

Attention Constraints and Liquidity Provision: An Experimental Study

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Abstract

This paper uses an experimental asset market to investigate the role of attention constraints on the market maker's ability to provide liquidity and, thus, on the overall liquidity of the market. The market contains salient features of a market making system in an order-driven market, as well as informed and uninformed traders. The experiment consists of a repeated measures design with market-specific (e.g., trading activity and time), asset-specific (e.g., information value), and behavioral explanatory factors (e.g., attention constraints and trading motive). In this way, the paper precludes the use of very noisy measures of attention constraints seen in previous studies. *The experimental data will be collected during the last quarter of this current year. The statistical and economic findings will then be available and added to this paper.*

JEL Classification: D47, G02, G10, G14

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I. Introduction

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 microstructure models suggest that the presence of market makers is a key determinant of market liquidity. In these models, the costs to market makers of maintaining a market presence can have a significant impact on market liquidity and on the price formation process (Grossman & Miller, 1988). Traditional models attribute these costs mainly 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. More recently, however, several studies have suggested behavioral factors affect the market maker's decision making process.

Individuals are known to have a limited capacity for information processing (Kahneman, 1973).¹ In a setting where individuals have to attend to several tasks simultaneously, their ability to optimally allocate attention across these multiple 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 in order to reduce costs (Kahneman & Tversky, 1973). This reliance on heuristics may induce processing errors. Market makers are

¹ This notion is closely related to the theory of bounded rationality (Simon, 1957). 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.

often required to allocate their attention across multiple assets and this allocation effort may have an effect on the degree of liquidity in the markets they trade in.²

Previous studies have shown that the main challenge in examining the role of attention is the difficulty in measuring attention and its allocation across tasks in financial market settings (Corwin & Coughneour, 2008). In this paper, I examine the effects of attention constraints in an experimental setting. The use of an experimental setting overcomes this challenge by precluding the use of proxies such as trading volume (Hou, Peng, & Xiong, 2009), internet search volume (Da, Engelberg, & Gao, 2011) and earnings announcements (Chakrabarty & Moulton, 2012). In an experimental setting, the demands on the attention of the individual can be controlled and its effects on market characteristics such as liquidity and efficiency can be isolated.

In a market where the participation of market makers provides an important source of liquidity, attention constraints may have a significant impact on the market's degree of liquidity. Corwin and Coughenour (2008) argue 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. The market maker's allocation of attention may be primarily directed at extracting information about the value of the stock. Harris and Panchapagesan (2005) find that NYSE specialists obtain information from order flow and use this information to compete for liquidity provision. In this paper, I provide experimental evidence of these ideas.

² 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 (Corwin & Coughneour, 2008).

This paper contributes to the literature in the following ways: (1) to my knowledge, this is the first experimental study to look at the effect of attention constraints on financial markets. Several empirical studies have tested this effect on financial markets, but none have studied this effect within an experimental setting where the individual's ability to allocate attention can be directly controlled for; (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 (Corwin & Coughneour, 2008; Hou, Peng, & Xiong, 2009). 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. Market liquidity is an elusive concept to understand and, more importantly, to measure. For this reason, 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 per market fixed while changing the degree of attention constraints on the individual. A large number of previous studies test attention effects by simply increasing the number of tasks the individual must attend to. This, in turn, will decrease 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 market 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 (Huang & Liu, 2004). In this paper's experimental design, market makers trade randomly selected generic assets completely

eliminating the effects of this endogeneity bias; (6) it examines the trading behavior of the market maker controlling for inventory risks. There is a vast 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 (Garman, 1976). 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.

The remainder of the 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 and variable measurement. Section 6 presents the results. Section 7 concludes.

II. Literature Review

Early work in the attention literature can be traced back to the notion of bounded rationality (Simon, 1957). The theory of bounded rationality and its business applications suggest that individuals have a limited capacity to gather and process information and, thus, may not be able to make fully informed and rational decisions (Simon, 1972; Simon, 1982). When dealing with information capacity constraints, individuals naturally rely on heuristics or mental shortcuts to arrive at satisfactory (not necessarily optimal) solutions (Kahneman, Slovic, & Tversky, 1982). This reliance on heuristics may induce biases in the individual's financial decision-making process leading to less-than-optimal outcomes in financial markets.

The traditional finance literature has attempted to explain empirical anomalies by emphasizing the role of market imperfections. For example, Grossman and Stiglitz (1980) develop a market equilibrium model where prices reflect the information of informed individuals but only partially

and where not all individuals are informed. Barry and Brown (1984) attempt to explain the small firm anomaly by developing a model of market equilibrium where there is less information available about some of the securities than about others. Black (1986) 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. Merton (1987) departs from the notion of a perfect market by assuming that investors know only about a subset of all available securities. These traditional finance models attempt to explain market anomalies by assuming away 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” (Merton, 1987).

