Theoretical Economics Letters, 2017, 7, 862-913
http://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

Market Making, Liquidity Provision, and Attention Constraints: An Experimental Study

Juan F. Cabrera

Anisfield School of Business, Ramapo College of New Jersey, Mahwah, New Jersey, USA
Email: jcabrera@ramapo.edu

How to cite this paper: Cabrera, J.F. (2017) Market Making, Liquidity Provision, and Attention Constraints: An Experimental Study. *Theoretical Economics Letters*, **7**, 862-913.
https://doi.org/10.4236/tel.2017.74061

Received: April 25, 2017
Accepted: June 13, 2017
Published: June 16, 2017

Abstract

This paper uses an experimental electronic market to investigate the effect of limited attention on the market maker's ability to provide liquidity and, thus, on aggregate market liquidity. I find that higher demands on the market maker's attention worsen her ability to provide liquidity but do not reduce the aggregate level of market liquidity. This effect is only significant in less active markets. Furthermore, the aggregate level of market liquidity remains unaltered across both highly active and inactive markets, suggesting a reactive strategy by informed traders who step in to compete with market makers during high information intensity periods when their attention allocation efforts are compromised. In fact, in markets with a higher information value, the effect of attention constraints on the liquidity provision ability of market makers is greater. This implies that informed traders may not only exploit their informational advantage against uninformed traders but they may also use it to reap a higher share of liquidity-based profits. Finally, the market maker's trading performance measured by her profit share and ability to manage her inventory worsens when demands on her attention are greater.

Keywords

Limited Attention, Attention Constraints, Market Making, Market Liquidity, Liquidity Provision, Experimental, Behavioral, Microstructure

1. Introduction

Market microstructure models suggest that the presence of market makers is a key determinant of market liquidity.[1] In these models, the costs to market mak-

[1]A market maker is a firm or individual who assumes the risk of holding certain number of shares of a security to facilitate the trading of that security. Market makers' main function is to provide liquidity to markets, especially those that are relatively less liquid. They provide liquidity by posting binding bid and ask quotes and standing ready to trade at those posted quotes. In this way, market makers are responsible for making a fair and orderly market in one or more securities.

ers of maintaining a market presence can have a significant impact on market liquidity and the price formation process [1]. Traditional models attribute these costs to inventory and adverse selection risks. They argue that these risks affect the market maker's decision-making process and, therefore, her liquidity provision abilities. Several recent studies, however, have suggested that behavioral factors also influence the market maker's decision-making process.

Individuals have a limited capacity for information processing [2].[2] In a setting where individuals must attend to several tasks simultaneously, their ability to optimally allocate attention across tasks may affect their decision-making processes and, consequently, the outcomes. As the number of tasks individuals must attend to increases, the constraints on their attention become tighter. Furthermore, limited processing power may induce individuals to rely on heuristics reducing costs but potentially inducing processing errors [2]. In this paper, I investigate the role of attention constraints on the market maker's ability to provide liquidity and, thus, on market quality. Market makers are often required to allocate their attention across multiple assets and this effort may influence the degree of liquidity in the markets they trade in.[3]

Previous studies have shown that the main challenge in examining the role of attention is the difficulty in measuring attention and its allocation within financial market settings [3]. In this paper, I examine the effects of attention constraints in an experimental setting. The use of an experimental setting overcomes the aforementioned challenge by precluding the use of proxies such as trading volume [4], Internet search volume [5] and earnings announcements [6]. In an experimental setting, the demands on the individual's attention can be controlled and its effects on market characteristics such as liquidity and efficiency can be isolated.

In a market where market makers are an important source of liquidity, attention constraints could materially impact the market's degree of liquidity. [3] argues that if attention constraints limit the ability of a market maker to allocate her efforts across stocks, her ability to provide liquidity for a given stock should be negatively related to the attention requirements of other stocks in her portfolio. Also, the market maker's allocation of attention may be primarily directed at extracting information about the value of the stock. [7] finds that specialists in the New York Stock Exchange (NYSE) obtain information from order flow and use this information to compete for liquidity provision. In this paper, I provide experimental evidence of these ideas.

This paper contributes to the literature in the following ways: (1) to my

[2]This notion is closely related to the theory of bounded rationality [8]. Bounded rationality recognizes that individuals are not fully rational when making decisions. They have informational and computational limitations. Bounded rationality states that individuals gather some (but not all) available information, use heuristics to make the process of analyzing the information tractable, and stop when they have arrived at a satisfactory, not necessarily optimal, decision.

[3]An example of this market setting is the role of the specialist in the New York Stock Exchange (NYSE). Some specialists are only required to trade on one stock, while others are often required to trade on several stocks at the same time. In this sense, the NYSE's market structure provides an ideal setting to test the effect of attention constraints on the specialists' decision making process and market quality across stocks and over time [3].

knowledge, this is the first experimental study to observe the effects of attention constraints on financial markets. Several empirical studies have tested this relationship, but none have studied this effect within an experimental setting where the individual's ability to allocate attention can be directly controlled; (2) it measures the individual's attention constraints in a way that precludes the use of noisy and potentially endogenous empirical proxies. Recent studies have used proxies of attention that may allow for substantial confounding effects such as trading volume [3] [4]. A well-designed experimental setting can isolate the effect of attention constraints without the need to rely on noisy empirical proxies; (3) it provides a variety of liquidity measures and distinguishes between market liquidity and liquidity provision. Market liquidity is an elusive concept to understand and, more importantly, to measure. The use of several distinct measures of liquidity increases the reliability and robustness of the study; (4) it provides a more "pure" measure of the limited attention effect by keeping the total amount of attention available in a market fixed while changing the degree of attention constraints on the traders. Many previous studies test attention effects by simply increasing the number of tasks the individual must attend to. This, in turn, decreases the amount of attention available on a per-task basis. In this paper, I attempt to find attention effects in an environment where the amount of attention available to a given task remains unchanged; (5) it eliminates the effects of the endogeneity problem between the asset characteristics and the marker maker's portfolio. Empirical studies based on either cross-sectional or times-series analyses allow for an endogeneity bias whereby the allocation of a given asset to the market maker's portfolio may be influenced by the characteristics of the asset itself [9]. This paper's experimental design consists of market makers trading randomly selected generic assets, eliminating the effects of this endogeneity bias; (6) it examines the trading behavior of the market maker controlling for inventory risks. There is ample literature providing evidence of the significant impact of inventory risk on the market maker's decision-making process and, thus, on her ability to provide liquidity [10]. This factor may be difficult to control for in empirical work. This experimental study controls for inventory effects, isolating the impact of attention constraints on the market maker's behavior. In summary, this paper contributes significantly to the experimental literature by examining the role of attention constraints on financial markets. The use of a controlled experimental setting overcomes many of the challenges seen in empirical studies such as the ability to measure the allocation of attention and isolate its effect on trading behavior and market quality.

The remainder of this paper is organized as follows: Section 2 reviews the related literature; Section 3 describes the nature of the market and develops the hypotheses; Section 4 discusses the advantages and design of the experimental setting; Section 5 describes the statistical methodology; Section 6 presents the results; Section 7 concludes.

2. Literature Review

Early work in attention literature can be traced back to the notion of bounded rationality [8]. The theory of bounded rationality and its business applications suggests that individuals have a limited capacity to gather and process information and, thus, may not be able to make fully informed and rational decisions [11] [12]. When dealing with information capacity constraints, individuals naturally rely on heuristics or mental shortcuts to arrive at satisfactory (not necessarily optimal) solutions [13]. This reliance on heuristics may induce biases in the individual's financial decision-making process leading to less-than-optimal outcomes in financial markets.

Traditional finance literature has attempted to explain empirical anomalies by emphasizing the role of market imperfections. For example, [14] develops a market equilibrium model where prices only partially reflect the information of informed individuals, and where not all individuals are informed. [15] attempts to explain the small firm anomaly by developing a model of market equilibrium where there is less information available for some of the securities than for others. [16] coined the term "noise traders," referring to those individuals who trade for non-informational reasons and implying that not all individuals have access to (or trade based on) all available market information. [17] departs from the notion of a perfect market by assuming investors only know about a subset of all available securities. These traditional finance models attempt to explain market anomalies by assuming the "perfection" of markets while retaining, within their models, the idea of perfectly rational market participants. In fact, Robert C. Merton states "although I must confess to a traditional view on the central role of rational behavior in finance, I also believe that financial models based on frictionless markets and complete information are often inadequate to capture the complexity of rationality in action" [17].

Researchers have attempted to complement the efforts of traditional models in explaining market anomalies by challenging the viability of the rationality assumption.[4] In other words, they study financial markets under the premise that individuals' limited capacity to process information may prevent them from making fully rational decisions, leading to less-than-optimal outcomes [18]. Several studies have explored the role of limited attention in explaining market anomalies. For example, [19] develops a model in which limited attention explains both under- and overreaction to two earnings components: earnings surprises and operating accruals. [20] compares investors' reactions to earnings announcements on Friday, when investors' attention is less likely, to their response on other weekdays. They find that Friday announcements have a 15% lower immediate response and a 70% higher delayed response. Similarly, [21] studies investors' reactions to earnings announcements made during non-trading hours. They find greater underreaction during these hours. [22] categorizes the information contained in earnings announcements as harder-to-process/soft (qualitative) and easier-to-process/hard (quantitative) information to examine

[4]Perfectly rational individuals are those individuals who make utility-maximizing decisions, apply unlimited processing power to any available information, and hold preferences well-defined by standard expected utility theory.

the role of information processing costs when explaining post earnings announcement drift.

Although these studies focus on the timing and information content of earnings announcements as a way of measuring the effect of investors' attention constraints, other studies have attempted to directly quantify the level of these constraints using empirical proxies. For example, [4] studies how attention affects asset price dynamics through investors' under-and overreactions to information. To measure investor's attention, they use trading volume as a proxy in their cross-sectional analysis and the state of the market (rising or falling markets) in their time-series analysis. [5] proposes a novel measure of investor attention using the aggregate Google search frequency. They find evidence of short-term predictability based on this search volume measure. Reference [3] measure the degree of attention a NYSE specialist can provide to any stock as an inverse function of trading activity and absolute returns of all other stocks in the specialist's portfolio.

The aforementioned literature is aimed at identifying the determinants of investor attention such as trading volume, the state of the market, and the timing of earnings announcements. There is, however, a parallel stream of literature on limited attention that focuses on the process through which individuals allocate their limited attention. For example, [23] provides an equilibrium model to analyze the effect of information capacity constraints in which investors optimally allocate their information capacity across multiples sources of uncertainty. [24] argues that investors allocate attention first to market and sector-wide information and then to firm-specific information. They provide evidence that this pattern of attention allocation helps explain the covariation in asset returns and, thus, has implications for return predictability. Similarly, [25] argues that, given the large number of stocks to choose from, investors naturally allocate more attention to "attention-grabbing" stocks (e.g. stocks in the news). This allocation process, in turn, has implications for their trading decisions.

Examining the effects of attention constraints on investor behavior can be challenging due to the difficulty in observing how investors allocate their attention or even which securities are in their opportunity set [6]. To overcome this challenge and provide more direct evidence of the limited attention effect, some studies have recently examined market settings where a designated market maker plays a significant role [3] [6]. In contrast to the wide-ranging investor's opportunity set, designated market makers are only responsible for providing liquidity for a well-defined set of securities. This market setting allows researchers to directly identify the set of securities across which market makers must allocate their attention.

The traditional microstructure models attribute the market maker's decisions and their effects on market equilibrium to costs associated with inventory risks [10]-[29] and adverse selection risks [30] [31] [32] [33]. [4] [7], however, provide a behavioral alternative to help explain the decision-making process of market makers and its impact on market quality. [3] tests the hypothesis that the ability of NYSE specialists to provide liquidity for a given stock is negatively related to the attention requirements of other stocks in his portfolio. Furthermore, they hypothesize that specialists devote more attention to their more active stocks, reducing their provision of liquidity to other stocks in their portfolios. In a more recent study, [6] examines the ability of market makers to provide liquidity around earnings announcements. They find that when some stocks in the market maker's portfolio have earnings announcements, liquidity is lower for other non-announcement stocks in the portfolio. They also find that half of the liquidity decline can be attributed to attention constraints while the other half is explained by the market maker's inventory.[5] These papers provide robust evidence of the significant role of limited attention on the degree of market liquidity and, thus, on the quality of the market.

In summary, the finance literature has taken significant steps to challenge the notion of perfectly rational agents in support of the notion of bounded rationality [8] whereby informational and computational limitations prevent investors from making optimal investment decisions. The role of limited attention has been studied extensively in an attempt to uncover evidence supporting this notion. In this effort, previous empirical studies have provided a wealth of evidence but have faced a significant challenge in providing pure proxies of attention and isolating its effects on the investor's decision-making process as well as its implication for market quality. For this reason, this paper is aimed at providing more robust evidence of the effect of limited attention. More specifically, I study the market maker's ability to provide liquidity by directly testing the hypotheses proposed by [3], and other related hypotheses. In doing so, I examine the effect of limited attention within a highly controlled laboratory experiment that allows me to directly measure the demands on the individual's attention, avoiding the need to use noisy measures of attention. To my knowledge, this is the first experimental study to examine the effect of limited attention on financial markets.

3. Market Structure and Hypotheses

In this section I discuss the basic structure of the market with a focus on the role of the market maker as a liquidity provider. Among the market design issues discussed in this section are the information structure and market transparency, the market maker's management of inventory risk, and the structure of attention

[5] According to [6], they distinguish themselves from [3] in that they use an exogenous attention-demanding event (*i.e.* earnings announcement) instead of trade-based measures of attention such as high trade volume which could be endogenous (e.g. the market maker may induce a higher trading volume by providing more aggressive quotes). Furthermore, [6] claim to be the first empirical study of attention constraints to control for inventory risk management. They hypothesize that the when the NYSE specialist acquires a large inventory position in one stock, she provides less liquidity for all other stock on her panel. Thus, inventory risk management may influence the ability of the specialist to provide liquidity. They find that about half the effect of earnings announcements on non-announcement stocks is due to specialist inventory risk management, but after controlling for inventories, there still find a significant effect attributable to the specialist's attention constraints. To control for inventory effects, they use two empirical proxies: (1) the absolute value of the closing dollar inventory for all stocks on the specialist's panel on the previous trading day, and (2) the change in the absolute value of the aggregate dollar inventory for all announcement stocks on the panel on the same trading day.

and its allocation across markets. I then formulate the hypotheses tested in this study.

3.1. The Nature of the Market

Electronic markets have surged in popularity as a platform for trading not only equities but a wide spectrum of financial assets as well. There are a variety of ways in which these electronic markets can be and have been organized.[6] Despite the varied and distinct structure of these markets, there seems to be a common theme: most equity markets contain some form of market making. A study by the U.S. Securities and Exchange Commission (SEC) finds that, as of September 2009, the three largest U.S. equity trading centers are the NASDAQ, NYSE and NYSE Arca, which account for 47.3% of the trading volume in National Market System (NMS) stocks.[7] A quick glance at the trading rules for these three U.S. registered exchanges reveals a significant role played by some form of designated market maker.[8] In an earlier study, [34] investigates 30 stock markets worldwide and find that the majority of countries follow one of three types of market making systems: (1) the quote-driven market making system, (2) the centralized market making system in an order-driven market, and (3) the non-centralized market making system in an order-driven market.[9] More importantly, they find that the vast majority of stocks in developed markets, including the low liquidity stocks, are obliged to use a form of market making.

In this paper, I use an experimental market setting that contains salient features of a market making system in an order-driven market:[10] continuous trading with the required participation of market makers, different levels of pre-

[6]Although the complexity of electronic trading venues worldwide makes their classification a daunting task, trading platforms can be broadly grouped into two categories based on their reliance on market makers: quote-driven markets and order-driven markets. In a quote-driven market, a market maker takes the opposite side of every transaction. Order-driven markets feature trading between public investors without the intermediation of a market maker. Electronic markets can also be classified by their degree of continuity. Periodic markets allow trading only at specific points in time (e.g. call auctions) while continuous markets allow trading at any point in time while the market is open [35]. Nowadays, however, most electronic trading platforms are a hybrid with features consistent with several of these market type classifications. One of the more prominent hybrid trading platforms is the New York Stock Exchange (NYSE).

[7]In general, NMS stocks are those that are listed on a U.S. national securities exchange [36].

[8]Many U.S. exchanges and Electronic Communications Networks (ECNs) offer liquidity rebates to proprietary trading firms when resting orders that add liquidity are accessed by those seeking to trade immediately by taking liquidity [36]. In this way, these trading venues allow proprietary trading firms to act as market makers. The main difference between these traders and designated or authorized market makers is that proprietary trading firms do not have an obligation to provide liquidity, continuity and maintain a fair and orderly market as designated market makers do.

[9][34] base their classification on the following four dimensions: execution system (quote driven versus order driven), market location (floor based versus screen based), level of competition (monopolistic versus competitive) and the presence of a market making system. The three types of market making systems mentioned here do not distinguish between electronic and floor-based markets. Reference [34] also provides a 4-type classification that disaggregates the centralized market making system into two sub-categories: on that is floor-based and another that is electronic.

