36.29% | 32.19% |
| b | $0.0000 | $0.0000 | $0.0000 | 0.00% | 0.00% | 0.00% |
| C | $0.0000 | $0.0000 | $0.0000 | 0.00% | 0.00% | 7.35% |
| e | $0.0000 | $0.0000 | $0.0034 | 0.00% | 0.00% | 1.03% |
| h | $0.0000 | $0.0000 | $0.0000 | 0.00% | 0.00% | 0.04% |
| J | –$0.0055 | $0.0000 | $0.0000 | 5.46% | 1.15% | 2.22% |
| k | –$0.0010 | $0.0025 | $0.0020 | 4.20% | 1.93% | 2.70% |
| L | $0.0000 | $0.0000 | –$0.0009 | 0.00% | 0.00% | 1.13% |
| m | $0.0000 | –$0.0029 | –$0.0039 | 3.63% | 2.10% | 3.02% |
| N | $0.0000 | $0.0000 | $0.0000 | 0.00% | 0.00% | 0.00% |
| O | $0.0000 | $0.0000 | –$0.0015 | 0.00% | 0.00% | 1.85% |
| q | $0.0000 | $0.0000 | $0.0000 | 0.00% | 0.00% | 0.00% |
| r | $0.0040 | –$0.0029 | –$0.0030 | 46.35% | 47.90% | 41.87% |
| t | $0.0017 | $0.0000 | $0.0000 | 0.02% | 0.00% | 0.00% |
| V | $0.0000 | $0.0025 | $0.0000 | 0.00% | 10.64% | 0.00% |
| x | $0.0000 | $0.0000 | $0.0028 | 0.00% | 0.00% | 0.19% |
| y | $0.0000 | $0.0000 | $0.0028 | 0.00% | 0.00% | 0.05% |

Note. Panel A is an approximation of the fee structure that can be found on Nasdaq Trader. Panel B is calculated based on the total traded volume for each exchange from 1 April 2016 to 30 April 2017.

**Table A2a: Pre-Pilot Average Logarithm for the Total Number of NBBO Price Set**

| | *Treatment* | | | *Control* | | |
|---|---|---|---|---|---|---|
| | Average | St. Deviation | N. Obs. | Average | St. Deviation | N. Obs. |
| Very liquid | 3.22 | 0.85 | 135 | 3.17 | 0.81 | 135 |
| Liquid | 3.37 | 1.01 | 141 | 3.25 | 1.15 | 141 |
| Illiquid | 2.30 | 1.36 | 131 | 2.24 | 1.30 | 131 |

Note. The summary statistics for the average logarithm of the total number of NBBO price set across BX and Nasdaq pre-stock day from 1 April to 1 October 2016.

**Table A2b: Difference-in-Differences Analysis for the Average Logarithm of the Total Number of NBBO Price Set**

| *Panel A: Very liquid* | G1 | G2 | G3 |
|---|---|---|---|
| Intercept | 3.27 | 3.27 | 3.13 |
| | (26.26)*** | (23.64)*** | (26.80)*** |
| Group | –0.20 | –0.03 | 0.07 |
| | (1.10) | (0.14) | (0.43) |
| Pilot | 0.09 | 0.3 | 0.12 |
| | (0.49) | (1.62) | (0.74) |
| Group*Pilot | –1.18 | –1.46 | –1.05 |
| | (4.51)*** | (5.55)*** | (4.7)*** |
| Adjusted $R^2$ | 0.30 | 0.31 | 0.20 |
| N. Observations | 168 | 168 | 204 |
| *Panel B: Liquid* | G1 | G2 | G3 |
| Intercept | 3.47 | 3.32 | 3.34 |
| | (22.03)*** | (27.53)*** | (18.89)*** |
| Group | –0.09 | –0.06 | –0.24 |
| | (0.39) | (0.34) | (0.91) |
| Pilot | 0.25 | 0.13 | 0.32 |
| | (1.22) | (0.78) | (1.35) |
| Group*Pilot | –1.50 | –1.22 | –1.02 |
| | (4.72)*** | (4.74)*** | (2.95)*** |
| Adjusted $R^2$ | 0.27 | 0.20 | 0.15 |
| N. Observations | 160 | 248 | 156 |
| *Panel C: Illiquid* | G1 | G2 | G3 |
| Intercept | 2.31 | 2.28 | 2.3 |
| | (11.28)*** | (11.58)*** | (10.98)*** |
| Group | –0.20 | –0.03 | 0.03 |
| | (0.67) | (0.10) | (0.11) |
| Pilot | 0.2 | 0.19 | 0.23 |
| | (0.67) | (0.69) | (0.77) |
| Group*Pilot | –0.79 | –0.94 | –0.25 |
| | (1.96)** | (2.62)*** | (0.58) |
| Adjusted $R^2$ | 0.07 | 0.09 | 0.00 |
| N. Observations | 168 | 164 | 192 |