Researchers have attempted to complement the efforts of traditionalists³ in explaining market anomalies by challenging the viability of the rationality assumption.⁴ In other words, they (i.e., behavioralists) 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 solutions (DeBondt & Thaler, 1985; Shefrin & Statman, 1985). In particular, several studies have explored the role of limited attention in explaining market anomalies. For example, Hirshliefer, Lim, and Teoh (2011) develops a model in which limited attention explains both under- and overreaction to two earnings components, earnings surprises and the operating

³ I refer to “traditionalists” as those people who attempt to explain empirical market anomalies by emphasizing the role of market imperfections while assuming that market participants are fully rational. I refer to those people who attempt to explain market anomalies by emphasizing the role of human imperfections as “behavioralists.”

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.

accruals component. Della Vigna and Pollet (2009) compare investors' reaction 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, Bagnoli, Clement and Watts (2005) study investors' reactions to earnings announcements made during non-trading hours. They find greater underreaction during these hours. Engelberg (2008) categorizes the information contained in earnings announcement as harder-to-process/soft (qualitative) and easier-to-process/hard (quantitative) information in order to examine the role of information processing costs in 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, Hou, Peng and Xiong (2009) study 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. Da, Engelberg and Gao (2009) propose a novel measure of investor attention using aggregate search frequency in Google. They find evidence of short-term predictability based on this search volume measure. Corwin and Coughneour (2008) 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, Peng (2005) provides an equilibrium model to analyze the effect of information capacity constraints in which investors optimally allocate their information capacity across multiple sources of uncertainty. Peng and Xiong (2006) argue 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 assets returns and, thus, has implications for return predictability. Similarly, Barber and Odean (2008) argue that, given the large number of stocks to choose from, investors naturally allocate more attention “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 (Chakrabarty & Moulton, 2012). In order to overcome this challenge and provide more direct evidence of attention constraints’ effects, some studies have recently tested this effect in market settings where a designated market maker plays a significant role (Corwin & Coughneour, 2008; Chakrabarty & Moulton, 2012). 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 effect on market equilibrium to costs associated with inventory risks (Garman, 1976; Stoll, 1978; Amihud & Mendelson, 1980; Ho & Stoll, 1981; Easley & O’Hara, 1992) and adverse selection risks (Bagehot, 1971; Copeland & Galai, 1983; Glosten & Milgrom, 1985; Easley & O’Hara, 1987). Corwin and Coughneour (2008) and Chakrabarty and Moulton (2012), however, provide a

behavioral alternative to help explain the decision-making process of market makers and its impact on market quality. In particular, Corwin and Coughneour (2008) test 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 portfolio. In a more recent study, Chakrabarty and Moulton (2012) examine 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 this paper, I set out to provide further evidence of the effect of limited attention on the market maker's ability to provide liquidity by directly testing the hypotheses proposed by Corwin and Coughneour (2008) and other related hypotheses. In doing so, I contribute to the existing literature by overcoming a major challenge associated with measuring attention and its allocation across tasks in a financial market setting. The previously mentioned studies have measured attention using a variety of empirical proxies some of which could be very noisy. Here, however,

⁵ According to Chakrabarty and Moulton (2012), they distinguish themselves from Corwin and Coughneour (2008) 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, Chakrabarty and Moulton (2012) claim to be the first empirical study of attention constraints to control for inventory risk management. They hypothesize that when the NYSE specialist acquires a large inventory position in one stock, she provides less liquidity for all other stocks on her panel. Thus, inventory risk management may have an effect on 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, they 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.

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 while avoiding the need to use noisy measure of attention. To my knowledge, this is the first experimental study to examine the effect of limited attention on financial markets.

III. Market Structure and Hypotheses

In this section I discuss the basic structure of the market with a particular 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 and its allocation across markets. I then formulate the hypotheses tested in this study.

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. 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 finds that, as of September 2009, the three largest U.S. equity trading centers are the NASDAQ, NYSE and NYSE Arca accounting

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 (Madhavan, 2000). 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).

for 47.3% of the trading volume in NMS stocks.⁷ A quick glance at the trading rules of these three U.S. registered exchanges reveals a significant role played by some form of designated market maker.⁸ In an earlier study, Charitou and Panayides (2009) investigate 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 market¹⁰: continuous trading with the required participation of market makers, different levels of pre-trade transparency, 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 among themselves via the limit order book (acting as competitors to the market maker), and they can enter limit and market orders that trade against the market maker's quotes (acting as counterparties to the market maker).

⁷ In general, NMS stocks are those that are listed on a U.S. national securities exchange (U.S. Securities and Exchange Commission, 2010).

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 (U.S. Securities and Exchange Commission, 2010). 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 Charitou and Panayides (2009) 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. Charitou and Panayides (2009) also provide a 4-type classification that disaggregates the centralized market making system into two sub-categories: one that is floor-based and another that is electronic.

¹⁰ In order 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.