[10]To control for the level of demand on the market maker's attention, the experimental market design consists of two environments: a centralized setting where there is only one market maker per stock and a non-centralized setting where two market makers submit their quotes on a continuous basis for the same stock.

trade transparency across traders, price-time priority rules, instantaneous trade reporting rules, and order submission and cancellation functionality for both market and limit orders. In this setting, all potential buyers and sellers (informed and uninformed) can trade directly with each other via the limit order book (acting as competitors to the market maker), and can enter limit and market orders that trade against the market maker's quotes (acting as counterparties to the market maker).

The Role of the Market Maker

In this experimental market, market makers act primarily as liquidity providers, submitting limit orders continuously from their own accounts. They are required to quote (binding) bid and ask prices at all times. At the same time, the market allows for public buyers and sellers (informed or uninformed) to trade directly with each other via the limit order book, effectively competing with the market maker. In addition, the market maker has exclusive access to the book and, thus, the order flow in real time. Other traders can only observe the best market bid and ask prices. Altogether, these features foster a trading environment where the market maker's quotes reflect both her intentions as well as the interest of the entire market.

Market makers are required to post bid and ask prices on a continuous basis. This requirement, however, does not necessarily provide extra liquidity in the market. The market maker can avoid trading by entering orders that are non-competitive.[11] There are several reasons, however, why this possibility may not play a substantial role in the behavior of the market maker. First, the trading behavior of the market maker is primarily profit-motivated. The main source of revenue for the market maker is the difference between the bid and the ask prices she quotes (*i.e.* the bid-ask spread). Therefore, the market maker has a strong incentive to trade a large volume of shares and this can only be achieved with aggressive quotes. Second, the main goal of this study is to uncover any potential differences in the market maker's liquidity provision ability under different attention constraint scenarios. The *level* of liquidity provision under either scenario is not as important as the *change* in the level of liquidity provision across scenarios. Finally, studies have shown that designated market makers have a significant positive impact on the quality of markets, especially the less liquid ones. For example, [37] concludes that the designated market maker can improve the terms of trade offered by public limit orders, at least for less liquid securities by simply maintaining a market presence.

Information and Disclosure

Undoubtedly, varying degrees of information in the market are the fundamental basis for trade.[12] The varying degrees of information are the result of ei-

[11]Non-competitive orders consist of submitting limit buy (sell) orders with a price that is lower (higher) than other bid (ask) prices outstanding on the limit order book. The lower (higher) the bid (ask) price is, the less likely it is that the order submission will result in a trade and the less competitive the order is.

[12]There are of course other bases for trading that may arise due to non-informational reasons. Among those reasons I find trading related to institutional mandates, portfolio rebalancing needs and noise [16]. Traders whose trading is motivated by non-informational reasons are known as uninformed traders.

ther (1) asymmetric information (*i.e.* traders may have access to different information sets) and/or (2) opinion dispersion (*i.e.* traders may perceive the same information set differently, creating disagreement regarding the asset value).

In a model with asymmetric information, the market maker loses on average to those traders with superior information. This phenomenon is widely accepted and known as adverse selection risk.[13] There are several experimental studies that model the effect of adverse selection risk on the behavior of market makers. [38] manipulates the degree of information asymmetry by separating traders into two groups: a group of informed investors who learn some information about the value of the security, and a group of market makers who learn no such information. In aggregate, however, the market has perfect information on the value of the security. [39] develops a market setting that also contains two groups of traders: a group of informed traders who have superior information and a group of uninformed traders who face liquidity needs (*i.e.* they trade for exogenous non-informational reasons).[14] In this paper, the information structure combines features of both studies. The experimental market contains three distinct groups of traders with varying degrees of information. First, informed traders have superior information because the value of the security is known to them within a narrow range. Second, uninformed traders do not have any information about the fundamental value. They trade because of exogenous, liquidity-based needs. Finally, and similar to uninformed traders, market makers do not have any information about the value of the security; however, they have exclusive access to the limit order book and the market's order flow in real time.[15]

Information disclosure and the resulting transparency of the market, have significant implications on the degree of liquidity, the level of competition, and the informational efficiency of markets. [40] finds that a higher level of transparency improves the informational efficiency of the market, causes opening spreads to widen, and allows market makers to benefit at the expense of informed and uninformed traders. More importantly, they find that post-trade transparency (*i.e.* trade disclosure) can have important effects on market quality, while pre-trade transparency (*i.e.* quote disclosure) seems to have little effect.

This paper's experimental market features a high degree of post-trade transparency for all traders. Trades are instantaneously reported to all traders. The degree of pre-trade transparency, however, is different across trader types in order to motivate trading and to simulate the main features of a market making

[13]The origin of this concept is usually credited to the work of [30] and it was first formalized in a one-period model where the market maker's decision problem was affected by a fraction of traders who possessed superior information [31].

[14]Informed traders can also be described as traders who have private information about value which allow them to predict future price changes. Uninformed traders can also be seen as traders who must fill an order before some deadline which may arise when traders need to invest or disinvest exogenous cash flows [40].

[15]All three types of traders (market makers, informed and uninformed) have access to the market's best bid and ask/offer prices (*i.e.* BBO) and to the entire history of the BBO and transaction prices in real time.

system in an order-driven market [42]. Informed traders have access to the security's fundamental information (*i.e.* a narrow range containing the fundamental value of the security), market makers have access to all market information (e.g. current BBO and the state of the entire limit order book)[16], and uninformed traders have access to the best bid and best ask prices only.

Inventory Management

In addition to adverse selection risk, it is well understood that risk averse market makers must incorporate their inventory levels into their quote-setting process, especially during times of large order imbalances. This idea can be traced back to the work of [10]. The market maker's portfolio holdings may move away from her desired portfolio, resulting in a level of risk (*i.e.* inventory risk) and return that is inconsistent with her personal preferences [26]. In an experimental study, [38] analyzes the ability of the market maker to control her inventory position. He finds that market makers manage their inventories in real time by revising their quotes. Furthermore, he finds that inventory management is more prominent in settings where the degree of information asymmetry is more pronounced. Therefore, the amount of liquidity a market maker provides is likely to be affected by her inventory position in addition to any potentially binding attention constraints [6].

In order to control for potential effects of inventory risk on the trading behavior of market makers, the experimental design lets market makers accumulate any ending inventory position without penalty. Any shares in inventory remaining at the end of trading are ignored, in the sense that they do not alter the profit/loss performance of the market maker.[17] In this way, market makers are not required to protect themselves from the arrival of overnight news (*i.e.* overnight risk), eliminating inventory-driven trading such as the selling/buying of shares towards the end of the trading session in an attempt to end with a flat position (*i.e.* zero shares in inventory).[18] The market maker does, however, manage her inventory during continuous trading to protect herself from informed trad-

[16]Fundamental information can be seen as information relevant to the investment decision such as the state of the economy, recent structural changes in the industry where the company operates, the company's financial statements, the current strategy of the firm's management, etc. Market information would be information relevant to the trading decision such as current quotes, recent high and low prices, opening and closing prices, submissions, cancellations and standing orders in the limit order book, etc.

[17]This implies that, unlike other traders, the market maker's ending position is not marked to fundamental value. This feature precludes the market from being a zero-sum game (*i.e.* the sum of the profit/losses across all traders in a trading session does not equal zero). To illustrate this point, imagine a market maker who sells a share to an uninformed trader at $80 when the fundamental value of the share is $50. If the uninformed trader keeps that share until the end of the trading period, he would suffer a loss of $30 (*i.e.* marked to value). The market maker, however, does not receive a gain of $30 unless she covers her position (*i.e.* buys a share) prior to market closing. And even if she does cover her position, the gain will depend on the purchase price, which may not equal $50.

[18][43] finds that lagged NYSE specialist inventories and trading revenues predict market liquidity. According to their study, specialists usually earn positive trading revenue on intraday round-trip transactions but are more exposed to the possibility of losses on inventories held for longer periods such as overnight. Their findings provide empirical evidence of the effect of overnight risk on the behavior of the market maker. Therefore, controlling for end-of-trading inventory effects is paramount.

ing (*i.e.* adverse selection risk). Increasing inventory deviations away from zero provide the market maker with information signals about trading decisions of other traders, some of who may be informed.

Overall, in this market, inventory management has an asymmetric and positive effect on the market maker's trading behavior. The market maker can monitor her inventory and revise her quotes reducing her exposure to informed trading without the constraint of ending with a flat position. Thus, the experimental design not only encourages a more aggressive price-quoting behavior by the market maker, but it also helps isolate the effect of limited attention by removing the influence of a substantial non-attention factor. In this way, the design permits for a more robust examination of the effects of attention constraints on the market maker's ability to provide liquidity to one or more markets.

Attention Allocation

Structural market features may influence the market maker's ability to allocate attention and provide liquidity effectively. Two points are worth considering: (1) the availability of attention per unit of information intensity is fixed[19], and (2) market makers may face competition from traders with lower attention constraints.

Most empirical studies look at the effect of market makers' attention constrains on financial markets by examining different levels of information intensity. These studies use empirical proxies to measure the level of information intensity for a stock and, thus, its demand on the attention of traders. Some examples of those proxies are earnings news [6], trading volume [4], Internet search frequency [5], absolute returns [3], among others. Although these studies examine the market maker's decision making process based on her individual limited attention capacity, they fail to incorporate the effects of structural features designed to increase the amount of attention available for a stock during times of high information intensity. In other words, they fail to keep the amount of attention available per unit of information intensity fixed. For example, in the NYSE, each security can only be assigned to one specialist. There are, however, several market features that help alleviate the demands on the specialist's attention, particularly during times of high information intensity. These features in turn, help ensure that the liquidity of the stock handled by a specialist is not affected by demands on her attention when information about other stocks in her panel increases in intensity. Some of these features are the reassignment of stocks across panels (*i.e.* variable panel size)[20], the availability of relief specialists, and the introduction of the Hybrid market which provides specialists with electronic trading tools and, more importantly, allows off-floor market makers to be

[19][25] defines attention-grabbing stocks as those that are in the news, stocks that are experiencing an unusually high trading volume, or stocks with extreme one-day returns. In the spirit of this concept, I define an attention-grabbing stock as one with a high number of information intensity "units" relative to other stocks.

[20]Once allocated, reassignments of stocks across specialist firms are rare but reassignments of stocks within a specialist firm are relatively common [3]. In fact, [6] shows that during the NYSE's Hybrid rollout period (October, 2006 until January, 2007) the number of specialist panels and, thus, the number of specialists significantly decreased from roughly 345 panels to 285 panels.

opportunistic by trading in some stocks during times when specialists are busy attending to other stocks in their panel [6].[21] Combined, the structural features of the specialist system can be seen as an attempt to keep the amount of attention available per unit of information intensity fixed; even though the specialist herself may see the demands on her individual attention vary over time.

In this paper, the experimental market design keeps the amount of attention available for the set of securities fixed on a per-unit basis across low and high attention constraints environments.[22] This allows me to control for the amount of attention allocated across stocks and isolate the effects attention constraints on the market maker's ability to provide liquidity.

The second structural implication is the impact of other traders who face lower attention constraints (*i.e.* they trade on a smaller set of securities or trade on securities with lower information intensity). For example, informed traders may behave similar to market makers, yet trade on a fewer number of stocks. Previous studies find evidence that informed traders provide a significant amount of liquidity to the market [39].[23] They find that informed traders in electronic order-driven markets become net suppliers of liquidity when they see their informational advantage depleted. Furthermore, a study by the U.S. SEC has found that proprietary firms, also known as high-frequency traders, take advantage of low-latency systems and liquidity rebates by submitting large numbers of non-marketable orders which provide liquidity to the market electronically.

This competitive feature is explicitly modeled in the experimental market by allowing market makers to trade in more than one stock while restricting the trading of informed traders to only one stock. This feature is similar to the non-centralized market making design in an order-driven market as described by [34]. In this type of market, there is more than one trader providing market making services and liquidity to the market. Also, designated market makers compete with other traders (who may have lower attention constraints) for order flow.

3.2. Hypotheses

The complexity of modern-day stock markets, coupled with the interdependence of trader's decisions, makes empirical studies of traders' behavior vulnerable to a

[21]In their paper, [6] explicitly states the following: "Unfortunately, the data we have do not indicate when a relief specialist is called in, so we are unable to isolate those events in our analysis."

[22]In the low attention constraint environment, there are two market makers and each market maker can only trade on one market (e.g. market maker A can only trade security A and market maker B can only trade security B). In this environment, the market maker has low demand on her attention because she allocates her entire attention capacity to one security. In the high attention constraint environment, there are still two market makers but here both market makers are obligated to provide liquidity to both markets (e.g. both market makers (A and B) must trade securities A and B simultaneously). By keeping number of market makers fixed across trading environments, I keep the aggregate amount of attention available fixed across environments, but, more importantly, I keep the availability of information on a per-market basis fixed. I control for trading volume so that it does not vary across attention constraint environments.

[23]A current example that is consistent with these findings can be found in the NYSE. Specialists in the NYSE face competition from off-floor traders. These are high-frequency traders who provide a substantial amount of liquidity to the NYSE stocks effectively competing with the specialist.

myriad of confounding effects. Given the experimental nature of this paper and the impracticality of perfectly replicating complex institutions such as the NYSE's Hybrid market, the experimental market implements only institutional features of interest in a simplified setting. These institutional features, however, are enough to provide a direct test of the paper's relevant hypotheses and shed light on the behaviors of market makers in a less restrictive setting. Furthermore, this study aims to improve the robustness of previous empirical results by avoiding the use of noisy proxies, controlling for potential statistical and behavioral biases, isolating the pure effect of the market maker's attention constraints, and addressing other confounding effects that have not been previously addressed or simply cannot be measured in empirical studies.

[3] examines individual NYSE specialist portfolios and test whether liquidity provision is affected as specialists allocate their attention across stocks. More specifically, they argue that if limited attention forces a specialist to allocate effort across stocks, her ability to provide liquidity for a given stock should be negatively related to the attention demands of other stocks in her portfolio, all else held constant. They refer to this hypothesis as the Limited Attention Hypothesis (LAH). They further hypothesize that the effects of limited attention should be most evident for inactive securities.[24] They find significant evidence supporting both hypotheses. This paper provides a test of predictions similar to those made by the LAH. More formally, I test the following hypotheses:

- *Hypothesis* 1: The liquidity provision ability of the market maker and, thus, the degree of market liquidity decreases as the market maker's attention constraints increase.

To test this hypothesis, the experimental design consists of two main environments: a condition where market makers are only responsible for providing liquidity to one market, and another condition where market makers are responsible for providing liquidity to two distinct markets simultaneously. The degree of liquidity is measured and compared across these two environments.

To support this hypothesis, I predict that the liquidity measures will deteriorate more significantly when the market maker is responsible for providing liquidity in two markets simultaneously relative to one market only. In other words, I expect to see market liquidity (e.g. bid-ask spread) as well as the amount of liquidity provided by the market maker (e.g. number of limit orders posted) worsen, on average, when the market maker operates in two simultaneous markets as opposed to only one.

- *Hypothesis* 2: The reduction in the market maker's liquidity provision (and overall market liquidity) caused by higher attention constraints is more evident for the least active securities.

To test this hypothesis, the experimental design consists of two distinct markets with different levels of trading activity. Both markets always have the same

[24][3] provides two reasons for this hypothesis: (1) market makers participate in a larger fraction of trades and provide a larger proportion of liquidity for inactive securities, and (2) market makers are less likely to divert attention from active securities because they put more capital at risk and derive a large fraction of their profits when trading these securities.

number of informed traders and market makers. One of the two markets (*i.e.* high activity market), however, consists of twice as many uninformed traders. Uninformed traders are given an exogenous motive for trading a given number of shares.[25] Therefore, varying the number of uninformed traders across markets (two in one market and four in the other) produces different levels of trading activity.

To support this hypothesis, I predict that the liquidity measures will deteriorate more significantly in the market that has a low level of trading activity (*i.e.* relatively inactive) if market makers are responsible for trading in two markets simultaneously rather than one market only. In other words, I expect to see a significant increase in the bid-ask spread and a decrease in the number of limit order posted by the market maker only in the less active market, and when the market maker is responsible for trading on both markets. I do not expect to see any effect on the liquidity measures in markets with a high level of trading activity.

Numerous studies have examined the strategic behavior of traders and the information content of their strategies. Not only do traders' decisions determine market prices but they also impact market liquidity. The trader's decision as to whether to be patient or impatient has a direct impact on the degree of market liquidity.[26] [41] provides a model that derives optimal submission strategies for informed and uninformed traders. He suggests that informed traders have a transitory informational advantage and their trading strategy depends primarily on the quality of their information. He shows that when information value is high, informed traders use market orders, lowering market liquidity. Informed traders may, however, supply liquidity in less active markets.[27] He also shows that uninformed traders initially use limit orders but progressively use more aggressive orders (e.g. market orders or more aggressively priced limit orders) as the trading deadline approaches. In summary, this study highlights the importance of information value and its impact on the strategic trading decisions of all traders.