*Note*. The effect of the tick pilot program on the average logarithm for the total number of orders setting the NBBO. In line with Bertrand, Duflo and Mullainathan (2004), the observations were averaged over the pre-pilot and post-pilot period to minimise potential serial autocorrelation issues. The dependent variable was an average logarithm for the total number of orders setting an NBBO per security period MPID. The independent variables were as follows: a dummy variable that discriminates between the treatment and control group; *Pilot*, which is a dummy variable that distinguishes between the pre and post-pilot period, and their interaction variable. To account for heteroskedasticity, the t-statistics reported in parentheses were calculated using White's standard errors. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

## Table A3: Pre-Pilot Summary Statistics for the Percentage of Banks' Orders Labelled as 'Agent'

| | *Treatment* | | | *Control* | | |
|---|---|---|---|---|---|---|
| | Average | St. Deviation | N. Obs. | Average | St. Deviation | N. Obs. |
| Very liquid | 79.13% | 6.11% | 135 | 79.84% | 6.66% | 135 |
| Liquid | 72.83% | 8.77% | 141 | 74.40% | 9.43% | 141 |
| Illiquid | 65.29% | 14.86% | 131 | 64.85% | 13.81% | 131 |

*Note.* The average percentage of times that a bank's orders improving the NBBO was labelled as '*Agent*' between 9:30 am and 4:00 pm between 1 April 2016 and 1 October 2016.

## Table A4a: Wilcoxon Signed Rank Sum Test Between the Time Bucket T and T-1 of the Pre-Pilot Average Daily Percentage of Aggressive Orders on Very Liquid

| *Δ Aggressiveness* | | *Proprietary Traders* | | | *Banks* | | | *Agency Firms* | | |
|---|---|---|---|---|---|---|---|---|---|---|
| T | T-1 | *Δ* | Stat. | P-Val. | *Δ* | Stat. | P-Val. | *Δ* | Stat. | P-Val. |
| 10:30 | 10:00 | 14.80% | 67535 | 0.00 | 3.97% | 60380 | 0.00 | 9.77% | 60488 | 0.00 |
| 11:00 | 10:30 | 1.51% | 41148 | 0.01 | 0.07% | 36950 | 0.78 | 2.01% | 41955 | 0.00 |
| 11:30 | 11:00 | 0.49% | 38036 | 0.38 | 0.00% | 36472 | 0.99 | 0.11% | 36746 | 0.87 |
| 12:00 | 11:30 | -0.03% | 36358 | 0.96 | -0.47% | 33528 | 0.11 | -0.62% | 34885 | 0.39 |
| 12:30 | 12:00 | -0.08% | 36205 | 0.89 | -0.11% | 35742 | 0.70 | 0.53% | 37856 | 0.44 |
| 13:00 | 12:30 | 0.04% | 36566 | 0.95 | -0.31% | 34284 | 0.23 | -0.21% | 35866 | 0.75 |
| 13:30 | 13:00 | 0.04% | 36560 | 0.95 | 0.10% | 37078 | 0.73 | -0.19% | 35955 | 0.79 |
| 14:00 | 13:30 | 0.22% | 37070 | 0.73 | 0.30% | 38485 | 0.26 | 0.20% | 36964 | 0.78 |
| 14:30 | 14:00 | 0.57% | 38148 | 0.35 | 0.18% | 37593 | 0.53 | 0.15% | 36862 | 0.82 |
| 15:00 | 14:30 | 0.21% | 37035 | 0.75 | 0.64% | 40768 | 0.02 | 1.45% | 40446 | 0.03 |
| 15:30 | 15:00 | 0.37% | 37502 | 0.56 | 0.42% | 39456 | 0.10 | -1.06% | 33573 | 0.11 |
| 16:00 | 15:30 | -3.39% | 26829 | 0.00 | 1.62% | 49727 | 0.00 | 4.06% | 47349 | 0.00 |