The Role of the Market Maker

In the experimental market, market makers act primarily as liquidity providers submitting limit orders continuously from their own account. They are required to quote (binding) bid and an 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 simply 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, in this market, 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 she can only achieve that by aggressively quoting bid and ask prices. Second, the main goal of this study is to uncover any potential differences in the market maker's liquidity provision ability under different attention constraints environments (high and low). The *level* of liquidity provision under either environment is not as important as it is the *change* in the level of liquidity provision across environments. Finally, studies have shown that designated

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.

market makers have a significant positive impact on the quality of markets, especially for less liquid ones. For example Venkataraman and Waisburg (2007) conclude 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 is the fundamental basis for trade.¹² The varying degrees of information are the result of either (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, if some traders have superior information then the market maker loses on average to those traders. 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. Bloomfield (1996) 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. Bloomfield et al. (2005) develop a market setting that also contains two groups of traders: a group of informed traders who have superior information

¹² There are of course other bases for trading that may arise due to non-informational reasons. Among those reasons we have trading related to institutional mandates, portfolio rebalancing needs and noise (Black, 1986). Traders whose trading is motivated by non-informational reasons are known as uninformed traders.

¹³ The origin of this concept is usually credited to the work of Bagehot (1971) 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 (Copeland & Galai, 1983).

and a group of liquidity 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 of these studies. The experimental market contains three very 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 very narrow range. Second, uninformed traders do not know have any information about the security 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. They do, however, 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, has significant implications for the degree of liquidity, the level of competition, and the informational efficiency of markets. Bloomfield and O'Hara (1999) find that a higher level of transparency improves the informational efficiency of the market, it causes opening spreads to widen, and it benefits market makers 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.

In this paper's experimental market, I model a market with a high and equal 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 system in an order-driven market (Charitou & Panayides, 2009). In this market, informed traders have access to the security's fundamental

¹⁴ Informed traders can also be described as traders who have private information about value which allow them to predict future price changes. Liquidity traders can be seen as uninformed traders who must fill an order before some deadline which may arise when traders need to invest or disinvest exogenous cash flows (Harris L. , 1998).

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.

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 only to the current best bid and best ask.

Inventory Management Risk

In addition to adverse selection risk, it is well understood that risk averse market makers must incorporate their inventory levels, especially during times of large order imbalances, as an input in their quote-setting decisions. This idea can be traced back to the work of Garman (1976) and it is known as inventory risk. In providing liquidity, the market maker's portfolio holdings may move away from her desired portfolio resulting in a level of risk and return which may be inconsistent with her personal preferences (Stoll, 1978). In an experimental study, Bloomfield (1996) analyzes the ability of the market maker to control its inventory position. He finds that market makers manage their inventories in real time by revising their quotes. Furthermore, they find 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 for one security is likely to be affected by her inventory position in addition to any potentially binding attention constraints (Chakrabarty & Moulton, 2012).

In order to control for the potential effects of inventory management on the trading behavior of market makers, I allow the market maker to accumulate any inventory position without penalty.

Any shares in inventory remaining at the end of trading are simply ignored in the sense that they will not alter the profit/loss generated by the market maker during the trading session. In this

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.

way, market makers are not required to protect themselves from the arrival of overnight news (i.e., overnight risk) avoiding 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).¹⁷ The market maker does, however, have to manage her inventory during continuous trading in order to protect herself from informed trading (i.e., adverse selection risk). Increasing deviations in inventory away from zero provides the market maker with information signals about trading decisions of other traders some of whom 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 (effectively managing her inventory) in order to reduce her exposure to informed trading while not being constrained to ending with a flat inventory position. Thus, the experimental market 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 constraint. 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

The main purpose of this paper is to examine the “pure” effect of attention constraints on the ability of the market maker to provide liquidity. There may be, however, market structure

¹⁷ Comerton-Forde et al. (2010) find 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.

implications on the market maker's decision to allocate its attention across securities. There are two points worth considering: (1) the availability of attention per unit of information intensity is fixed¹⁸ and (2) market makers may face competition from traders with lower attention constraints.

Most empirical studies look at the effect of market maker's attention constraints 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 (Chakrabarty & Moulton, 2012), trading volume (Hou, Peng, & Xiong, 2009), internet search frequency (Da, Engelberg, & Gao, 2011), absolute returns (Corwin & Coughneour, 2008), 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 particular 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)¹⁹, the availability

¹⁸ Barber and Odean (2008) define 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 units of information intensity "units" relative to other non-attention-grabbing stocks.

¹⁹ Once allocated, reassignments of stocks across specialist firms are rare but reassignments of stocks within a specialist firm are relatively common (Corwin & Coughneour, 2008). In fact, Chakrabarty and Moulton (2012) show

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 trade opportunistically by trading in some stocks during times when the specialists are busy attending to other stocks in their panel (Chakrabarty & Moulton, 2012).²⁰ Combined, these 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.²¹ This allows me to control for the amount of attention allocated across stocks and isolate the effects of different levels of attention constraints on the individual market maker's ability to provide liquidity.

The second possible structural implication on the market maker's attention allocation decision 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 a lower information intensity). For example, informed traders may behave like market makers but trade on a fewer number of stocks. Previous studies find evidence that informed traders provide a significant amount of liquidity to the market

that during the NYSE' 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.