Similar to [41], [7] studies the role of information on the strategic behavior of market participants. In their study, they include a market-making feature by empirically examining the role of the specialist in the NYSE. Under the premise that that specialists compete with other traders for the provision of liquidity, [7] finds strong evidence that specialists use their unique access to the limit order book to make strategic trading decisions. More specifically, they find that if ag-

[25]Refer to the "Experimental Design" section for a detailed description of the different types of traders in the experimental market and their respective motives for trading.

[26]Patient traders are willing to wait to trade. They are likely to use limit orders effectively becoming liquidity suppliers. Impatient traders must trade quickly. They are likely to use market orders (or marketable limit orders) reducing the level of market liquidity.

[27][39] and [44] extend the work of [41] to show that informed traders may become liquidity suppliers once their information advantage has been depleted (toward the end of the trading period). The dual role of informed traders as demanders and suppliers of liquidity is a common theme across these two studies. [41] notes that informed traders' informational advantage is only transitory and that they may become liquidity suppliers when their information becomes public especially if bid-ask spread are wide and trading deadlines are distant.

gregate order information is valuable, specialists use this information to profit. In this way, specialists do not only reduce their own exposure to adverse selection risk, but they may also increase adverse selection risk for uninformed traders. Furthermore, they show that these results are stronger for active stocks where the competition is more intense.

Evidently, valuable information drives the strategic behavior of traders with an informational advantage, as well as the behavior of uninformed traders whose trading decisions may be reactive. Informed traders possess information about the fundamental value while market makers can extract this information from their exclusive access to the order book. These two types of traders may use their information to compete for market making profits. Higher attention constraints on the market maker may then lower her ability to extract information and compete effectively. Moreover, the reduced ability of the market maker to extract information makes informed traders' information even more valuable. This, in turn, increases the market maker's adverse selection risk, further reducing her ability and/or willingness to provide liquidity. In order to explore the role played by information value and traders' strategic behavior on liquidity across different attention constraints environments, I test the following hypotheses:

- *Hypothesis* 3: Higher attention constraints lower the market maker's abilities to extract information from the market, worsening her informational disadvantage (relative to informed traders) and hampering her ability to provide liquidity.

To test this hypothesis, the experimental design consists of securities (or trials) with different degrees of information value. Informed traders receive an information signal (*i.e.* a narrow range that contains the security' fundamental value) prior to the start of trading. Some trading trials consist of fundamental values with large absolute deviations from the prior expected value of $50 (high information value) while other fundamental values are near the prior expected value (low information value). In this way, the value of the informed traders' information is controlled across securities.

To support this hypothesis, I predict that the liquidity measures will deteriorate more significantly in markets with high information value (*i.e.* large informational advantage of informed traders) if market makers are responsible for trading in two markets simultaneously rather than one market only. In other words, I expect to see a significant increase in the bid-ask spread and a decrease in the number of limit order posted by the market maker only in markets where informed traders have a large informational advantage, and when the market maker is responsible for trading on both markets. I do not expect to see any effect on the liquidity measures in markets where informed traders have little to no informational advantage.

- *Hypothesis* 4: The market maker's ability to provide liquidity effectively, and thus, her trading performance (based on optimal quote revisions) is reduced as her attention constraints increase.

To test this hypothesis, I assess the market maker's trading performance and liquidity provision abilities across the two attention-constraint environments. To measure the market maker's trading performance, I consider her dollar profits. The market maker's ability to optimally revise her quotes would be indicative of a superior trading performance and should, in turn, lead to higher profits.[28]

To support this hypothesis, I predict that the market maker profit share will be significantly lower when the market maker is responsible for providing liquidity in two markets simultaneously relative to one market only. In other words, I expect to see dollar profit, but more importantly, profit share decline, on average, when the market maker operates in two simultaneous markets as opposed to only one.

4. Experimental Study

In this section, I provide a detailed description of both the experimental design and the laboratory market.

4.1. Experimental Design

In this paper, I use a full-factorial repeated measures (balanced) design with a total of six factors (three within-subject factors and three between-subject factors).[29] In such a design, each subject or experimental unit is observed repeatedly under different treatments.[30] The objective of this design is to investigate factors affecting the ability of the market maker to provide liquidity. More specifically, the experiment was designed to examine how the liquidity provision ability of market makers differs with (1) market characteristics such as trading activity and time, (2) asset characteristics such as the relative value of the security's information to traders, and, (3) behavioral characteristics such as constraints on the market maker's attention capacity and the trading motives of different market participants.

In order to manipulate the level of trading activity, at the beginning of each trial, traders are randomly assigned to one of two markets. Excluding market makers, one market consists of two informed traders and four uninformed traders, while the other market consists of two informed traders and only two uninformed traders. All traders know the level of trading activity in their selected market.

[28][7] finds stronger evidence of the market maker's optimal quoting decisions in actively traded markets than in less active market. They state that "specialists use this information [information contained in the limit order book] in ways that favor them (and sometimes the floor community) over limit order traders. The results are more evident for active stocks where the competition between specialists and limit order traders is more intense." Unfortunately, the experimental design does not allow for a test of this experimental finding. In this experimental design, each market contains the same number of informed traders. Thus, the level of competition between market makers and informed limit order traders does not vary across markets.

[29]Between-subject factors are those that differ for separate subjects, but for a single subject are always the same. Within-subject factors are those that vary across the different observations coming from the same subject [45].

[30]A repeated measures design has the advantage being economical because each member is measured under all treatments or conditions. This advantage is particularly important when the number of treatments is large.

Attention constraints on market makers are manipulated by varying the number of markets the market maker must attend to. In one trading environment, each market maker is constrained to trading in one market so she can allocate her entire effort and attention to one stock (*i.e.* low attention constraints). On the other trading environment, the market maker must attend to two markets by quoting and updating her bid and ask quotes in both markets simultaneously (*i.e.* high attention constraints).

Information value is manipulated relative to a prior expected value of $50. All traders know that fundamental values are randomly drawn from a normal distribution with a mean of 50. Only a subset of traders (*i.e.* informed traders) is given a narrow range containing the fundamental value (*i.e.* the information range). Thus, these traders have an informational advantage over the other traders. The magnitude of their informational advantage is a direct function of the value of their information. To manipulate this factor, some securities are given a value near the prior expected value of $50 (*i.e.* low information value) while other securities carry extreme values or values far away from the prior expected value (*i.e.* high information value).[31] More specifically, securities with a high information value have realizations that are between $20 and $30 from the expected value, and securities with low information value have realizations that are no more than $10 from the expected value.

The traders' trading motive is manipulated by randomly assigning them to different trader types. There are three types of traders (market makers, informed traders, and uninformed traders), and each type has unique characteristics across several dimensions such as information, market transparency, trading capabilities, sources of profit, among others. At the beginning of each trial, traders are randomly assigned to one of these three types. Overall, there are two market makers, four informed traders, and six uninformed traders in each trial.

Time is manipulated to characterize the liquidity provision strategy of the market maker. During the trading trial, trading decisions are examined at the end of each 24-second time interval for a total of five decision points. The segmentation of time facilitates the study of the time series properties of the market.

Overall, the experimental market uses a full-factorial repeated measures design with six factors and varying number of levels for each factor: attention constraints (high, low), information value (high, low), time (five time intervals of 24-second periods), trading activity (high, low), trader type (informed trader, uninformed trader, market maker), and cohort (four cohorts of 12 participants each). The first three are within-subject factors, as they vary across different observations coming from the same subject. The last three are between-subject factors, as they vary for different subjects, but remain constant for a single subject.

[31] [39] refers to this factor as extremity based on the idea that extreme values provide informed traders with higher-value information. There may be other, more direct, techniques to model and control for information value. For example, providing informed traders with information ranges of different sizes would directly determine the value of their information. Informed traders presented with a narrower information range would produce a more precise estimate of value than traders presented with a wider range of possible fundamental values. In this paper, I chose to follow the design in [39] to make my findings comparable to theirs.

Controls

A primary benefit of an experimental study is the ability to control features of the experimental design that might influence behavior but are not the focus of the study [40]. More specifically, in a repeated measures design, it is important to control for order and carry-over effects [46].

Order effects result when the ordinal position of the treatments biases participant responses [46]. In order to eliminate possible order effects, I vary the treatment order across cohorts. Two cohorts are presented first with the low-attention-constraints setting followed by the high-attention-constraints setting, while the other two cohorts trade in the opposite order.[32] To control for possible effects of differences across securities, I follow a design similar to the one used in [39]. Not only are different cohorts presented with different treatment orders, but each cohort also trades a subset of security pairs that are identical in terms of their information value. More specifically, each cohort trades a total of 20 security pairs with different attention-constraints orderings while keeping the ordering of a subset of 12 security pairs unaltered.[33] Only this subset of security pairs is included in the statistical analysis. **Table 1** illustrates this design. The information value varies across trials (or security pairs) but remain identical across attention-constraints orderings (and cohorts).

Carry-over effects (also known as learning or practice effects) can be significant in a repeated measures design. These effects occur when an effect from one treatment changes (carries over to) participants' responses in the following treatment condition [46].[34] In this experimental design, traders' actions may change simply because they become better and more familiar with the trading features of the market. For example, over time (and across securities) the market maker may increase its provision of liquidity to the market simply because she becomes more comfortable with the functionality of the trading platform and/or better at reading the order flow. To control for these effects, an in-depth training session is held prior to running the experimental market. Participants receive extensive training in the mechanics of the trading platform (*i.e.* trading functionality of the software) and in the mechanics of the market (*i.e.* trader types, nature of the limit order book, role of the market maker).[35] They also take part in a

[32]The technique where conditions are presented to different participants in a different order is known as counterbalancing. This technique is commonly used in experimental designs to control for order effects [46].

[33]A security pair refers to an experimental trial. Each trial consists of two markets or securities. In a given trial, these two securities have the same information value. Their deviation from the expected value of $50 is not exactly equal but they are within the same narrow range ($0 to $10 for the low-information-value securities and $20 to $30 for the high-information-value securities). In this design, all four cohorts trade a subset of trials (or security pairs) in the same order. Thus, the subset of security pairs traded, as a whole, does not only have identical deviations from the expected value but they are also traded in the exact same order across cohorts.

[34]Learning effects may violate the independence assumption for the error terms in standard ANOVA. Fortunately, a special feature of repeated measures analysis is a series of corrections to the standard statistics tests if violations are detected [45].

[35]Also, most participants had been exposed to this trading simulation before taking part in the training session and experimental session. This further mitigates any learning effects that may arise during the trading sessions.

Table 1. Security values. This table presents the absolute deviations of security fundamental values from a prior expected value of 50. The absolute deviations are common to all cohorts and are presented to them in the same order shown in the table. The actual value of the securities traded is a function the expected value and the absolute deviations presented in this table. For example, in trial 2, the fundamental value for stock 1 could be either 50 + 27 (=77) or 50 − 27 (=23). Each cohort trades a total of 20 securities or trials. Half of the cohorts trade the first 10 securities under low attention constraints and the second 10 securities under high attention constraints (*i.e.* Order 1), while the rest of the cohorts trade under high attention constraints first (*i.e.* Order 2). Half of the securities contain a high level of information value (their values have realizations that are between 20 and 30 of the expected value) while the other half contain a low level of information value (their values have realizations that are within 10 of the expected value). The level of information value is determined by the absolute deviation of the fundamental value from the expected value of 50, and thus, it is presented to all cohorts in the same order. Only trial numbers that appear in bold are included in the statistical analysis. Data associated with trials that do not appear in bold are discarded.

Trial #	Information value	Order 1		Order 2	
		Low constraints first		High constraints first	
		Stock 1	Stock 2	Stock 1	Stock 2
1					
2	High	27	29	27	29
3	Low	1	8	1	8
4					
5	High	20	22	20	22
6					
7	Low	4	6	4	6
8	Low	9	3	9	3
9	High	30	22	30	22
10					
11					
12	Low	10	2	10	2
13	High	26	21	26	21
14					
15	Low	1	9	1	9
16					
17	Low	7	5	7	5
18	High	25	30	25	30
19	High	24	29	24	29
20					

series of practice trials that are identical to the actual experimental trials.[36] Furthermore, altering the ordering of treatments may also help mitigate these carry-over effects.

[36]The data from these practice trials is not included in the statistical analysis.

Another concern relates to the different levels of intelligence, motivation, and familiarity with the experimental environment across different participants and cohorts [40]. Apart from having all four cohorts trade in all experimental settings, each trader in a given cohort is also randomly assigned to a trader type (informed trader, uninformed trader, or market maker) and to a market (high activity market or low activity market) at the start of trading for each security. The random assignment of participants helps minimize the possibility of differences across trader types and market dynamics being driven by individual differences.[37]

Subjects, Training, and Incentives

The experiments were conducted in the Global Financial Markets Trading Lab at the Anisfield School of Business (ASB) at Ramapo College of New Jersey. The trading simulation software was provided by Financial Trading System (FTS) via its FTS Interactive Markets trading simulator. This trading simulator was largely adapted to match this paper's experimental market design. Each trading session involved a cohort of 12 participants. All participants were undergraduate business students.

Participants were given detailed written instructions and were told to carefully review these instructions prior to the trading sessions.[38] In addition, all participants experienced extensive training for the experiment. They attended a 90-minute training session. The session consists of three parts: (1) a 30-minute discussion of the written instructions, including an overview of the experimental market and the trading software (e.g. trading functionality, mechanics of the limit order book, trading rules such as price-time priority, the role of the market maker, etc.), (2) a 15-minute trading simulation where participants learn the basics of the trading software by trading and openly discussing any challenges they may have in using the software, and (3) a 45-minute practice session where participants trade in the experimental markets replicating the exact dynamics of the experiment (e.g. random assignment to trader types and markets, trading trials with a pre-trading and a main trading phase, etc.).

Notwithstanding the importance of adequate training, financial experiments must offer participants monetary incentives. The fundamental method of experimental economics is to create a setting that implements some institutional features of interest and then provide participants with incentives to maximize utility within that setting [47]. To create these incentives, I adopt the reward structure in [39]. Actual winnings, denominated in U.S. dollars, for each session are calculated by subtracting a floor from each trader's winnings in laboratory dollars and then multiplying by a U.S. dollar conversion rate. The participants know neither the floor value nor the conversion rate.[39] These two parameters are

[37]Bloomfield *et al.* [39], discuss the issue of the house money effect whereby losing traders could take on excessive risk. Similar to their approach, I mitigate this effect by making the traders' actual level of trading loses unknown. This can be achieved by subtracting trading losses from an unknown floor level to determine their actual payoffs.

[38]A copy of the experiment written instructions is given in **Appendix**.

[39]These two values remain unknown to participants during the entire session to mitigate any potential risk-seeking behavior among participants who have low of negative balances (*i.e.* house money effects) and any other gaming behavior.

set equal to values that yield average cash winnings of US$ 15.00 per participant per hour of trading with a minimum payment of US$ 5.00.[40]

4.2. Laboratory Market

The laboratory market resembles the mechanism of a market making system in an order-driven electronic market.[41] This market contains traders with different trading motives and different levels of information (*i.e.* asymmetric information), and it allows for trading rules, reporting rules, and trading functionality that are similar to those used in many large stock exchanges worldwide [34].

The Market

The basic setting features a double-auction electronic market with the addition of market makers who are obligated to provide liquidity for a well-defined set of securities (*i.e.* one or two securities). The market allows for continuous trading, a limit order book that is visible to the market maker, limit order and market order functionality, price-time priority rules, post-trade transparency, and order cancellation capabilities. Besides the presence of market makers, the market contains informed traders who possess information about the fundamental value of the security and uninformed traders who face liquidity needs (*i.e.* they trade on the basis of exogenous non-information reasons).

The Traders

There are three trader types: (1) informed traders, (2) uninformed traders, and (3) market makers.[42] Informed traders possess superior information regarding the fundamental value of the security. The value is determined before the trading trial starts and informed traders are shown a narrow range containing this value. For example, if the fundamental value is determined to be $23, informed traders may be told that the value is somewhere between $11 and $31. Informed traders can enter limit orders and market orders into the order book. They are able to see their own outstanding orders but they cannot see the orders of other traders. They can, however, see the market's highest bid and the lowest ask. Informed traders earn a profit every time they buy (sell) shares at a price below (above) the fundamental value. Uninformed traders do not possess information regarding the value of the security. Instead they have a trading "target" which is known to them before the trading trial begins. The target may have different directions for different uninformed traders. For example, a trader may have a target of −20 shares (*i.e.* an instruction to sell 20 shares) while another trader may have a target of +20 (*i.e.* an instruction to buy 20 shares). The goal of uninformed traders is to meet their target at the most favorable prices possible.

[40] A detailed description of the reward structure for this experiment is given to participants in the written instructions (see Appendix).

[41] [48] uses a similar electronic order-driven laboratory market to test the price efficiency behavior of markets when short sales constraints are binding. Their design, however, does not incorporate designated market makers.