*Note.*The Wilcoxon rank sum test is used to test the median of the differences (*Δ)* in pre-pilot average daily percentage of aggressive orders between two time buckets on securities having a pre-pilot average quoted spread lower than $0.04. The analysed variable for this regression was the average percentage of the total buy (sell) orders with a limit price higher (lower) than the NBBO midpoint price and IOC and FOK orders entered by each market participant group per stock-time bucket.

**Table A4b: Wilcoxon Signed Rank Sum Test Between the Time Bucket T and T-1 of the Pre-Pilot Average Daily Percentage of Aggressive Orders on Liquid**

| *Δ Aggressiveness* | | *Proprietary Traders* | | | *Banks* | | | *Agency Firms* | | |
|---|---|---|---|---|---|---|---|---|---|---|
| T | T-1 | Δ | Stat. | P-Val | Δ | Stat. | P-Val | Δ | Stat. | P-Val |
| 10:30 | 10:00 | 11.87% | 67391 | 0.00 | 3.56% | 63695 | 0.00 | 6.67% | 62611 | 0.00 |
| 11:00 | 10:30 | 3.55% | 48925 | 0.00 | 0.46% | 42948 | 0.10 | 1.21% | 44440 | 0.02 |
| 11:30 | 11:00 | 0.83% | 42074.5 | 0.23 | 0.17% | 40844 | 0.58 | 0.10% | 40181.5 | 0.83 |
| 12:00 | 11:30 | 0.32% | 40738 | 0.61 | 0.03% | 39935 | 0.93 | -1.01% | 35826 | 0.04 |
| 12:30 | 12:00 | 0.42% | 41156 | 0.47 | 0.31% | 41586 | 0.35 | 0.15% | 40335 | 0.77 |
| 13:00 | 12:30 | 0.39% | 41037 | 0.51 | -0.29% | 38025 | 0.37 | 0.23% | 40631 | 0.65 |
| 13:30 | 13:00 | 0.32% | 40810 | 0.59 | -0.04% | 39502 | 0.89 | -0.13% | 39252 | 0.79 |
| 14:00 | 13:30 | 0.72% | 42126 | 0.22 | 0.46% | 42525 | 0.15 | 0.85% | 43013 | 0.09 |
| 14:30 | 14:00 | 1.43% | 44358 | 0.02 | 0.24% | 41215 | 0.45 | 0.26% | 40742 | 0.61 |
| 15:00 | 14:30 | 0.18% | 40336 | 0.77 | 0.35% | 41893 | 0.27 | 1.22% | 44367 | 0.02 |
| 15:30 | 15:00 | 0.84% | 42346.5 | 0.18 | 0.31% | 41800 | 0.29 | -0.21% | 39003 | 0.70 |
| 16:00 | 15:30 | -2.81% | 31871 | 0.00 | 2.38% | 56470 | 0.00 | 6.51% | 57991 | 0.00 |

*Note.*The Wilcoxon rank sum test is used to test the median of the differences (Δ) in pre-pilot average daily percentage of aggressive orders between two time buckets on securities having a pre-pilot average quoted spread between $0.04 and $0.11. The analysed variable for this regression was the average percentage of the total buy (sell) orders with a limit price higher (lower) than the NBBO midpoint price and IOC and FOK orders entered by each market participant group per stock-time bucket.