²⁰ In their paper, Chakrabarty and Moulton (2012) explicitly state 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."

²¹ 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 will allocate 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.

(Bloomfield, O'Hara, & Saar, 2005).²² 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 has similarities to the non-centralized market making design in an order-driven market as described by Charitou and Panayides (2009). 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.

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 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 will only implement 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 to shed light on the behavior of market makers under a less restrictive setting. Furthermore, this study aims at improving the robustness of previous empirical results by avoiding the use of noisy proxies,

²² 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.

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.

Corwin and Coughneour (2008) examine individual NYSE specialist portfolio 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 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.²³ They find significant evidence supporting both of these hypotheses. This paper provides a direct 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.

In order 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.

- *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.

²³ Corwin and Coughneour (2008) provide 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.

In order to test this hypothesis, the experimental design consists of two distinct markets with different levels of activity or volume. Both markets have the same number of informed traders and market makers at all times, however, one of the markets consists of two more uninformed traders than the other. All uninformed traders are given an exogenous motive for trading a similar number of shares.²⁴ Therefore, varying the number of uninformed traders across markets (two in one market and four in the other) produces different levels of trading activity across markets.

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.²⁵ Harris (1998) 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 will use market orders lowering market liquidity. They may, however, supply liquidity in less liquid and/or less active markets (e.g., wide bid-ask spreads).²⁶ He also shows that liquidity traders will initially use limit orders but they will progressively use more aggressive orders (e.g., market orders or higher (lower) priced limit buy (sell) orders) as the trading deadline approaches. In

²⁴ 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.

²⁵ 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.

²⁶ Bloomfield et al. (2005) and Anand et al. (2005) extend the work of Harris (1998) 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. Harris (1998) 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.

summary, this study highlights the importance of information value and its impact on the strategic trading decisions of all traders (i.e., informed and uninformed).

Similar to Harris (1998), Harris and Panchapagesan (2005) study the role of information on the strategic behavior of market participants. In their study, however, they include a market making feature by empirically examining the role of the specialist in the NYSE. Under the premise that specialists compete with other traders (who use limit orders) for the provision of liquidity, Harris and Panchapagesan (2005) find strong evidence that specialists use their unique access to the entire limit order book to make strategic trading decisions. More specifically, they find that if aggregate order information is valuable, specialists will use this information to profit. In this way, specialists do not only reduce their exposure to adverse selection risk but they may increase adverse selection risk for uninformed traders. Furthermore, they show that these results are stronger for active stocks where the competition between the specialist and the limit orders is more intense.

Evidently, valuable information drives the strategic behavior of any trader with an informational advantage as well as the behavior of uninformed traders whose trading decisions may be reactive. Informed traders possess information about the security value while market makers can derive the security value from their unique access to the order book. These two types of traders may then compete not only for profits but for the provision of liquidity. Tighter attention constraints on the market maker may then lower her ability to extract information from the order book 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. 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, making her informational disadvantage (relative to informed traders) greater and hampering her ability to provide liquidity.

In order 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 of value that contains the security value) prior to the start of trading. Some trading trials consist of security values with large absolute deviations from the prior expected value of \$50 (high information value) while other security values are near the prior expected value (low information value). In this way, the value of the informed traders' information is controlled across securities. Because market makers may extract security value information from the limit order book as trading progresses, their information value may increase lowering the information advantage of informed traders. To explore this idea, I split each trading trial into six 20-second intervals and assess the traders' trading decisions and liquidity measures at the end of each interval.

- *Hypothesis 4:* The ability of the market maker to provide liquidity through optimal and reactive quote revisions is reduced as her attention constraints increase.

In order 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 profits and participation rate. To measure the market maker's ability to provide liquidity, I consider her quote revision decisions. These set of measures should be, however, highly correlated. The market maker's ability to optimally

revise her quotes coupled with a high rate of participation in the market should lead to higher profits.²⁷

IV. Experimental Study

In this section I discuss the main advantages of using experimental settings to test economic and financial models. Besides the avoidance of using complex and imperfect statistical techniques, I address the issues of relaxing otherwise restrictive assumptions and mitigating potential behavioral biases as it pertains to this study. I then provide a detailed description of the experimental design and the laboratory market.

Advantages of the Experimental Design

There are a number of well-known advantages linked to the use of laboratory experiments to test economic models. Laboratory experiments allow for extremely simple settings that facilitate clear inferences. The ability to control variables in the experiment provides for a greater degree of assessing causality. More importantly, experiments allow the researcher to overcome key problems associated with empirical data analysis such as omitted-variable biases, unobservable variables (e.g., amount of attention allocated to a security)²⁸, and self-selection problems. These advantages are common to all well-designed experiments. I now turn to two other advantages worth noting and discuss how they related to this paper's experimental market design.

²⁷ Harris and Panchapagesan (2005) find 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.

²⁸ The difficulty researchers have in measuring attention constraints and the resulting measurement errors from using empirical proxies can be substantial. These measurement errors are avoided in well-designed experimental settings.