[42] The experiment's written instructions (see Appendix) refer to these three types of traders as follows: (1) informed traders, (2) liquidity traders, and (3) dealers.

At the end of the trading trial, uninformed traders who fail to reach their targets receive a penalty of $100 for each share in inventory short of the target. For example, an uninformed trader with a target of 20 shares who never reaches a position of 20 shares and ends the trading trial with an inventory of 18 shares will receive a penalty of $200. The penalty is large enough that uninformed traders are better off hitting the exact target even if the prices at which they transact are unfavorable. The use of targets captures the notion that uninformed traders are trading for exogenous reasons related to liquidity needs. Similar to informed traders, uninformed traders can enter limit orders and market orders into the order book. They are only able to see their own outstanding orders but they can also see the highest bid and the lowest ask for the entire market. Uninformed traders take a loss every time they buy (sell) shares at a price above (below) the fundamental value. The third type of trader is the market maker. Similar to uninformed traders, market makers do not know the fundamental value. However, unlike the other two types of traders, market makers are able to see the entire limit order book (*i.e.* all outstanding limit orders entered by traders in the market). Market maker scan enter market orders but, unlike the other two trader types, they cannot enter limit orders. Instead, they quote a single bid price and a single ask price. Furthermore, market makers cannot cancel their quotes; they can only update their quotes. This feature prevents market makers from exiting the market and ensures their continuity as liquidity providers.

In summary, the three types of traders have substantially different degrees of market information accessibility and trading capabilities. More importantly, traders have substantially different motivations for trading. Informed traders trade with the aim of maximizing their profit based on their informational advantage. Uninformed traders trade with the aim of minimizing their loss while meeting their exogenous liquidity needs. Market makers have an obligation to trade and provide liquidity to the market; they are compensated for their liquidity provision services by earning the difference between their quoted bid and ask prices.

The Order Book

The laboratory market features an electronic book of orders (*i.e.* limit order book) with the participation of designated market makers. Traders are permitted to enter limit orders and market orders. Limit orders are instructions to buy (sell) securities at a price not higher (lower) than the instructed limit price. This type of orders provides the trader with price certainty (*i.e.* the trader will not buy (sell) at a price higher (lower) than the limit price) but it carries execution risk (*i.e.* the order may never execute). Market orders are instructions to buy (sell) securities at the best available price. Unlike limit orders, market orders do not provide traders with price certainty but they do eliminate execution risk.

The order book consists of two books: a bid book and an ask book. The bid book maintains a list of all outstanding bid orders and the ask book maintains a list of all outstanding ask orders. The order book allows for the automated crossing or execution of orders. All market orders immediately cross with the best-priced limit orders outstanding. In this sense, market orders are marketable. Limit orders can also be marketable. If a trader enters a bid (ask) order with a price higher (lower) than the lowest (highest) ask (bid), the orders immediately cross. Limit orders that are conservatively priced and fail to cross immediately after they are entered are known as non-marketable limit orders. These orders remain on the order book until they are crossed by a marketable order from another trader.

In this market, all bids and asks must have integer prices between 0 and 100, inclusive. The maximum number of shares allowed per order is one. Traders can, however, enter multiple orders at the same price. Traders can enter both limit orders and market orders at any time during the trading trial. Traders, except for the market maker, can also cancel their outstanding limit orders at any time. The trading functionality provides traders with the flexibility to cancel individual orders, cancel all bids (or asks) at once, or cancel all outstanding orders at once.

The Trading Trial

Each trading trial takes place in two phases: (1) pre-trading phase and (2) main trading phase.

- *Pre-Trading Phase:* The pre-trading phase lasts 20 seconds during which traders can enter and cancel as many orders as they wish. During this period, no trades are executed. Marketable orders do not result in a trade. The crossing orders are simply kept on the order book and at the end of the pre-trading phase the order book is purged of these orders in the following way: if the highest bid crosses with the lowest ask, the more recent of the two orders is deleted from the book. This process is repeated until the highest bid price is below the lowest asking price.
- *Main Trading Phase:* The main trading phase lasts 120 seconds during which traders are permitted to enter and cancel as many limit and market orders as they wish. During this period, trades can be executed. Here, participants can trade continuously and they are free to pursue dynamic order placement and cancellation strategies.

The Trading Session

The experimental design includes four cohorts of 12 traders each, for a total of 48 participants. A cohort is a group of traders who always trade together in one trading session. A trading session is a 90-minute period where participants take part in a series of independent trading trials. In other words, each cohort trades 20 securities sequentially. Each of the 20 trading trials consists of 12 participants randomly divided into two groups with each group trading on a different security or market. A group of at least 7 traders trades one security, while a group of at least 5 traders trade the other security. Before the beginning of each trading trial, traders are randomly assigned to a trader type, achieving the following overall trader type distribution: two market makers, four informed traders, and six uninformed traders. Each market has two informed traders each for all 20 trials. One market has four uninformed traders while the other has only two uninformed traders.[43] In one block of 10 trials, each market maker is required to participate in only one market (*i.e.* low attention constraints environment). In the other 10 trials, both market makers are required to participate in both markets simultaneously (*i.e.* high attention constraints environment). Figure 1 provides a graphical description of a trading session.

5. Statistical Methodology

In this section, I provide a broad overview of the statistical methodology used to

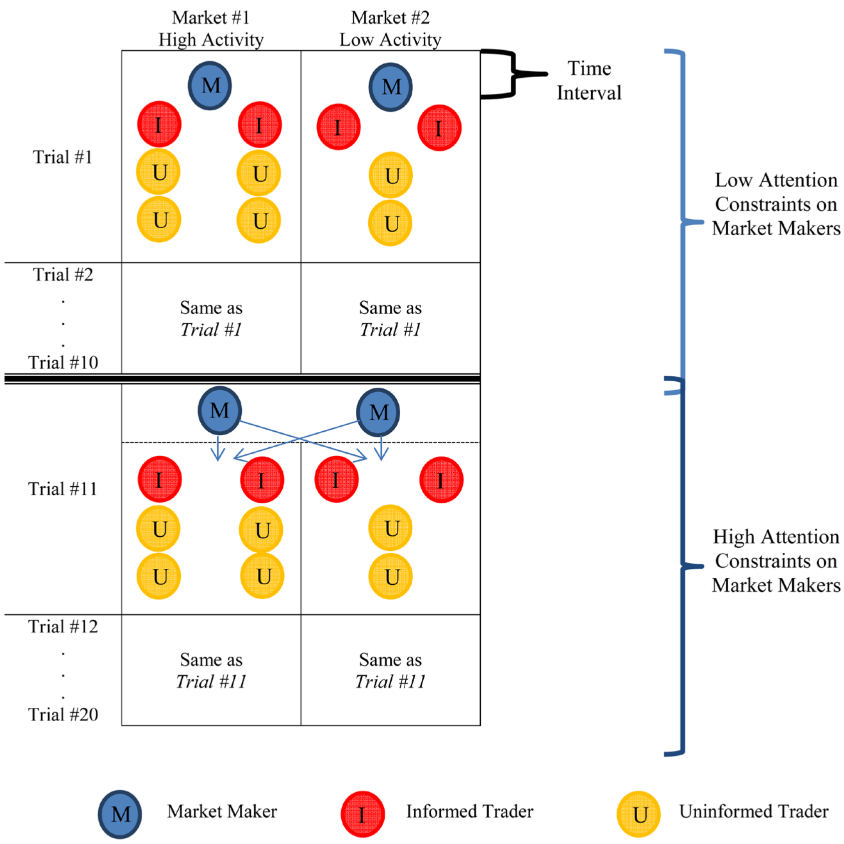


Figure 1. Trading session. This figure depicts the layout of a single experimental trading session. Each session consists of 20 trials. Each trial consists of two securities or markets: (1) a market with a high level of trading activity that features two informed traders and four uninformed traders and (2) a market with a low level of trading activity that features two informed traders and only two uninformed traders. Each trial also contains two market makers. The participation of the market makers in each of these two markets depends on the experimental treatment. In ten of the trials, each market maker trades exclusively in a separate market (*i.e.* low attention constraint treatment). In the other ten trials, both market makers are required to trade on both markets at the same time (*i.e.* high attention constraints treatment). The ordering of the attention constraints factor is manipulated across cohorts. This figure presents only one of two possible orderings with low attention constraints being imposed first. Information value (not shown) is manipulated across trials. Time interval refers to a window of time such as a 24-seconds interval.

[43]To manipulate the level of trading activity, the number of uninformed traders is different across the two markets. All uninformed traders regardless of the market they are in have a target with an absolute value of 20 shares. Therefore, the greater the number of uninformed traders in a given market, the greater the level of trading activity.

analyze the experimental data. The exact nature of the statistical methodology depends on the hypothesis being tested and, thus, may be different for each hypothesis test in this paper. A more detailed description of the statistical methodology used for each hypothesis is provided in the next section.

The statistical methodology used to test this paper's hypotheses is repeated-measures analysis of variance (ANOVA) with between-subject factors. As with any ANOVA, repeated-measures ANOVA tests the equality of means. However, repeated-measures ANOVA is used when all members of a sample are measured under several different treatments. As the sample is exposed to each treatment in turn, the measurement of the dependent variable is repeated. This design reduces the problem, common in experimental economics, of overstating statistical significance by assuming that repetitions of the same actions by the same group of subjects are independent events [49]. Repeated measures designs are classified by the number of between-subject and within-subject factors. In order to understand the statistical analysis, it is necessary to first specify the applicable between- and within-subject combination. This paper's experimental design has a total of three between-subject factors and three within-subject factors. However, statistical tests for each of the hypotheses may require the use of only a subset of factors.[44] Thus, to test for statistical significance, I compute the average of the dependent variable for each treatment (or cell) as defined by the appropriate subset of factors relevant to a given hypothesis.

A factorial ANOVA provides a methodology to test a variety of effects: (1) a significant *main effect* means that there is a difference between at least two levels of a factor with respect to mean scores on the response (or dependent) variable, (2) an interaction is a condition in which the effect of one factor on the response variable is different at various levels of another factor, and (3) a significant *simple effect* means that there is a significant relationship between a factor and the response variable at *a given level* of another factor [46]. To illustrate these three effects, let's look at the second hypothesis put forth in this paper: the reduction in the market maker's liquidity provision (caused by higher attention constraints) and, thus, in market liquidity, is more evident for the least active securities. In this case, the response variable is some measure of liquidity. A significant attention main effect (without an attention/activity interaction effect) means that attention constraints exert a similar influence on the liquidity of a market across all levels of trading activity. A significant attention/activity interaction effect means that the impact of attention constraints on liquidity is different in markets with different levels of market activity. Finally, a significant attention/activity interaction effect suggests the presence of significant simple effects. The activity factor has two levels: low and high. Therefore, there could be two

[44]In experimental sciences, it is not unusual to find a design described as "one between-subject and two within-subject repeated measures" [45]. The type of design is, thus, hypothesis-specific. For example, to test the first hypothesis, only two factors may be needed: attention constraints and trader type, making the statistical design a "one between-subject and one within-subject repeated measures." The second hypothesis, however, requires an additional between-subject factor: market activity.

separate simple effects: (1) a simple effect of attention for the low-activity market and (2) a simple effect of attention for the high-activity market. In other words, testing for simple effects of attention is similar to testing for attention main effects, but it is done for only one activity level at a time.

The relevant type of effect depends on the nature of the hypothesis and on the significance of the interaction effect. If the interaction effect is significant, there is no need to test for main effects, as these results would be misleading.[45] Instead, it is appropriate to test for simple effects. If the interaction effect is not significant, however, simple effects may be ignored and main effects should be tested instead. For the sake of consistency, and more importantly, appropriateness, the statistical tests, when applicable, begin with a test of the interaction effect and then are sequenced as follows:

- If the interaction effect is not significant, I proceed to test for main effects for each of the factors being considered. If any of the main effects are significant, I provide contrast tests and/or multiple comparison tests for any significant main effects.[46]
- If the interaction effect is significant, I proceed to interpret a profile plot to gain some insight on the nature of the interaction.[47] Then, I test for any relevant simple effects. Similar to main effects, if a given simple effect is significant, I provide contrast tests and/or multiple comparison tests.

6. Results

The focus of this analysis is on the effect of attention constraints on the ability of market makers to provide liquidity to the market, and thus, on market liquidity. I begin with preliminary summary statistics to provide a sense of how typical is the aggregate behavior resulting from these experiments. I then examine the liquidity effect mentioned above.

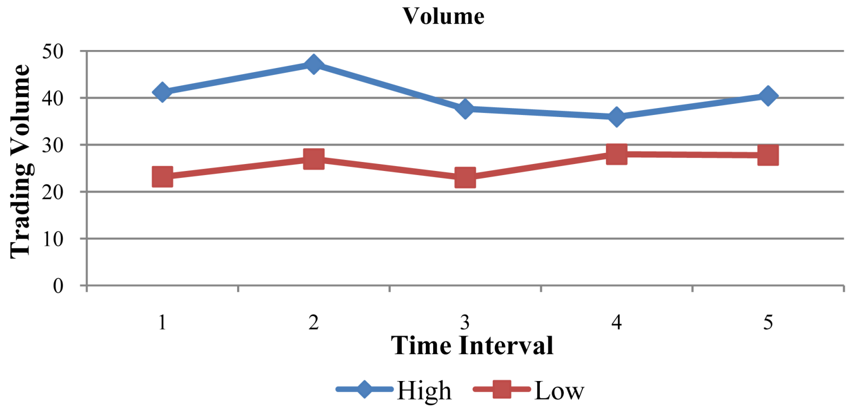
6.1. Summary Statistics

Figure 2 presents the evolution over time of three market-wide variables: trading volume, bid-ask spread, and pricing error. These statistics were computed separately for markets with a high level of trading activity and for markets with a low level of trading activity. The aim of these plots is to evaluate how well the

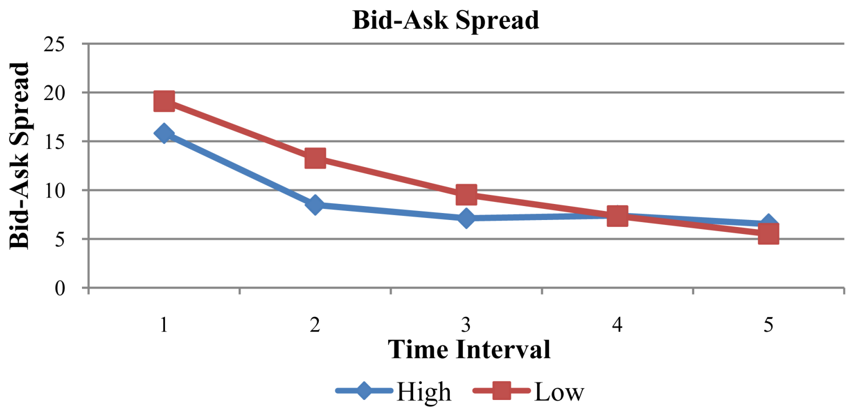
[45]If there is a significant attention/activity interaction effect, a significant attention effect becomes misleading as it suggests that attention constraints exert a significant influence on liquidity across both levels of activity contradicting the interaction effects. For this reason, a significant interaction effect precludes the existence of a meaningful main effect.

[46]Contrasts tests examine statistical significance of the difference between a given factor level (e.g. high attention constraints) and the selected benchmark factor level (e.g. low attention constraints). Multiple comparison tests determine which pairs of factor levels are statistically different. Of course, if the factor for which the main effect is significant has only two levels, the contrast test and the multiple comparison test would be equivalent. In this case, there would only be a need to use one of these tests.

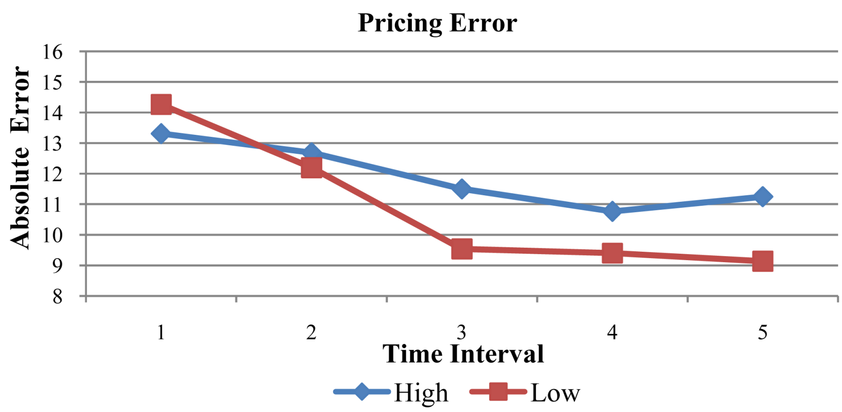
[47]A profile plot graphs the means of the response variable for each of the factor/level combinations or treatments. For example, this paper's second hypothesis consists of two factors (*i.e.* attention constraints and market activity) with two levels each (*i.e.* low and high). Thus, the profile plot would consist of four points, each point representing the mean of the response variable (*i.e.* liquidity measure) for a given attention/activity combination.