**Table A4c: Wilcoxon Signed Rank Sum Test Between the Time Bucket T and T-1 of the Pre-Pilot Average Daily Percentage of Aggressive Orders on Illiquid**

| *Δ Aggressiveness* | | *Proprietary Traders* | | | *Banks* | | | *Agency Firms* | | |
|---|---|---|---|---|---|---|---|---|---|---|
| T | T-1 | Δ | Stat. | P-Val | Δ | Stat. | P-Val | Δ | Stat. | P-Val |
| 10:30 | 10:00 | 5.36% | 50847 | 0.00 | 4.58% | 57195 | 0.00 | 3.67% | 47249 | 0.00 |
| 11:00 | 10:30 | 2.42% | 40203.5 | 0.00 | -0.29% | 32647 | 0.33 | 1.35% | 38746 | 0.01 |
| 11:30 | 11:00 | 1.64% | 38048.5 | 0.03 | -0.19% | 33418 | 0.60 | 0.12% | 34704 | 0.83 |
| 12:00 | 11:30 | 0.05% | 34449 | 0.94 | 0.10% | 34792 | 0.79 | 0.31% | 35360 | 0.55 |
| 12:30 | 12:00 | 0.34% | 35058 | 0.67 | 2.28% | 44252 | 0.00 | 0.04% | 34460 | 0.94 |
| 13:00 | 12:30 | 0.50% | 35092.5 | 0.55 | -0.25% | 33258 | 0.54 | -0.40% | 32991 | 0.44 |
| 13:30 | 13:00 | 0.01% | 34092 | 0.99 | 0.20% | 35123 | 0.64 | 0.47% | 35899 | 0.36 |
| 14:00 | 13:30 | 0.44% | 35268 | 0.59 | 0.16% | 34979 | 0.70 | 1.26% | 38543.5 | 0.01 |
| 14:30 | 14:00 | 1.85% | 38009.5 | 0.03 | 0.02% | 34401 | 0.96 | 0.19% | 34999 | 0.70 |
| 15:00 | 14:30 | -0.20% | 33922.5 | 0.82 | 0.17% | 35044 | 0.68 | -1.00% | 30969.5 | 0.05 |
| 15:30 | 15:00 | 0.13% | 34590.5 | 0.88 | -1.41% | 28077 | 0.00 | 1.18% | 38286 | 0.02 |
| 16:00 | 15:30 | -1.37% | 31803 | 0.15 | 2.07% | 42980 | 0.00 | 4.68% | 46503 | 0.00 |

*Note.*The Wilcoxon rank sum test is used to test the median of the differences (Δ) in pre-pilot average daily percentage of aggressive orders between two time buckets on securities having a pre-pilot average quoted spread higher than $0.11. The analysed variable for this regression was the average percentage of the total buy (sell) orders with a limit price higher (lower) than the NBBO midpoint price and IOC and FOK orders entered by each market participant group per stock-time bucket.

**Table A5: Pre-Pilot Revenue ($)**

| | Low quoted spread | | Medium quoted spread | | High quoted spread | |
|---|---|---|---|---|---|---|
| | Market Makers | Opportunistic | Market Makers | Opportunistic | Market Makers | Opportunistic |
| Revenue | $15.61 | $123.29 | $38.22 | $101.86 | $72.12 | $11.51 |
| | ($550) | ($2,112) | ($1,029) | ($2,315) | ($1,108) | ($1,908) |

Note. The table contains the pre-pilot average revenues per dollar traded. In line with Carrion (2013), Revenues measures the difference in volume-weighted average price between the sell and buy transactions multiplied by the maximum between the purchased and the sold volume per dollar traded. This measure was calculated from 1 April 2016 to 1 October 2016. Standard deviations are reported in parentheses.