Restrictive Assumptions

The complexity of financial institutions²⁹ which are unavoidably affected by often unobservable characteristics of human behavior makes theoretical and empirical analyses very difficult and often impossible. Bloomfield et al. (2005) state that “most theoretical studies make their analyses tractable by imposing highly restrictive assumptions. These assumptions raise concerns about the robustness of their conclusions.” A key advantage of experimental studies is that they allow the researcher to examine financial phenomena in settings that are more robust and less restrictive than theoretical behavioral models are. More specifically, they allow the researchers to relax assumptions imposed in theoretical models that are highly restrictive but necessary in behavioral models of finance. These assumptions may be classified as following: (1) structural assumptions which describe the institutions in which agents interact, (2) behavioral assumptions which characterize agent’s preferences and decision-making abilities, or (3) equilibrium assumptions which describe the solution concepts used to predict behavior (Bloomfield & Anderson, 2010).

Microstructure models are noticeable for the highly restrictive assumptions imposed in order to make their particularly complex settings tractable. For example Glosten and Milgrom (1985) model a pure dealership market where investors (i.e., non-dealer traders) are only allowed to use market orders. This structural restriction precludes investors from having to optimally choose the type of order to submit, in turn, restricting the behavior and decision-making ability investors. Models of market making often impose restrictions on the behavior of the market maker. Similar to Glosten and Milgrom (1985), Ho and Stoll (1981) model a single-dealer market where she

²⁹ An institution does not refer to a financial organization or a firm. Institutions, in this context, refer to a structure or mechanism governing the behavior of agents such as the distribution of information or a set of trading rules.

(i.e., the dealer) can only trade with public investors in a passive way (i.e., she sets prices and waits until a transaction occurs). In this model, the dealer can only provide liquidity to the market but she cannot take liquidity restricting her ability to manage her inventory. Risk neutrality is another behavioral assumption often found in traditional market making models. Easley and O'Hara (1987) construct a model with more than one risk-neutral market maker. They assume risk neutrality in order to remove the influence of the market makers' risk preferences from equilibrium prices. A broader but still highly restrictive assumption that these traditional models have in common is the notion that economic agents are perfectly rational. In fact, Glosten and Milgrom (1985) assume that the market maker knows the probabilistic structure of the information arrival process and makes correct statistical inferences from observed data.³⁰

This variety of assumptions are aimed at simplifying the market setting in order to make the agents' behavior and resulting market equilibrium tractable. Experimental studies allow the researchers to relax these theoretical assumptions and, thus, possibly make novel contributions to our understanding of financial markets. In this paper, the experimental design permits market makers to take liquidity by initiating trades with other traders. In this way, the market makers have a greater ability to manage their inventory. The design allows other traders (i.e., non-market makers) to submit both limit and market orders effectively letting these traders compete with the market maker by supplying liquidity to the market. Furthermore, the use of human subjects puts no restrictions on the risk preferences and the rationality of the market makers and any other

³⁰ Note that restrictive assumptions on the behavior and decision-making abilities of economic agents are also common in behavioral models. Theoretical studies of the effects of attention constraints on economic decision making typically assume that agents incorporate information signals into their own beliefs via rational Bayesian updating (Hirshleifer & Teoh, 2003; Peng, 2005)

traders in the market. Therefore, the experimental design relaxes many highly restrictive assumptions without losing its ability to track the market equilibrium outcomes.

Behavioral Biases

Although many well-known decision biases are influenced by limits to attention (e.g., narrow framing and availability bias), there are also unrelated biases that may have confounding effects on the relationship between limited attention and the liquidity provision ability of the market maker. Some behavioral biases may directly affect the behavior of the market maker while others may affect the behavior of public investors, indirectly affecting the market maker's trading decisions (i.e., the market maker must strategically react to the trading of both informed and uninformed traders). Fortunately, a well-designed experimental design can mitigate the effect of these biases.

Familiarity bias occurs when investors hold a portfolio of assets biased toward "familiar" assets compared to an unbiased portfolio derived from a theoretical model (Foad, 2010). Similar to investors, market makers may be required to hold a portfolio of assets (e.g., the NYSE specialist may be assigned to a panel that contains more than one stock). One or more of the assets in the portfolio may be more familiar to the market maker (e.g., the company may be in the news regularly or it may sell popular household products). This may cause the market maker to pay more attention to a specific set of assets and, in turn, provide more liquidity to those markets. This bias may also affect other traders in the market further complicating the isolation of the attention constraints effect. To eliminate the possible effect of the familiarity bias, the experimental market design contains generic securities that no trader can become "familiar"

with. Furthermore, on each trial traders will be randomly assigned to a given security in order to prevent traders from becoming more familiar with one security over the other.