(a)



(b)



(c)

Figure 2. Marketwide summary statistics. I divide each trading trial into five time intervals of 24 seconds each. For each trial, I sum the number of shares traded in each interval to obtain the trading volume per interval. (a) shows the trading volume for each interval averaged across trials and cohorts. The bid-ask spread is the difference between the highest-prices market bid and the lowest-priced market ask. I calculate the average bid-ask spread in each time interval; (b) shows the bid-ask spread for each interval averaged across trials and cohorts. The pricing error is obtained as the absolute value of the difference between the price midquote and the fundamental value. For each interval, I average the pricing error; (c) shows the pricing error for each interval averaged across trials and cohorts. The graph labeled "Low" summarizes the data for the low-activity market only while the graph labeled "High" summarizes the data for the high-activity market only.

experimental market behaves. Each panel divides trading into five 24-second intervals.

A particularly important aspect of this study is the inducement of different levels of trading activity across markets.[48] To evaluate the success of my efforts, I compute the trading volume by summing over the number of trades in each time interval and averaging these numbers across all trials and cohorts. (a) provides the summary statistics of the trading volume measure for each market. As expected, the trading volume in the high-activity market is significantly larger than the trading volume in the low-activity market. Approximately 200 shares are traded in a typical high-activity market, while less than 130 shares are traded, on average, in low-activity markets. This difference in trading volume across markets is also consistent across time. Markets with an expected high level of activity have a larger volume of trading than the low-activity markets throughout the entire trading day. Furthermore, (a) shows that volume exhibits a slight "U" shape with high levels of trading activity near the second time interval and again toward the end of the trading day. The increase in trading volume during the last trading interval reflects the trading behavior of uninformed traders rushing to hit their trading targets. This shape is observed for both experimental markets and it is consistent with the observed shape of trading volume in equity markets. Overall, these results provide strong support for the ability of the experimental design to induce the desired level of trading activity across markets.

(b) shows the time series behavior of the market's bid-ask spread. Each data point is computed as the average bid-ask spread for the 24-second time interval. Irrespective of market activity, the spread declines from an average of \$17.5 in the first interval to an average of nearly \$6 in interval five, resulting in a threefold decrease in the size of the spread. Panel C shows the average pricing error, calculated as the absolute value of the deviations of the mid-quote from the fundamental value. The pricing error decreases by an average of roughly 30% from the opening time to its lowest point near closing time. These patterns suggest that markets behave reasonably well, in light of theoretical, archival, and experimental studies. Of particular importance is that these experimental markets appear to gradually incorporate information, a feature consistent with market efficiency.

As a robustness check, I also compute the dollar mispricing in each of the two markets. Figure 3 presents the evolution of the mispricing variable over time. Once again, irrespective of the level of market activity, the markets behave reasonably well. The average dollar mispricing across both markets remains at two or less dollars for the entire duration of the trading trial. The average dollar mispricing for markets with a high level of trading activity is equal to \$1.43. This average is not statistically different from zero ($p = 0.6179$). Markets with a low

[48]The experimental design consists of two markets: low and high trading activity. Both markets consist of the same number of market makers and informed traders. The high-activity market contains twice as many uninformed traders as the low-activity market. This asymmetric distribution of the number of experimental subjects promotes different levels of trading activity across the two markets.

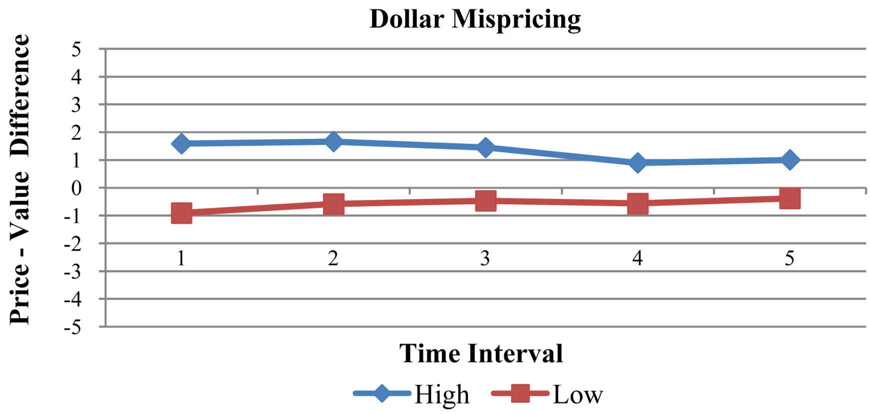


Figure 3. Marketwide mispricing. This figure plots the average dollar mispricing (measured as the dollar difference between the market price and the fundamental value) for each of two markets: (1) the low-activity market ("Low") and (2) the high-activity market ("High"). The mispricing variable is computed separately for each of five 24-second time intervals. For each interval, the dollar mispricing is averaged across all trials and all cohorts.

level of trading activity have an average dollar mispricing equal to −$0.11. Similar to high-activity markets, this average is not statistically different from zero ($p = 0.9427$). These results imply that the experimental markets are efficient.

The ability of markets to incorporate information into security prices depends on informed traders exploiting their informational advantage, which should result in positive profits for the informed group as a whole. This implies that all other groups experience an information disadvantage and should expect to lose money. Market makers are, however, a profit-motivated group with privileged access to the market's order flow. Their trading motive as well as informational access should allow market makers to mitigate and even eliminate their informational disadvantage as trading occurs. Uninformed traders, on the other hand, should expect to lose money to both informed traders and market makers.

The experimental markets indeed produce the expected results. Figure 4 shows that informed traders and market makers generated a positive profit in a typical trial. Informed traders generated an average profit of $292 and market makers generated an average profit of $180, while uninformed traders lose on average $82.[49] The figure also shows that these experimental markets are not a zero-sum game. Unlike other trader types, the market makers' ending inventory positions are not market to value, but are instead ignored in their profit calculation. This market feature was designed to control for the effect of inventory risk on the trading behavior of the market makers.

In summary, these results imply that informed traders not only have an informational advantage but they successfully trade on it. Also, market makers are able to successfully use their privileged access to order flow. This provides further evidence that the markets are well behaved.

[49]It should be noted that there are more informed traders and uninformed traders than market makers in the experimental market design. Overall, at any one point in time, there are six uninformed traders, four informed traders, and only two market makers.

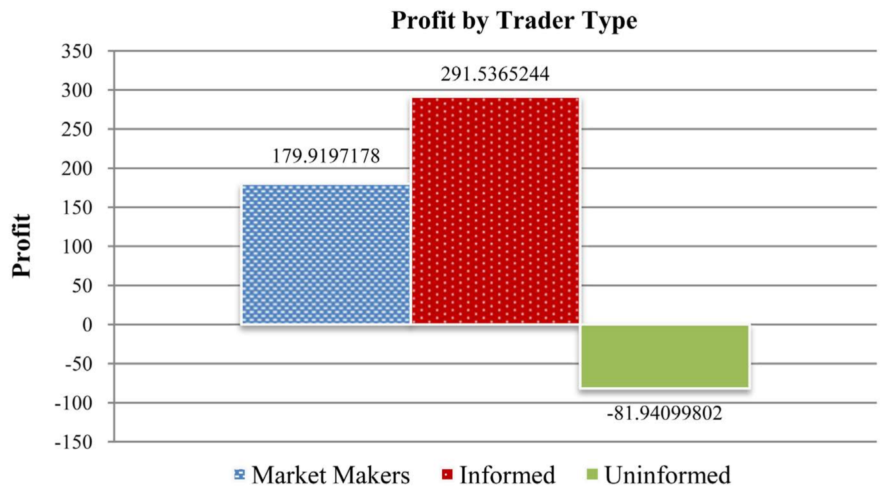


Figure 4. Dollar profits by trader type. Profit is measured as the dollar gain/loss for each trader in a given trial. This figure shows the average profit across all trials and cohorts for each of three different types of traders: (1) market makers, (2) informed traders, and (3) uninformed traders. On average, informed traders generate the largest average profit of $292 in a trial. Market makers generate an average profit of $180 per trial while uninformed traders took a loss of $82 in a typical trial.

6.2. Testing the Hypotheses

Attention Constraints and Liquidity

This paper's first hypothesis predicts that, when the demand on the market maker's attention constraints is high, her liquidity-provision abilities worsen. This, in turn, decreases the aggregate level of liquidity in the market. In order to test this hypothesis, this paper looks at the main effect of attention constraints on two broad sets of liquidity measures: (1) market maker's liquidity provision and (2) aggregate market liquidity. To measure the market maker's ability to provide liquidity, I compute the following three measures: the number of limit orders submitted by the market maker, the proportion of total limit orders submitted by the market maker, and the submission rate (computed as the number of limit orders the market maker submits divided by the sum of her limit and market orders).[50] To measure the aggregate level of liquidity, I use the quoted bid-asked spread and trading volume (computed as the number of shares traded within a time period). Table 2 summarizes the main effect findings.

(a) presents the measures of market maker liquidity provision. In markets with low attention constraints, market makers submitted an average of 49 limit orders per trial. This number was significantly reduced (to an average 22 limit orders) when the demands on the market markers' attention were high. The difference in the number of limit orders submitted is statistically significant with a p-value less than 0.01. Perhaps a better measure of liquidity provision is the percentage of the total number of limit orders submitted by a trader. Under low attention constraints, market makers submitted 18.72% of all limit orders in a typical trial. This proportion decreased by 6.41% in trials with high attention

[50]The submission rate variable is identical to the one presented in [39].

Table 2. Effect of attention constraints on liquidity. This table presents the main effect of attention constraints on several measures of liquidity. The table presents statistics (mean, difference in means, and *p*-values) for six distinct liquidity measures under both, markets with high and low attention constraints. (a) presents three measures of market maker liquidity provision: the number of limit order submitted by the market maker (# Limit), the proportion of total limit orders submitted by the market maker (% Limit), and the submission rate (computed as the number of limit orders a trader submits divided by the sum of her limit and market orders); (b) presents three market wide measures of liquidity: the dollar bid-ask spread ($ Spread), the percentage bid-ask spread relative to the best-priced ask (% Spread), and the trading volume (Volume). The difference in means for each liquidity measure is also shown together with the *p*-value resulting from the test of difference in means. *P*-values lower than 0.10 are considered statistically significant and highlighted in bold.

(a)

Attention constraints	# Limit	% Limit	Sub. rate
Low constraints	49	18.72%	47.50%
High constraints	22	12.31%	51.60%
Difference in means	27	6.41%	−4.10%
P-value	**<0.01**	**0.02**	0.40

(b)

Attention constraints	% Spread	$ Spread	Volume
Low constraints	18.67%	$11.27	174
High constraints	16.30%	$9.44	156
Difference in means	−2.37%	−$1.82	−$17.90
P-value	**0.09**	**0.05**	0.34

constraints. Once again, the difference between these two numbers is statistically significant ($p = 0.02$). Finally, the submission rate shows that there was no significant change in the market markers' order choice across attention constraint conditions. This measure, however, does not assess the market maker's contribution to market liquidity, but instead, describes her choice of trading strategy. Overall, (a) provides strong evidence on the negative effect of higher attention constraints on the market makers' contribution to market liquidity.

(b) looks at the impact of attention constraints (imposed on market makers) on the aggregate level of market liquidity. A quick look at all three measures of market liquidity illustrates the absence of a negative relationship between attention constraints and liquidity. In fact, there seems to be an increase in liquidity when the demand on the market makers' attention is greater. For example, the average percentage bid-ask spread in low-constraints markets is roughly 2.4% greater than in markets with high constraints (this difference is statistically significant with a *p*-value equal to 0.09). The average dollar spread yields similar results. Although trading volume remains unchanged across conditions, trading volume is a noisier measure of liquidity.

The contrast between the two sets of liquidity measures presented above could be explained by either the reaction of the market maker to higher attention demands placed on her, or the reaction of other traders (mostly informed) acting in an opportunistic manner. Market makers profit from the bid-ask spread, and having to allocate their attention across multiple tasks may push them to trade more aggressively (quote higher bids and lower asks) to achieve higher profits. This, in turn, narrows the spread. An alternative explanation is rooted in the reactions of other traders. Informed traders can exploit their informational advantage to generate profits but they can also earn additional income through liquidity provision. In markets where attention constraints on market makers are high, informed traders can step in to provide market making services, effectively competing against market makers. This would lead to either an improved or unchanged level of liquidity. A later section of this paper sheds some light on these ideas by evaluating the trading behavior of market makers and informed traders across different levels of attention constraints.

Attention Constraints, Liquidity, and Trading Activity

Reference [3] predicts that the effect of limited attention on the market makers' ability to provide liquidity should be more pronounced in inactive (or less active) markets. They base their prediction on the potential higher participation rate of market makers in less active markets and on the potential higher profits market makers can earn in the more active markets. These arguments not only suggest that market makers pay more attention to more active markets, but that their inattention has a bigger impact on less active markets. To test this hypothesis, the experimental design induces different levels of trading activity to each of the two markets. Previously, I have shown that the high-activity market has a significantly higher average trading volume than the low-activity market (refer to (a) in **Figure 2**). Here, I test the interaction effect of attention constraints and trading activity on liquidity. **Figure 5** summarizes the results of the interaction effect.

(a) presents the interaction effect on market wide liquidity. The statistical tests provide no significant interaction effect across all three measures of market wide liquidity (percentage spread, dollar spread, and trading volume).[51] The results are similar when I measure the liquidity provision of both market makers combined (see (b)). It is worth mentioning, however, that the percentage of limit orders submitted by market makers relative to all limit orders does respond to the interaction of trading activity and attention constraints. (b) shows that the share of market maker limit orders in low attention constraints markets is much larger when the market is less active relative to high-activity markets (the market makers' average share of limit orders is 22% in low activity markets compared to 15% in high activity markets). Furthermore, there is a significant decline in the market makers' share of limit orders when attention constraints intensify. This decline is only statistically significant ($p = 0.05$), however, for markets with a low

[51]Although it does appear to be a large difference in the percentage bid-ask spread across different levels of activity when constraints on the market makers' attention is high (*i.e.* simple effect of trading activity on liquidity in markets with high attention constraints), this difference is statistically insignificant ($p = 0.3162$).

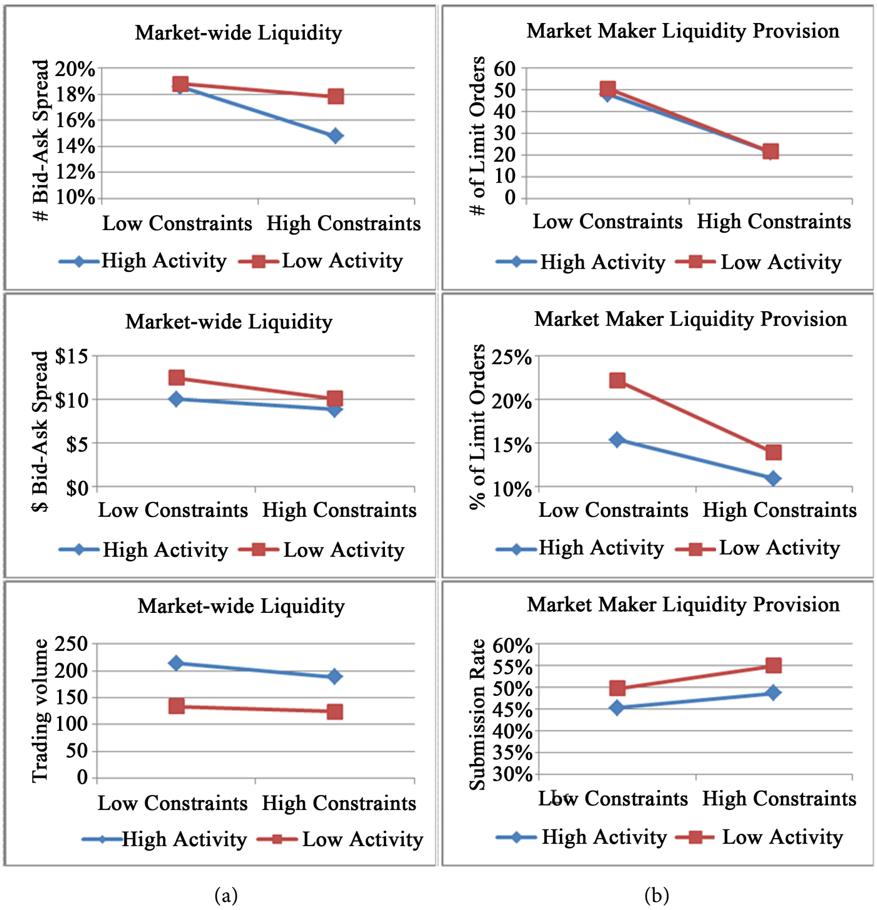


Figure 5. Effect of attention constraints and trading activity on liquidity. This figure plots the interaction effect of attention constraints and trading activity on several measures of liquidity. The figure examines the effect of attention constraints on liquidity across markets with different levels of trading activity. Each point on the panels plot the average value of the liquidity measure for each of four market conditions: (1) markets with low attention constraints on the market makers and low trading activity, (2) markets with low attention constraints on the market makers and high trading activity, (3) markets with high attention constraints on the market makers and low trading activity, and (4) markets with high attention constraints on the market makers and high trading activity. (a) presents three marketwide measures of liquidity: (a-1) the dollar bid-ask spread, (a-2) the percentage bid-ask spread (relative to the best-priced ask), and (a-3) the trading volume. (b) presents three measures of market maker liquidity provision: (b-1) the number of limit order submitted by the market maker, (b-2) the proportion of total limit orders submitted by the market maker, and (b-3) the submission rate (computed as the number of limit orders a trader submits divided by the sum of her limit and market orders.

level of trading activity. These results support the prediction in [3], as the effect of attention constrains on liquidity seems to be economically larger and statistically significant in less active markets.