## Table A6: Panel Regression for the Revenues

| | Revenues (USD) | | |
|---|---|---|---|
| | Market makers (1) | Opportunistic (2) | (2) - (1) |
| Ln(Volume+1) | -6.457 | 9.570 | 23.266 |
| | (1.650)* | (7.787)*** | (4.683)*** |
| Ln(Last price) | 7.229 | 10.039 | 12.858 |
| | (1.602) | (2.602)*** | (1.638) |
| Ln(Volatility+1) | -142.934 | 976.681 | 2,468.128 |
| | (0.418) | (2.863)*** | (3.448)*** |
| Fixed effect | Stocks | Stocks | Stocks |
| Adj. $R^2$ | -0.003 | 0.010 | 0.013 |
| N. Observations | 35,476 | 81,461 | 35,442 |

*Note*. The results of three panel regressions on the revenues per dollar traded. The dependent variable was the difference in volume-weighted average price between sell and buy transactions multiplied by the maximum between the purchased and the sold volume. The control variables were as follows: traded volume, last sale price and high–low volatility. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively. All metrics were calculated from 1 April 2016 to 1 October 2016.

## Table A7: Difference-in-Differences Analysis for the Revenues ($)

| *Panel A: Low quoted spread* | Market makers | | | Opportunistic traders | | |
|---|---|---|---|---|---|---|
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | -5.288 | -24.671 | 4.132 | 75.251 | 58.634 | 92.470 |
| | (0.523) | (2.254)** | (0.343) | (1.238) | (1.168) | (2.064)** |
| Post X Group | -41.473 | -19.042 | -26.602 | -12.158 | 103.202 | 144.721 |
| | (1.518) | (1.043) | (0.621) | (0.19) | (1.707)* | (2.225)** |
| Fixed effect | Stocks | Stocks | Stocks | Stocks | Stocks | Stocks |
| Adj. $R^2$ | 0.013 | 0.008 | 0.018 | 0.005 | 0.008 | 0.012 |
| N. Observations | 15,580 | 16,515 | 19,356 | 22,447 | 22,119 | 27,287 |
| *Panel B: Medium quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | -35.273 | -19.396 | -25.492 | 26.646 | 176.838 | 25.754 |
| | (0.821) | (0.618) | (0.847) | (0.256) | (2.01)** | (0.417) |
| Post X Group | -2.467 | -56.840 | -6.601 | -0.034 | -89.020 | 114.964 |
| | (0.054) | (1.414) | (0.172) | (0) | (0.828) | (1.28) |
| Fixed effect | Stocks | Stocks | Stocks | Stocks | Stocks | Stocks |
| Adj. $R^2$ | 0.005 | 0.007 | 0.010 | 0.008 | 0.009 | 0.007 |
| N. Observations | 10,348 | 13,273 | 8,870 | 20,236 | 30,547 | 19,079 |
| *Panel C: High quoted spread* | Market makers | | | Opportunistic traders | | |
| | G1 | G2 | G3 | G1 | G2 | G3 |
| Post | -48.199 | -28.288 | -78.595 | 80.427 | 130.140 | 287.268 |
| | (2.266)** | (0.427) | (2.152)** | (3.003)*** | (2.532)** | (2.172)** |
| Post X Group | -38.683 | -82.131 | -3.230 | -27.881 | -105.885 | -293.038 |
| | (0.479) | (0.915) | (0.064) | (0.601) | (1.929)* | (2.195)** |
| Fixed effect | Stocks | Stocks | Stocks | Stocks | Stocks | Stocks |
| Adj. $R^2$ | 0.062 | 0.019 | 0.005 | 0.008 | 0.012 | 0.005 |
| N. Observations | 3,111 | 2,905 | 5,678 | 14,060 | 13,022 | 16,502 |

*Note*. The results of the difference-in-differences regressions on opportunistic traders' and market makers' *revenues*. The dependent variable was the difference in volume-weighted average price between the sell and buy transactions multiplied by the maximum between the purchased and the sold volume. The independent variables were as follows: a dummy variable Post equals 1 if the securities start trading in nickels and 0 if otherwise and the dummy variable Group equals 1 for treatment securities and 0 if otherwise. Double clustered standard errors by stock day are reported in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.