Studies show that the overconfidence bias may help explain the familiarity bias. For example, Barber and Odean (2001) finds that more overconfident investors (e.g., men) not only tend to trade more than less confident investors but they trade more on those assets with which they are more familiar. Overconfidence can be defined as the belief that we have a greater ability to invest and trade than we actually do. The overconfidence bias affects all individuals; however, it may have a greater effect on investors during times of high information intensity (e.g., earnings announcements, abnormal returns, etc.). Several papers examine the effect of limited attention on financial markets across low and high information intensity environments (Barber & Odean, 2008; Chakrabarty & Moulton, 2012). The robustness of their results is, however, weakened by the inability to control for overconfidence in empirical work. To mitigate the possible effect of the overconfidence, this experimental study does not proxy attention constraints by using information-related measures such as earnings announcements and abnormal returns. Instead, the demand on the market maker's attention is controlled by measuring her ability to provide liquidity across two settings: a setting where she trades exclusively in one security (i.e., low attention constraints) and another setting where she trades in two securities at the same time (i.e., high attention constraints).³¹

³¹ It can be argued that the experimental market design mitigates the effect of a larger number of biases such as representativeness, availability and the endowment effect. Such a discussion, however, would divert attention away from the paper's main goal.

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).³² In such a design, each subject or experimental unit is observed repeatedly under different treatments.³³ 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 left to trade, (2) asset characteristics such as the relative value of the security's information to traders, and, more importantly (3) behavioral characteristics such as the 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 the market makers, one market will consist of two informed traders and four liquidity traders, two of which have a net positive target (+10 shares) while the other two have a net negative target (-10 shares). The other market will consist of two informed traders but only two liquidity traders (one liquidity trader has a net target of +10 shares while the other has a net target of -10 shares). All traders (informed, liquidity and market makers) are informed of the level of the trading activity in their selected market.³⁴

Attention constraints on the 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

³² 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 (Freund, Wilson, & Mohr, 2010).

³³ 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.

³⁴ This feature is characteristic of real markets where market participants are well aware of the relative level of trading activity in a stock. In the U.S., market participants would know that the stock of a large well-known company included in the S&P 500 index has a higher level of trading activity (i.e., more buyers and sellers in the market for this stock) than a small-cap publicly listed company.

to trading in one market so she can allocate her entire effort and attention to one stock. I call this the low attention constraints environment. 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 call this the high attention constraints environment. Each cohort trades 10 securities in the low-constraints setting and 10 securities in the high-constraints setting.

Information value is manipulated relative to a prior expected value of \$50. All traders know that security values are randomly drawn from a normal distribution with a mean of 50. Only a subset of traders (i.e., informed traders), however, is given a narrow range of values that contains the security value (i.e., the information range). Thus, these traders have an informational advantage over the other traders (i.e., market makers and uninformed 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) and other securities carry extreme values or values far away from the prior expected value (i.e., high information value).³⁵ More specifically, securities with a high information value have realizations that are at 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 traders 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

³⁵ Bloomfield et al. (2005) refer 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 security values. In this paper, I chose to follow the design in Bloomfield et al. (2005) in order to make my findings comparable to theirs.

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 20-second time interval for a total of six decision points. The segmentation of time facilitates the study of the time series properties of the market maker's behavior.

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 (six time intervals of 20-second periods), trading activity (high, low), trader type (informed trader, liquidity 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 differ for different subjects, but for a single subject are always the same.

Controls

A primary benefit of an experimental study is the ability to control over features of the experimental design that might influence behavior but are not the focus of the study (Bloomfield & O'Hara, 1999). In particular, in a repeated measures design, it is important to control for order and carry-over effects (O'Rourke, Hatcher, & Stepanski, 2005).

Order effects result when the ordinal position of the treatments biases participant responses (O'Rourke, Hatcher, & Stepanski, 2005). 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.³⁶ In order to control for possible effects of differences across securities, I follow a design similar to the one used in Bloomfield et al. (2005). Not only are different cohorts presented with different treatment orders but each cohort 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.³⁷ Only this subset of security pairs is included in the statistical analysis. Table 1 illustrates this design. Information values vary across trials (or security pairs) but remain identical, as a whole, across attention-constraints orderings (and cohorts). The values of the eight security pairs not included in the statistical analysis are randomly selected.

Insert Table 1

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 (O'Rourke, Hatcher, & Stepanski, 2005).³⁸ In this experimental design, the traders' actions may change simply because they

³⁶ 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 (O'Rourke, Hatcher, & Stepanski, 2005).

³⁷ 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 exactly 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.

³⁸ 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

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. In order 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).³⁹ They also take part in a series of practice trials that are identical to the actual experimental trials.⁴⁰ Furthermore, altering the ordering of the treatments may also help mitigate these carry-over effects.

Another concern relates to the different levels of intelligence, motivation, and familiarity with the experimental environment across different participants and cohorts (Bloomfield & O'Hara, 1999). Besides having all four cohorts trade in all experimental settings, each trader in a given cohort is randomly assigned to a trader type (informed trader, liquidity 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 that differences across trader types and market dynamics are driven by individual differences.⁴¹

detected (Freund, Wilson, & Mohr, 2010). Also, by using one observation from each cohort in the statistical analysis, the assumptions underlying the ANOVA tests are not violated by these carry-over effects (Bloomfield, O'Hara, & Saar, 2005).