Although the results from **Figure 5** provide some support for the hypothesis, the results are somewhat weak. To further examine this effect, I test the main effect of attention on liquidity provision for each of the two market makers separately. This testing structure provides a more pure analysis of the hypothesis. Under high attention constraints, both market makers are allowed to trade in both markets (*i.e.* low and high activity markets). Under low attention constraints, each market maker trades exclusively in one market. Table 3 provides a summary of the main effect of attention constraints on the liquidity provision of each market maker separately. Unlike the earlier test on Figure 5, Table 3 contrasts the degree of liquidity provision of a market maker focusing exclusively in one market (*i.e.* one level of trading activity). For example, it examines the number of limit orders submitted by a market maker when she traded exclusively in the low activity market (under low attention constraints), and measures it against the number of limit orders she submitted *only to the low activity market* when she had to attend to both markets simultaneously under (high attention constraints).

The top section of this table shows measures of liquidity provision for the market maker operating only in markets with high activity. The bottom section summarizes the results for the low-activity market maker. The average number of limit orders submitted by either trader (# Limit) declines significantly as the

Table 3. Effect of attention constraints on liquidity for each level of trading activity. This table presents the main effect of attention constraints on liquidity provision for each of two types of market makers: (1) a market maker operating in the market with high trading activity and (2) a market maker operating in the market with low trading activity. Liquidity provision is measured using three variables: the number of limit order submitted by the market maker (# Limit), the proportion of total limit orders submitted by the market maker (% Limit), and the submission rate (computed as the number of limit orders a trader submits divided by the sum of her limit and market orders). (a) presents statistical results for the high-activity market maker. It compares the average liquidity provision of the market maker trading only in the high activity market across low and high attention constraints. (b) presents statistical results for the low-activity market maker. It compares the average liquidity provision of the market maker trading only in the low activity market across low and high attention constraints. The difference in means for each liquidity measure is also shown together with the *p*-value resulting from the test of difference in means. *P*-values lower than 0.10 are considered statistically significant and highlighted in bold.

(a)

Activity/attention	# Limit	% Limit	Sub. rate
High/low	48	15.31%	45.30%
High/high	23	10.98%	49.54%
Difference in means	25	4.33%	−4.24%
P-value	**0.06**	0.20	0.35

(b)

Activity/attention	# Limit	% Limit	Sub. rate
Low/low	51	22.13%	49.70%
Low/high	22	13.50%	57.77%
Difference in means	29	8.63%	−8.07%
P-value	**0.10**	**0.05**	0.29

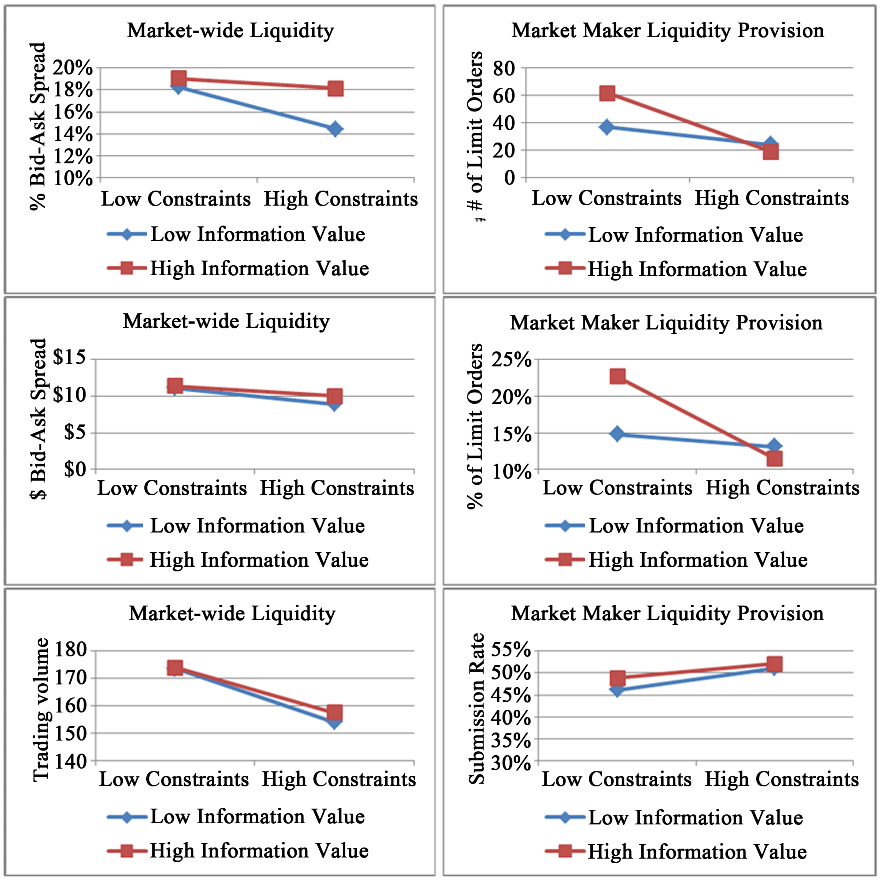
demands on their attention increase (p-values are equal to 0.06 and 0.10, respectively). The number of limit orders as a measure of liquidity, however, may be misleading as it does not control for the changes in market wide liquidity. To address this issue, Table 3 looks at the proportion of limit orders submitted by each market maker relative to the total number of limit orders in the market (% Limit). This measure of liquidity provision declines significantly only for the market maker operating in the low-activity market (there is an 8.63% reduction with a p-value equal to 0.05). For the high-activity market maker, the decline is smaller and it is not statistically significant ($p = 0.20$). These results suggest that attention constraints have a significant effect on liquidity provision primarily for market makers trading in less active markets. Overall, this section's statistical tests provide a strong support for the hypothesis.

Attention Constraints, Liquidity, and Information Value

In this section, I consider how the informational advantage of informed traders may hinder the liquidity provision ability of the market maker especially when the demands on her attention are high. Higher attention constraints on the market maker may lower her ability to extract information from the order flow making her less able to compete with limit orders for the provision of liquidity. Moreover, the reduced ability of the market maker to extract information from the book makes informed traders' information more valuable. This in turn, increases the market maker's adverse selection risk further reducing her ability and/or willingness to provide liquidity. To test this hypothesis, the experimental design consists of markets where informed traders are provided with highly valuable information and markets where the value of information is low. Figure 6 plots the interaction of attention constraints and information value on liquidity.[52]

(a) shows the interaction effect on market wide liquidity. Once again, the broad measures of market liquidity do not show the expected negative relationship with the demand on the market makers' attention. None of the interaction plots depicted in (a) provide statistically significant tests. (b) presents a very different story. The interaction effect is statistically significant for both the number and the proportion of limit orders submitted by market makers (p-values are 0.09 and 0.10, respectively). A closer look at the profile plots shows a dramatic attention-driven decline in the market makers' liquidity provision, primarily for markets with high information value. The number of limit orders submitted by market makers declines from an average of 62 under low attention constraints to an average of 16 under high attention constraints ($p < 0.01$). The proportion of limit orders submitted by market makers declines from an average of 23% under low attention constraints to an average of 11% under high attention constraints ($p < 0.01$). Although markets with low information values also experience a decline in liquidity provision, the decline is neither economically meaningful nor statistically significant.

[52]Securities with a high information value have realizations that are at between \$20 and \$30 from the expected value of \$50 (*i.e.* extreme values), and securities with low information value have realizations that are no more than \$10 from the expected value. In this sense, extremity or the fundamental value's deviation from the expected value is considered a measure of information value.



(a) (b)

Figure 6. Effect of attention constraints and information value on liquidity. This figure plots the interaction effect of attention constraints and information value on several measures of liquidity. The figure examines the effect of attention constraints on liquidity across markets with different levels of information value. Each point on the panels plot the average value of the liquidity measure for each of four market conditions: (1) markets with low attention constraints on the market makers and low information value, (2) markets with low attention constraints on the market makers and high information value, (3) markets with high attention constraints on the market makers and low information value, and (4) markets with high attention constraints on the market makers and high information value. (a) presents three marketwide measures of liquidity: (a-1) the dollar bid-ask spread, (a-2) the percentage bid-ask spread (relative to the best-priced ask), and (a-3) the trading volume. (b) presents three measures of market maker liquidity provision: (b-1) the number of limit order submitted by the market maker, (b-2) the proportion of total limit orders submitted by the market maker, and (b-3) the submission rate (computed as the number of limit orders a trader submits divided by the sum of her limit and market orders).

Overall, these results are consistent with this paper's third hypothesis. More importantly, these results shed some light on the asymmetric impact of attention constraints on the different sets of liquidity measures. Higher attention constraints on market makers have a significant negative effect on their liquidity provision but no effect on the aggregate level of market liquidity. These results suggest that the higher informational advantage of informed traders allows them to not only better exploit the uninformed traders, but it also increases their incentive to compete with market makers and earn additional spread-based revenue, especially in markets where market makers face high attention constraints.

Attention Constraints, Liquidity, and Trading Performance

A second dimension of the market maker's ability to provide liquidity is her effectiveness in revising her quotes and, in turn, her trading performance. To examine how effectively market makers provide liquidity under different degrees of attention constraints, this section looks at profit performance. Figure 4 shows that informed traders can generate an average profit of $292 while uninformed traders lose on average $82. Similar to informed traders, market makers generate an average profit of $180. If higher attention constraints have a negative effect on the market maker's trading performance, her average profit should be lower in markets where the demands on her attention are higher. In order to test this hypothesis, this paper looks at the main effect of attention constraints on trading profits.

Figure 7 shows the dollar profit for each trader type across both attention constraint environments. Under low attention constraints, the profit of each trader type is as expected, with uninformed traders losing an average of $187 while both informed traders and market makers generate a positive profit ($237 and $156, respectively). Under high attention constraints, both informed traders and market makers are able to generate a slightly higher positive profit ($346 and $204, respectively), and uninformed traders manage to increase their profit significantly by an average of $210 ($p = 0.08$). In other words, at a first glance, it looks like all three types of traders experience superior performance when the

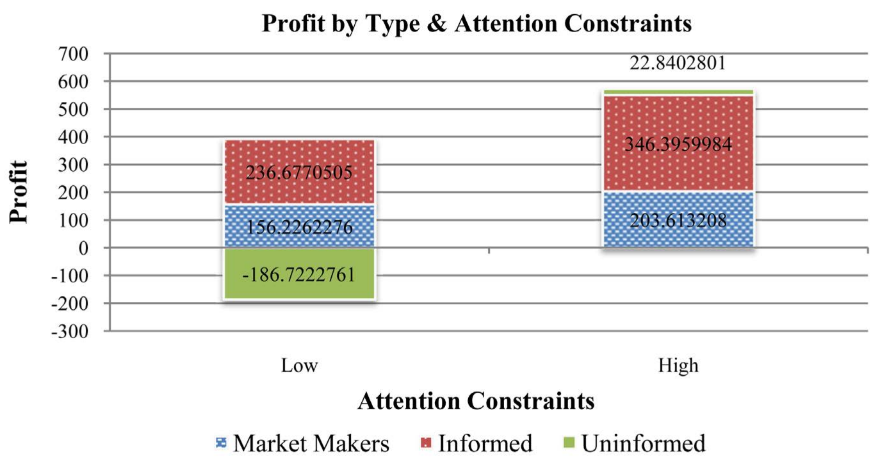


Figure 7. Effect of attention constraints and trader type on dollar profits. This figure plots the interaction effect of attention constraints and trader type on profit. The figure examines the effect of attention constraints on profit performance for each type of trader (market maker, informed, and uninformed). Profit is measured as the dollar gain/loss for each trader in a given trial. Profit is averaged for each of three different types of traders across two different attention constraint levels, generating a total of six conditions: (1) market makers under low attention constraints, (2) market makers under high attention constraints, (3) informed traders under low attention constraints on the market makers, (4) informed traders under high attention constraints on the market makers, (5) uninformed traders under low attention constraints on the market makers, and (3) uninformed traders under high attention constraints on the market makers.

demands on the market makers' attention are high.[53]

Although uninformed and informed traders do show an improvement in their trading performance across attention conditions, the increase in the average dollar profit of market makers does not necessarily mean a better trading performance. The market makers share of positive declines from 40% in a typical low attention constraints market to an average of 36% under high attention constraints.[54] In fact, market makers are the only ones that see their profit share decline (informed traders keep their profit share at 60% while uninformed traders manage to turn their losses into a profit). These results provide evidence of a redistribution of profit share away from market makers when the demands on their attention increase.

Besides the explicit costs of facing higher attention constraints (*i.e.* a lower profit share), market makers bear substantially higher implicit costs in the form of inventory risk-the market maker's portfolio may move away from the desired portfolio (e.g. a flat position). Ending the trading session with a non-zero inventory balance exposes the market maker to swings in the inventory value overnight. Figure 8 presents the average (absolute value) number of shares in the market makers' ending inventory (*i.e.* at the closing of the trading session). This figure clearly shows an economically meaningful increase in their ending invent-

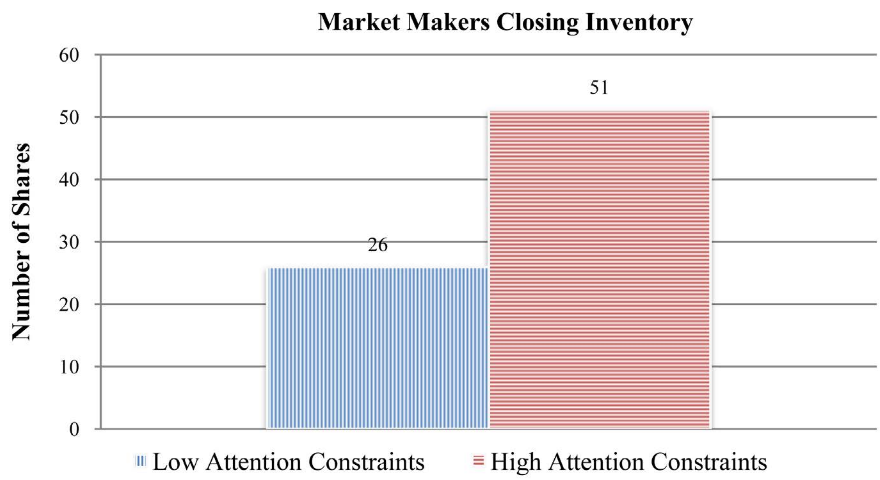


Figure 8. Effect of attention constraints on market makers' closing inventory. This figure shows the average (absolute value) number of shares in the market makers' closing inventory for two different levels of attention constraints (low and high). In a typical market with low attention constraints, market makers ended the trial with an inventory balance 26 shares away from a flat position (*i.e.* zero shares in inventory). The average inventory balance increased to 51 in markets with high attention constraints on the market makers.

[53]The experimental design does not replicate a zero-sum trading game. As explained above (see Inventory Management section), market makers are permitted to accumulate any inventory position without penalty, effectively eliminating overnight risk. The market design feature is needed to isolate the effect of limited attention on trading behavior by preventing any trading motivated by inventory management such as the selling or buying of shares toward the end of the trading session in order to end with a flat position (*i.e.* zero shares in inventory).

[54]The profit share is computed by dividing their trader's dollar profit by the sum of all positive profits.

tory, as market makers face higher attention constraints. Under low attention constraints, market makers end a typical trial with an inventory balance of 26 shares away from a flat position; this number doubles to an average of 51 shares under high attention constraints.

In summary, attention constraints have a meaningful negative effect on the market maker's ability to provide liquidity effectively, and thus, on her trading performance. This effect is captured by a combination of a decline in the market maker's share of the realized profits and her decreased ability to manage her ending inventory position.

7. Conclusions

A study released by the U.S. Securities and Exchange Commission in 2010 finds that roughly 50% of all U.S. equity trading volume occurs in exchanges that require some form of designated market maker. Furthermore, the advent of high-tech low latency trading, coupled with liquidity rebates offered to proprietary firms, makes market makers a sizable group in U.S. equity markets. This implies that market making not only provides equity markets with a vital source of liquidity but it is also a key determinant of overall market quality. This paper aims to explore the costs to market makers of providing liquidity, which has implications for many aspects of financial markets from return predictability to optimal asset allocation strategies.