³⁹ Also, all participants had been exposed to this trading simulation before they took part of this experiment. This further mitigates any learning effects that may arise during the trading sessions.

⁴⁰ The data from these practice trials is not included in the statistical analysis.

⁴¹ Bloomfield et al. (2005) 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 losses unknown. This can be achieved by subtracting trading losses from an unknown floor level to determine their actual payoffs.

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 via its FTS Interactive Markets trading simulator. This trading simulator was largely adapted to match this paper's the 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 session.⁴² 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 (Bloomfield & Anderson, 2010). In order to create these incentives, I adopt the reward structure in Bloomfield et al.

⁴² A copy of the experiment written instructions is given in the appendix.

(2005). Actual U.S. dollars winnings 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. Neither the floor value nor the conversion rate is known to the participants.⁴³ These two parameters are set equal to values that yield average cash winnings of US\$ 10.00 per participant per hour of trading with a minimum payment is US\$ 5.00.⁴⁴

Laboratory Market

The laboratory market used in this study is comparable to the market developed in Bloomfield et al. (2005). There are two main differences between their laboratory market and the one presented here. First, in this paper the degree of pre-trade transparency is different for all trader types with market makers having the greatest access to pre-trade market information. Second, the market consists of an electronic limit order book with the required participation of a market maker.⁴⁵

The laboratory market resembles the mechanism of a market making system in an order-driven electronic market. It contains traders with different trading motives and different levels of information (i.e., asymmetric information). And it allows for similar trading rules, reporting rules and trading functionality as those used in many large stock exchanges worldwide (Charitou & Panayides, 2009).

The Market

The laboratory market contains features that resemble trading in a market making system in an order-driven electronic market. The basic setting features a double-auction electronic market

⁴³ 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.

⁴⁴ A detailed description of the reward structure for this experiment is given to participants in the written instructions (see appendix).

⁴⁵ Bloomfield et al. (2005) used a pure electronic limit order market where all traders (informed and uninformed) have the same degree of pre-trade transparency (i.e., all traders were able to see the entire limit order book)

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 liquidity (i.e., 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) liquidity traders⁴⁶, and (3) market makers. Informed traders possess superior information regarding the value of the security. The security value is determined before the trading trial starts and informed traders are shown a narrow range that contains this value. For example, if the true value is determined to be \$23, informed traders may be told that the value is somewhere between \$22 and \$28. 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 highest bid and the lowest ask for the entire market. Informed traders earn a profit every time they buy (sell) shares at a price below (above) the security value. Liquidity 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 a different direction for different liquidity traders. For example, a trader may have a target of -10 shares (i.e., an instruction to sell 10 shares) while another trader may have a target of +10 (i.e., an instruction to buy 10 shares). The

⁴⁶ These traders are also known as uninformed traders. In fact, Harris (1998) refers to this type of trader as an uninformed liquidity trader.

goal of liquidity traders is to meet their target at the most favorable prices possible. At the end of the trading trial, liquidity traders who fail to meet their exact targets receive a penalty of \$100 for each share in inventory above or below the target. For example, a liquidity trader with a target of 10 shares and who ends the trading trial with an inventory of 12 shares will receive a penalty of \$200. The penalty is large enough that liquidity 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 liquidity traders are trading for exogenous reasons related to liquidity needs (i.e., they are uninformed). Similar to informed traders, liquidity 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. Liquidity traders take a loss every time they buy (sell) shares at a price above (below) the security value. The third type of trader is the market maker. Similar to liquidity traders, market makers do not know the security value. However, unlike the other two types of traders, market makers are able to see the entire limit order book (i.e., the outstanding orders entered by all traders in the market). Market makers are able to enter market orders but unlike the other two trader types, market makers cannot enter limit orders on the book. Instead, they simply quote a bid price and an ask price. Furthermore, market makers cannot cancel their quotes. They can only update their quotes (i.e., change their bid and ask prices) with new, either more or less aggressive, 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, however, traders have substantially different motivations for trading. Informed traders trade with the aim of maximizing their profit based on their informational advantage. Liquidity traders trade with the aim of minimizing their

loss while meeting their exogenous liquidity needs. Market makers have an obligation to trade in order to provide liquidity to the market. They are compensated for their liquidity provision services by earning the difference between their quoted bid and ask prices (i.e., the quoted bid-ask spread).

The Order Book

The laboratory market features an electronic book of orders (i.e. limit order book) with the participation of designated liquidity providers (i.e., 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 provide 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 (i.e., highest market bid or lowest market ask). Unlike limit orders, market orders do not provide the trader with price certainty but they do eliminate the 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 will immediately cross with best priced limit orders outstanding (i.e., the highest-prices bid or the lowest-priced ask). 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 order will immediately cross and, therefore, it is a marketable order. Limit orders that are conservatively priced and do not 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 are allowed to enter both limit orders and market order 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 her outstanding orders at once.