Traditional models of market microstructure attribute the costs of market making to two primary sources: adverse selection risk and inventory risk. More recently, however, researchers have emphasized the role of behavioral factors on the function of market makers. In this study, I examine the effect of limited attention within a controlled experimental setting that precludes the use of noisy proxies, controls for potential statistical and behavioral biases, and isolates the pure effect of market maker's attention constraints on liquidity.

As the constraints on the market maker's attention become more significant, her ability to provide liquidity to the market may worsen. I test this prediction and find that, under high attention constraints, the number of limit orders as well as the proportion of limit orders submitted by the market makers decline significantly. Aggregate market liquidity, however, is not affected. These results suggest that while the market maker is busy attending to multiple tasks, other traders, such as informed traders, step in to compete for liquidity provision via limit order submissions.

Markets for less active stocks may source a larger portion of their liquidity from market making activities. At the same time, market makers have a lower financial incentive to allocate attention to those markets. These ideas suggest that the effect of limited attention may be greater in less active markets. Once again, I find that, although market wide liquidity is not affected by attention constraints at any level of trading activity, the market maker's liquidity provision deteriorates. Consistent with this paper's hypothesis, I find that limited attention has a significant negative impact on liquidity provision, primarily for market makers operating in less active markets.

The ability of market makers to extract information from order flow could worsen when attention constraints are high. This, in turn, could hamper their ability to provide liquidity effectively. Informed traders may be able to better exploit their information advantage during times when the market maker's attention is highly constrained. I test this notion and find that informed traders use their informational advantage to not only exploit uninformed traders, but to also compete with market makers, especially in markets where they face high attention constraints. A related result is the deterioration in the market maker's trading performance. I find evidence that higher attention constraints lower the market maker's share of realized profits and lessen her ability to manage her inventory.

From a broad perspective, this study provides robust evidence on the importance of behavioral factors in the investor's decision-making process as well as the quality of the markets in which these investors trade. A better understanding of the role on these factors on financial markets can help investors make better informed decisions and would lead to more informationally efficient markets. From a narrower perspective, this study sheds light on the effect of attention constraints on the market maker's ability to provide liquidity while staying profitable. Market makers can be an invaluable source of liquidity, especially in less active markets. For this reason, it is important to understand how the liquidity of these markets suffers during times of heightened information intensity when the market makers' attention capacity is compromised. This paper's findings bring doubt to the notion that market makers (particularly designated market makers) are effective in providing liquidity and continuity to less active markets, especially under stressful times.

In addition to providing experimental evidence to help bridge the relationship between behavioral constraints, trading behavior and market quality, this paper has practical implications for both market design and portfolio allocation strategies. Market design is paramount especially for securities that are not actively traded, where the role of market makers is a key feature in preserving a fair and orderly functioning of these markets. Understanding the effect of attention constraints on market makers can contribute to more ideal designs. Furthermore, this effect can help enhance the portfolio allocation strategies of market participants providing market making services. These practical implications open the door for further research with the aim of creating more efficient market designs and structures where the liquidity of less active markets can be significantly enhanced. This research may address questions related to the need for market makers and potential incentive structures that may encourage or discourage their participation.

References

[1] Grossman, S.J. and Miller, M.H. (1988) Liquidity and Market Structure. *Journal of Finance*, **43**, 617-633. https://doi.org/10.1111/j.1540-6261.1988.tb04594.x

[2] Kahneman, D. and Tversky, A. (1973) On the Psychology of Prediction. *Psychological Review*, **80**, 237-251. https://doi.org/10.1037/h0034747

[3] Corwin, S.A. and Coughneour, J. (2008) Limited Attention and the Allocation of Effort in Securities Trading. *Journal of Finance*, **63**, 3031-3067. https://doi.org/10.1111/j.1540-6261.2008.01420.x

[4] Hou, K., Peng, L. and Xiong, K. (2009) A Tale of Two Anomalies: The Implications of Investor Attention for Price and Earnings Momentum.

[5] Da, Z., Engelberg, J. and Gao, P. (2011) In Search of Attention. *Journal of Finance*, **66**, 1461-1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x

[6] Chakrabarty, B. and Moulton, P.C. (2012) Earnings Announcements and Attention Constraints: The Role of Market Design. *Journal of Accounting and Economics*, **53**, 612-634.

[7] Harris, L.E. and Panchapagesan, V. (2005) The Information Content of the Limit Order Book: Evidence from NYSE Specialist Trading Decisions. *Journal of Financial Markets*, **8**, 25-67.

[8] Simon, H. (1957) A Behavioral Model of Rational Choice. In: Simon, H., Ed., *Models of Man*: *Social and Rational*, John Wiley & Sons, New York, NY, 24-60.

[9] Huang, R.D. and Liu, J.W. (2004) Do Individual NYSE Specialists Subsidize Illiquid Stocks? Working Paper.

[10] Garman, M.B. (1976) Market Microstructure. *Journal of Financial Economics*, **3**, 257-275.

[11] Simon, H. (1972) Theories of Bounded Rationality. In: McGuire, C. and Radner, R., Eds., *Decicion and Organization*, North-Holland Publishing Company, Amsterdam, 161-176.

[12] Simon, H. (1982) Models of Bounded Rationality: Behavioral Economics and Business Organization. Vol. 2, MIT Press, Cambridge, MA.

[13] Kahneman, D., Slovic, P. and Tversky, A. (Eds.) (1982) Judgement under Uncertainty: Heuristics and Biases. Cambridge University Press, Cambridge, England.

[14] Grossman, S.J. and Stiglitz, J.E. (1980) On the Impossibility of Informationally Efficient Markets. *The American Economic Review*, **70**, 393-408.

[15] Barry, C.B. and Brown, S.J. (1984) Differential Information and the Small Firm Effect. *Journal of Financial Economics*, **13**, 283-294.

[16] Black, F. (1986) Noise. *Journal of Finance*, **41**, 529-543. https://doi.org/10.1111/j.1540-6261.1986.tb04513.x

[17] Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *Journal of Finance*, *42*, 483-510. https://doi.org/10.1111/j.1540-6261.1987.tb04565.x

[18] DeBondt, W. and Thaler, R. (1985) Does the Stock Market Overreact? *Journal of Finance*, **80**, 793-805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

[19] Hirshliefer, D., Lim, S.S. and Teoh, S. (2011) Limited Investor Attention and Stock Market Misreactions to Accounting Information. *Review of Asset Pricing Studies*, **1**, 35-73. https://doi.org/10.1093/rapstu/rar002

[20] Della Vigna, S. and Pollet, J. (2009) Investor Inattention and Friday Earnings Announcements. *Journal of Finance*, **64**, 709-749. https://doi.org/10.1111/j.1540-6261.2009.01447.x

[21] Bagnoli, M., Clement, M.B. and Watts, S.G. (2005) Around-the-Clock Media Coverage and the Timing of Earnings Announcements. Working Paper, Purdue University, Purdue.

[22] Engelberg, J. (2008) Costly Information Processing: Evidence from Earnings Announcements.

[23] Peng, L. (2005) Learning with Information Capacity Constraints. *Journal of Financial and Quantitative Analysis*, **40**, 301-329. https://doi.org/10.1017/s0022109000002325

[24] Peng, L. and Xiong, W. (2006) Investor Attention, Overconfidence and Category Learning. *Journal of Financial Economics*, **80**, 563-602.

[25] Barber, B.M. and Odean, T. (2008) All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *The Review of Financial Studies*, **21**, 785-818. https://doi.org/10.1093/rfs/hhm079

[26] Stoll, H.R. (1978) The Supply of Dealer Services in Securities Markets. *Journal of Finance*, **33**, 1133-1151. https://doi.org/10.1111/j.1540-6261.1978.tb02053.x

[27] Amihud, Y. and Mendelson, H. (1980) Dealership Market: Market-Making with Inventory. *Journal of Financial Economics*, **8**, 31-53.

[28] Ho, T. and Stoll, H.R. (1981) Optimal Dealer Pricing under Transactions and Return Uncertainty. *Journal of Financial Economics*, **9**, 47-73.

[29] Easley, D. and O'Hara, M. (1992) Adverse Selection and Large Trade Volume: The Implications for Market Efficiency. *Journal of Financial and Quantitative Analysis*, **27**, 185-208. https://doi.org/10.2307/2331367

[30] Bagehot, W. (1971) The Only Game in Town. *Financial Analysts Journal*, **27**, 12-14. https://doi.org/10.2469/faj.v27.n2.12

[31] Copeland, T.E. and Galai, D. (1983) Information Effects and the Bid-Ask Spread. *Journal of Finance*, **38**, 1457-1469. https://doi.org/10.1111/j.1540-6261.1983.tb03834.x

[32] Glosten, L.R. and Milgrom, P.R. (1985) Bid, Ask and Transactions Prices in a Specialist Market with Heterogeneously Informed Traders. *Journal of Financial Economics*, **14**, 71-100.

[33] Easley, D. and O'Hara, M. (1987) Price, Trade Size and Information in Securities Markets. *Journal of Financial Economics*, **19**, 69-90.

[34] Charitou, A. and Panayides, M. (2009) Market Making in International Capital Markets: Challenges and Benefits of Its Implementation in Emergin Markets. *International Journal of Managerial Finance*, **5**, 50-80. https://doi.org/10.1108/17439130910932341

[35] Madhavan, A. (2000) Market Microstructure: A Survey. *Journal of Financial Markets*, **3**, 205-258. https://doi.org/10.1016/S1386-4181(00)00007-0

[36] U.S. Securities and Exchange Commission (2010) Concept Release on Equity Market Structure. U.S. Securities and Exchange Commission, Washington, DC.

[37] Vankataraman, K. and Waisburd, A.C. (2007) The Value of the Designated Market maker. *Journal of Financial and Quantitative Analysis*, **42**, 735-758. https://doi.org/10.1017/S0022109000004166

[38] Bloomfield, R. (1996) Quotes, Prices, and Estimates in a Laboratory Market. *Journal of Finance*, **51**, 1791-1808. https://doi.org/10.1111/j.1540-6261.1996.tb05226.x

[39] Bloomfield, R., O'Hara, M. and Saar, G. (2005) The "Make Or Take Decision" in an Electronic Market: Evidence on the Evolution of Liquidity. *Journal of Financial Economics*, **75**, 165-199.

[40] Bloomfied, R. and O'Hara, M. (1999) Market Transparency: Who Wins and Who Loses? *The Review of Financial Studies*, **12**, 5-35. https://doi.org/10.1093/rfs/12.1.5

[41] Harris, L. (1998) Optimal Dynamic Order Submission Strategies in Some Stylized

Trading Problems. *Financial Markets*, *Institutions & Instruments*, **7**, 27-74. https://doi.org/10.1111/1468-0416.00019

[42] Desai, H., Ramesh, K., Thiagarajan, S. and Balchandran, B. (2002) An Investigation of the Information Role of Short Interest in the NASDAQ Market. *Journal of Finance*, **57**, 2263-2287. https://doi.org/10.1111/0022-1082.00495

[43] Comerton-Forde, C., Hendershott, T., Jones, C.M., Moulton, P.C. and Seasholes, M.S. (2010) Time Variation in Liquidity: The Role of Market-Maker Inventories and Revenue. *Journal of Finance*, **65**, 295-331. https://doi.org/10.1111/j.1540-6261.2009.01530.x

[44] Anand, A., Chakrabarty, S. and Martell, T. (2005) Empirical Evidence on the Evolution of Liquidity: Choice of Market versus Limit Orders by Informed and Uninformed Traders. *Journal of Financial Markets*, **8**, 289-209.

[45] Freund, R.J., Wilson, W.J. and Mohr, D.L. (2010) Statistical Methods. 3rd Edition, Academic Press, Cambridge.

[46] O'Rourke, N., Hatcher, L. and Stepanski, E.J. (2005) A Step-by-Step Approach to Using SAS for Univariate & Multivariate Statistics. 2nd Edition, SAS Institute Inc., Cary.

[47] Bloomfield, R. and Anderson, A. (2010) Experimental Finance. In: Baker, H.K. and Nofsinger, J.R., Eds., *Behavioral Finance*, John Wiley & Sons, Inc., Hoboken, NJ, 113-130. https://doi.org/10.1002/9781118258415.ch7

[48] Cabrera, J.F. and Gousgounis, E. (2017) The Dynamics of Short Sales Constraints and Market Quality: An Experimental Approach. Working Paper.

[49] Bloomfield, R., O'Hara, M. and Saar, G. (2009) How Noise Trading Affects Markets: An Experimental Analysis. *The Review of Financial Studies*, **22**, 2275-2302. https://doi.org/10.1093/rfs/hhn102

Appendix

Experimental Trading Simulation

Instructions

In this trading session, you will participate in a total of 20 trials. In each trial, you will trade a different security that is valued in "laboratory dollars" (LAB$). At the end of the session, we will convert you trading gains into U.S. dollars (US$) to determine your payment. To trade these securities, you will be using the Financial Trading Services (FTS) trading software. Please refer to the sections below for a detailed overview of the FTS trading screen and instructions on how to login.

Ten Basic Terms

1. *Bid*—it is an order to *buy* shares at a stated price (the bid price). The bid price is the highest price the buyer is willing to pay for one share.
2. *Ask*—it is an order to *sell* shares at a stated price (the ask price). The ask price is the lowest price the seller is willing to receive for one share.
3. *Bid book*—it is a list ordered by price (highest price first) of all the bids traders have entered.
4. *Ask book*—it is a list ordered by price (lowest price first) of all the asks traders have entered.
5. *Best bid*—it is the bid with the highest price on the bid book.
6. *Best ask*—it is the ask with the lowest price on the book.
7. *Entering a bid*—a trader willing to *buy* shares at a stated price can submit a bid to the book. The bid will be held on the bid book until another trader chooses to "take" it.
8. *Entering an ask*—a trader willing to *sell* shares at a stated price can submit an ask to the book. The ask will be held on the ask book until another trader chooses to "take" it.
9. *Taking a bid*—a trader willing to *sell* shares can *take the highest bid* from the bid book in two ways: (i) she can directly sell to the highest bid or (ii) she can enter an ask with a price lower than the highest bid price.
10. *Taking an ask*—a trader willing to *buy* shares can *take the lowest ask* from the ask book in two ways: (i) she can directly buy from the lowest ask or (ii) she can enter a bid with a price higher than the lowest ask price.

The Trading Session

A trading session consists of trading 20 securities successively (*i.e.* 20 trials). Information about each security and each trader is generated right before the beginning of each trial. Traders will trade based on this information until the trial ends.[55] Prior to the start of a new trial, new information is generated.

The Trading Trial

You will start each trading trial with zero cash and zero shares of the security, however, negative cash balances (cash borrowing) and negative share balances

[55]A trial can be compared to one trading day in real markets. News about the value of the company is released prior to the market opening (*i.e.* overnight). Once the market opens, traders trade on this information. The difference in this simulated environment is that no additional information is released during the trial.

(short selling) are allowed.[56] Trading in each trial will be split into two parts: pre-trading and main trading.

Pre-trading (20 *seconds*)

During the pre-trading period, traders can enter orders (bids and asks), but no one can take them. This means that no actual trading will occur during this period. At the end the pre-trading period, the highest bid and the lowest ask will be paired up. If they "cross" (the bid is priced higher than the ask) the more recent order will be deleted and a new pair will be matched. This will be repeated until there are no crossing orders remaining. The purpose of this pre-trading period is to allow traders to enter orders into the book before trading takes place. In other words, traders will "build" the book before trading can take place.

Main Trading (120 *seconds*)

During the main trading period, all traders can enter bids and asks, and can also take the bids and asks posted by the other traders (*i.e.* orders can cross). In other words, during this period trading takes place. Executions follow price/time priority, meaning that orders at most competitive prices will be executed first. Orders at the same price level will be executed in following time priority; orders submitted first are also executed first.

The Security Value

The range of permissible prices in this trading session is between 0 and 100. The "true" value of the security is generated using a uniform probability distribution. In other words, all values within the 0 [10] 0 range are equally likely to be selected. The security value will be determined and shown only to *some* traders (*i.e.* the "informed" traders) prior to the beginning of each trial.

Remember that the *security value* and the *market price* are not necessarily the same thing**.** The market price is determined by the amount traders are willing to pay or accept (*i.e.* transactions), and may change as trading progresses during each trial. The security value is determined prior to the start of each trial and does not change during the trial.

Types of Traders

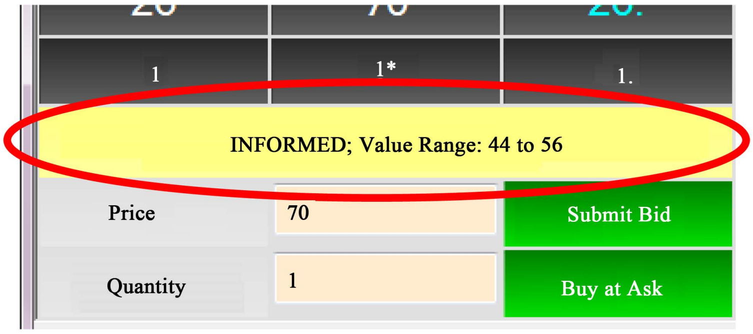
There are three types of traders: (i) informed traders, (ii) liquidity traders, and (iii) dealers. Each trader type will have different trading objectives and levels of information. Your trading screen will tell you what type of trader you are prior to the start of each trial. You will be randomly assigned a trader type before the beginning of each trial.

Informed traders

They *know* a narrow range for the "value" of the security, which they learn right before trading starts. They trade because they have valuable information regarding the security value. Therefore, they will earn a profit every time they buy (sell) a share at a price below (above) the security value. Information received by informed traders on their screen would look like this:

"INFORMED: Your value estimate is within 44 to 64"

[56]Short selling refers to the process of borrowing shares to sell them hoping that their value will go down. This strategy allows the trader to sell shares without owning them.



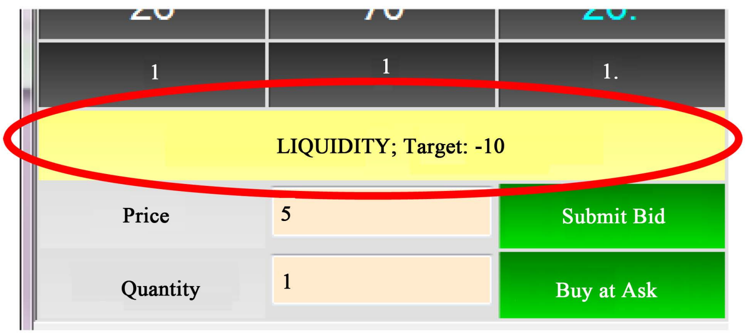
- They can *enter a bid* (order to buy) by entering a price and left-clicking on "Submit Bid."
- They can *enter an ask* (order to sell) by entering a price and left-clicking on "Submit Ask."
- They can *take bids* (sell at highest bid) by left-clicking on "Sell to Bid."
- They can *take asks* (buy at lowest ask) by left-clicking on "Buy at Ask."
- They can cancel individual or multiple orders.

Informed traders can see the market's best bid and best ask as well as their own orders on the book, but they cannot see other trader's orders. Also, they will be restricted to trading only one of the two available securities (either stock "HIACT" or stock "LOACT"). Information and trading functionality (*i.e.* the ability to buy or sell) will only be available for the one security they are able to trade.

Liquidity traders

They *do not know* the "value" of the security (*i.e.* they are "uninformed" traders). Therefore, they trade because of reasons other than information related to the security value. Liquidity traders are given a "target" number of shares they are required to trade before the end of the trial. This target does not need to be in the same direction for all liquidity traders. For example, some traders may be given a target of +20 (*i.e.* buy a *net* amount of 20 shares) while other traders may be given a target of −20 (*i.e.* sell a *net* amount of 20 shares). Typical information received by liquidity traders on their screen would look like this:

"LIQUIDITY: Your target is −20 shares"



- They can *enter a bid* (order to buy) by entering a price and left-clicking on "Submit Bid."

- They can *enter an ask* (order to sell) by entering a price and left-clicking on "Submit Ask."
- They can *take bids* (sell at highest bid) by left-clicking on "Sell to Bid."
- They can *take asks* (buy at lowest ask) by left-clicking on "Buy at Ask."
- They can cancel individual or multiple orders.

Similar to informed traders, liquidity traders can see the market's best bid and best ask as well as their own orders on the book, but they cannot see other trader's orders. Also, they will be restricted to trading only one of the two available securities (either stock "HIACT" or stock "LOACT"). Information and trading functionality (*i.e.* the ability to buy or sell) will only be available for the one security they are able to trade.

Liquidity traders incur a *penalty* of LAB$ 100 per share for failing to achieve their targets (once they reach their targets they are allowed to trade freely without penalty). These penalties are large enough that liquidity traders are always better off trading enough to hit their target, even if they must buy at very high prices or sell at very low prices to do so.

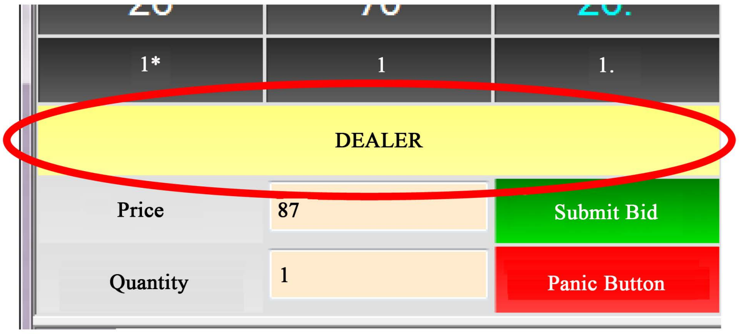
Dealers

They *do not know* the "value" of the security. They trade to provide liquidity to the market. They earn a profit from selling shares at the ask price *and* buying them at the bid price. In other words, they earn the difference between their bid price and their ask price (*i.e.* bid-ask spread). The security value *does not* affect the dealer's profit.

Inventory management is a very important task for dealers. Very high (low) inventories may indicate that the dealer's bid and ask prices are too high (low). Dealers profit from *both* buying and selling shares. Thus, they should set their bid and ask prices so that they create an incentive for other traders to take their bids and asks. Furthermore, they should ensure that their ask price is always higher than the bid price.

Although dealers are not informed about the value of the security, they are the only traders with access to all market information (*i.e.* they can observe the orders of all traders on the book). Typical information received by dealers on their screen would look like this:

"DEALER"



- They can *enter a bid* (order to buy) by entering a price and left-clicking on

"Submit Bid."

- They can *enter an ask* (order to sell) by entering a price and left-clicking on "Submit Ask."
- They can *take bids* (sell at highest bid) by left-clicking on "Sell to Bid."
- They can *take asks* (buy at lowest ask) by left-clicking on "Buy at Ask."
- They cannot cancel/clear any bids or asks. Bids (asks) can only be "revised" or updated by entering new a new bid (ask) order.

Dealers cannot enter multiple orders (bids and/or asks) on the book because each new order submitted by the dealer will *replace* the old order: (i) entering a new bid will automatically cancel her old bid and (ii) entering a new ask will automatically cancel her old ask. In other words, dealers simply *update* their orders (*i.e.* they enter quotes).

Dealers can see the market's best bid and ask as well as the *all orders* on the book. They may be able to trade *both* securities simultaneously (stock "HIACT" or stock "LOACT"). Information and trading functionality (*i.e.* the ability to buy or sell) may be available for both securities.[57]

Note that informed traders and dealers do not have a target. They can end the trial with any number of shares in inventory and will not be penalized.

Basic Trading Rules

- Once you enter an order on the book, you can only trade if someone takes the other side of your order. For example, if you have entered a bid to the book at LAB$ 20, it will remain on the book until another trader takes it (or until you cancel the order).
- You can't trade with yourself. If you enter an ask at LAB$ 70 and then you enter a bid at LAB$ 75, these two orders will not cross and they will both remain standing on the book.
- The maximum number of shares (*i.e.* quantity) you can enter per order is 1. However, you can enter multiple orders at any price point. For example, if you enter 3 *separate* bids (one share each) at LAB$ 52, you will have 3 shares listed at the LAB$ 52 price point.

Getting Paid

You will start each trial with a zero cash balance and a zero share balance. At the end of each trial, the shares you own ("n") pay an amount ("V") equal to the security "true value."

- If you have a *positive* share balance ($n > 0$), then "$n \times V$" LAB$ will be *added* to your cash balance.
- If you have a *negative* share balance ($n < 0$), then "$n \times V$" LAB$ will be *subtracted* from your cash balance.

The resulting cash balance is your trading gain/loss in LAB$. Any penalties assessed for failing to hit your exact target are deducted from your resulting cash balance decreasing your gain or increasing your loss.

Note that this method of calculating gains and losses applies only to informed

[57]In some trading trials market makers will have access to both securities simultaneously while in other trading trials access will be restricted to only one of the two securities. Before the start of the trials, you will be informed about your accessibility rights.

and liquidity traders. Dealers' profits are not affected by the security value. Below is a detailed description of how gains/losses are computed for each trader type:

- *Informed and liquidity traders* make money every time they buy a share for less than the security value or sell a share for more than this value. For example, buying a share with a security value of LAB$ 43 at a price of LAB$ 39 creates a gain of LAB$ 4. Selling that share at a price of LAB$ 55 creates a gain of LAB$ 12.
- *Dealers* make money every time they sell a share for more than the price they paid for it. For example, buying a share at a price of LAB$ 25 and then selling it at a price of LAB$ 31 creates a gain of LAB$ 6. You may also sell a share first at a price of LAB$ 34 to then buy it back at a price of LAB$ 30 for a gain of LAB$ 4.

Remember that you do not "get paid" in laboratory dollars (LAB$). These LAB$ need to be converted into US$ before you can get paid. The conversion will be done using the following formula:

$$\text{US\$ Winnings} = \text{Baseline} + \left(\text{Your LAB\$} - \text{Type} - \text{Average LAB\$}\right) \times \text{Conversion Rate}$$

You will not know the exact *baseline* or *conversion rate*. However, we will tell you three key facts:

1. The type-average LAB$ refers to the average LAB$ for only those traders that are of your same type (*i.e.* informed traders, liquidity traders, or dealers).
2. The *baseline* is a positive US$ amount. If your LAB$ at the end of the trial is equal to the average LAB$ for traders of your type, you will earn an amount of LAB$ equal to the baseline.
3. The *conversion rate* is positive, meaning that the more LAB$ you win, or the fewer you lose, the more US$ you take home.

The parameters (baseline and conversion rate) are set so that the *average* US$ winnings of US$15 per person per session (not including the training session). Finally, US$ are determined separately for each trading session. Losses in one session do not offset gains in another session.

Other Rules

Please do not talk with other traders or look at their computer screens without explicit permission from the experiment administrator. Please ask the administrator before leaving the room for any reason.

The Trading Screen

The FTS Trading Screen is the first screen that appears once you have successfully logged into the market. It is important to be familiar with its elements before beginning to trade. However, if at any time during trading you cannot remember what a particular object on the screen does, simply place your mouse over the object and a mouse-over description will appear.

Below is a description of the different features you will find on the trading screen (refer to the figure below):

1. **Bid**—it displays the current best (highest) bid (listing the price/quantity). If there is an asterisk (*) next to the price/quantity it means that your bid is the

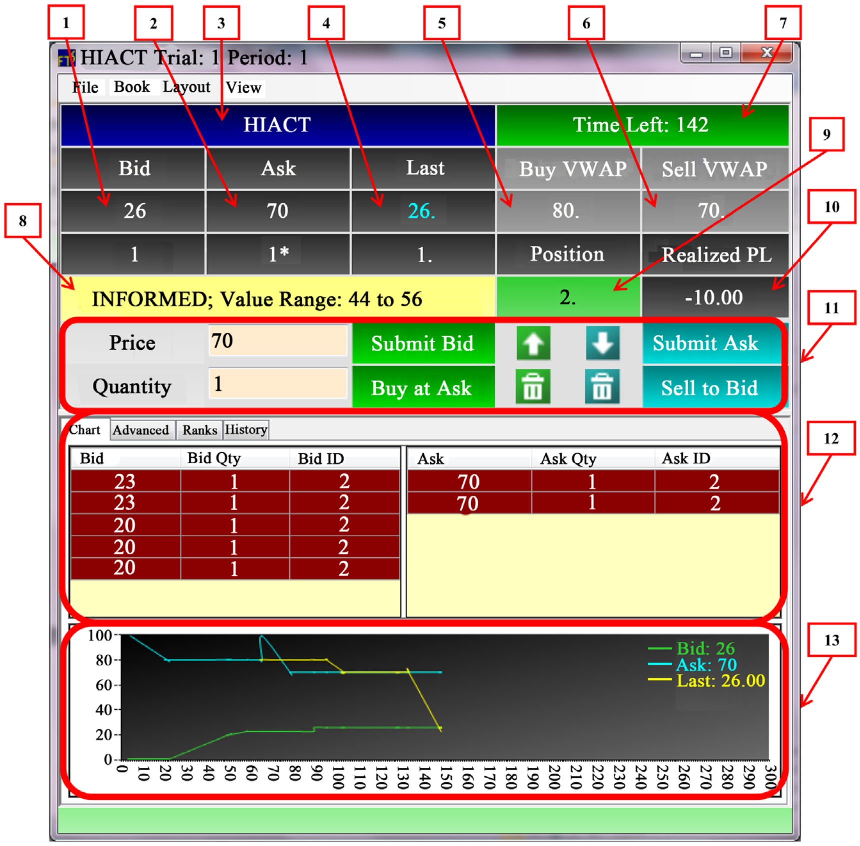
current best bid.

2. **Ask**—it displays the current best (lowest) ask (listing the price/quantity). If there is an asterisk (*) next to the price/quantity it means that your ask is the current best ask.
3. **Security Name**—this is the name of the security that you will be trading on each trial. There could be multiple security names listed. By left-clicking on a security name, you will access the security's market screen.
4. **Last**—it displays the last traded price. This box changes color according to how the last traded price changed relative to the previous last traded price.
5. **Buy WVAP**—it specifies the trader's volume-weighted average buying price. It is simply the average price the trader has paid for all shares purchased. It updates in real time.
6. **Sell WVAP**—it specifies the trader's volume-weighted average selling price. It is simply the average price the trader has received for all shares sold. It updates in real time.
7. **Time Left**—each trial specifies a particular amount of time. Once the market begins, Time Left will begin to count down. The time will reset after the completion of each trial (a bigger screen with the time left can be found on the upper right hand corner of the screen).
8. **Information Window**—here you will see information regarding the security value and the target number of shares that you are required to trade. This window will also display the type of trader you are.
9. **Position**—it specifies your current position in a security (*i.e.* the number of shares that you currently hold in inventory). If this number is positive, then you have a long position. If the number is negative this means you have a short position.
10. **Realized P & L**—it specifies the profit (or loss) of a trader based only on the shares that have been both purchased and then sold (or vice versa). It ignores any shares in the trader's inventory. It updates in real time.
11. **Trading Controls—**this section contains the buttons/fields that will allow you to trade. The buttons may be different for different traders. Please refer to the "Types of Traders" section (above) for a detailed explanation of the trading controls. Remember that to enter a bid and an ask on the book, you must first enter a price and a quantity:

a) *Price*—here you can enter a specified price for your order (*i.e.* bid price or ask price).

b) *Quantity*—here you can enter a specified quantity for your order. In this case, however, the quantity can only be equal to 1.

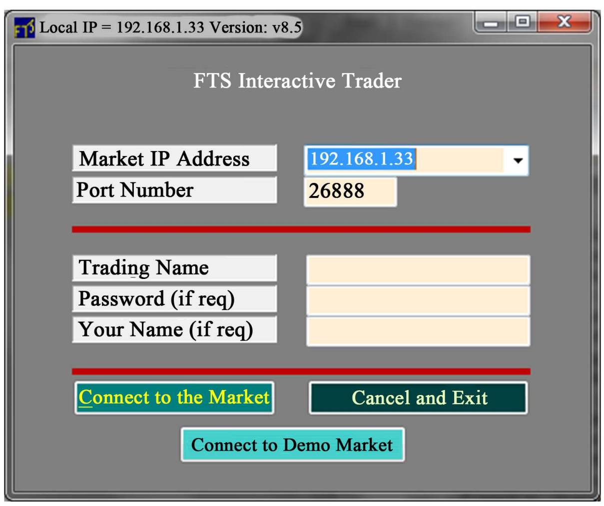
12. **Order Book**—this book collects all orders entered by all traders in the market. The *bid book* (left half) displays all bids with the highest-priced bid listed first. The *ask book* (right half) displays all asks with the lowest-price ask listed first. The top-listed bid and ask are the *market BBO* (best bid/offer, where offer and ask are equivalent terms).
13. **Bid/Ask/Price Graph—**it provides a graph of the evolution of the best bid, best ask, and traded prices over the trading trial. It updates in real time.



How to Login

You must wait until the administrator tells you that you can login. Once he/she does, you must follow these steps to login successfully:

1. Double click on the "Launch FTS System Manager" icon on your desktop.
2. Check "Student Applications."
3. Check "Download again before running."
4. On the drop-down menu, select "FTS Trader 2013 Version."
5. Click on "Run Selected Application."
6. The following screen will appear:



Enter the information provided to you by the administrator on the “Market IP Address”, “Trading Name” and “Password” (if required) cells. Leave all other cells untouched.

7. Click on “Connect to the Market”

Note: if you click on “Connect to Demo Market” you can see and interact with a demo of the trading screen. You do not need to enter any information to connect to the demo version. In order to get to the trading screen shown above, you first need to left-click on the red/white icon located to the right of the security name. This may be a good tool to become familiar with the software before the trading session).

8. You should now see the main trading screen. Wait for further instructions from the administrator.