The Trading Trial

Similar to Bloomfield et al. (2005), 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 30 seconds during which traders can enter and cancel as many orders as they wish. During this period no trades are executed. Any marketable orders (i.e., bids at prices above the lowest outstanding ask, asks at prices below the highest outstanding bid, and market orders) do not result in a trade. These 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 ask 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, however, trades can be executed. Here, traders 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 (i.e., twelve 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 (i.e., a cohort) randomly divided into two groups with each group trading on a different security or market. In other words, each trial consists of two markets running in parallel. A group of at least 7 traders will participate in one market while a group of at least 5 traders will participate in the other market. Before the beginning of each trading trial, traders will be randomly assigned to a particular trader type achieving the following overall trader type distribution: two market makers, four informed traders, and six liquidity traders. Both markets will have two informed traders each for all 20 trials, however, one market will have four liquidity traders while the other will only have two liquidity traders.⁴⁷ During the first 10 trials, each market maker will be required to participate in only one randomly selected market (i.e., low attention constraints environment). During the second 10 trials, both market

⁴⁷ The number of liquidity traders is different across the two markets in order to manipulate the level of trading activity. All liquidity traders regardless of the market they are in will have a target with an absolute value of 10 shares. Therefore, the greater the number of liquidity traders in a given market, the greater the level of trading activity.

makers will be required to participate in both markets simultaneously (i.e., high attention constraints environment). Figure 1 provides a graphical description of a trading session.

Insert Figure 1

V. Methodology and Measurements

In this section I provide a broad overview of the statistical methodology used to analyze the experimental data. The exact nature of the statistical methodology depends on the hypothesis being tested and, thus, may be different for each hypotheses tests in this paper. A more detailed description of the statistical methodology used for each hypothesis will be provided in the next section. Here, I also provide a description of the response variables used in the statistical analysis: market maker's liquidity provision and overall market liquidity.

Statistical Methodology

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 a number of different treatments. As the sample is exposed to each treatment in turn, the measurement of the dependent variable is repeated. A repeated measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. 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 (Bloomfield, O'Hara, & Saar,

2009). 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.⁴⁸ 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 different levels of another factor, and (2) 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 (O'Rourke, Hatcher, & Stepanski, 2005). To illustrate these three effects, let's take a look at the second hypothesis put forth in this paper: the reduction in the market maker's liquidity provision (caused by tighter 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) 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

⁴⁸ In experimental sciences, it is not unusual to find a design described as "one between-subject and two within-subject repeated measures" (Freund, Wilson, & Mohr, 2010). 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.

interaction effect suggests the presence of significant simple effects. The activity factor has two levels: low and high. Therefore, there could be two 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 one activity level at a time.

The relevant type of effect (i.e., interaction, main or simple effect) depends on the nature of the hypothesis but it also dependent 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.⁴⁹ Instead, it is appropriate to test for simple effects. If the interaction effect is not significant, however, simple effects should be ignored and main effects should be tested instead. For the sake of consistency, and more importantly, appropriateness, the statistical tests will always begin with a test of the interaction effect and then they will be sequenced as follows:

- If the interaction effect is not significant, I will proceed to test for main effects for each of the factors being considered. If any of the main effects are significant, I will provide contrast tests and/or multiple comparison tests (using Tukey's HSD procedure) for any significant main effects.⁵⁰
- If the interaction effect is significant, I will proceed to interpret a profile plot to gain some insight on the nature of the interaction.⁵¹ Then, I will test for any relevant simple effects.

⁴⁹ If there is a significant attention/activity interaction, an significant attention effect becomes misleading as it suggests that attention constraints exerts 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.

⁵⁰ 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.

⁵¹ 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)

Similar to main effects, if a given simple effect is significant, I will provide contrast tests and or multiple comparison tests.

Measuring the Response Variables

This paper investigates the role of attention constraints on the market maker's ability to provide liquidity and, thus, on the degree of market liquidity. Liquidity, however, is an elusive concept to measure.⁵² For this reason, in this paper, I use several distinct proxies for liquidity. Furthermore, I am interested in measuring not only the degree of market liquidity but also the market maker's contribution to the liquidity of the market. To this end, I provide two sets of liquidity measures: a set of measures that capture the overall degree of market liquidity, and a set of measures that captures the market maker's liquidity contribution (or provision).

Marketwide Liquidity

Market Maker's Liquidity Provision

Market Maker's Profit

Results

Conclusion

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.

⁵² Liquidity is known to have several dimensions or aspects. The main three dimensions are immediacy (the ability to trade quickly), depth (the ability to trade a large size), and width (the costs of trading) (Harris L. , 1998). Another known dimension of liquidity is resiliency or the ability of the market to return to equilibrium after a price movement during non-informational periods.

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Figure 1: Experimental Design for a Cohort

There are 4 cohorts of 12 participants each for a total of 48 participants. This is a full-factorial repeated measures design with the following factors:

- Between-subject factors (3): trading activity, trader type, and cohort
- Within-subject factors (3): attention constraints, information value, and time interval

The ordering of the attention constraints factor is manipulated across cohorts. Information value (not shown) is manipulated across trials.

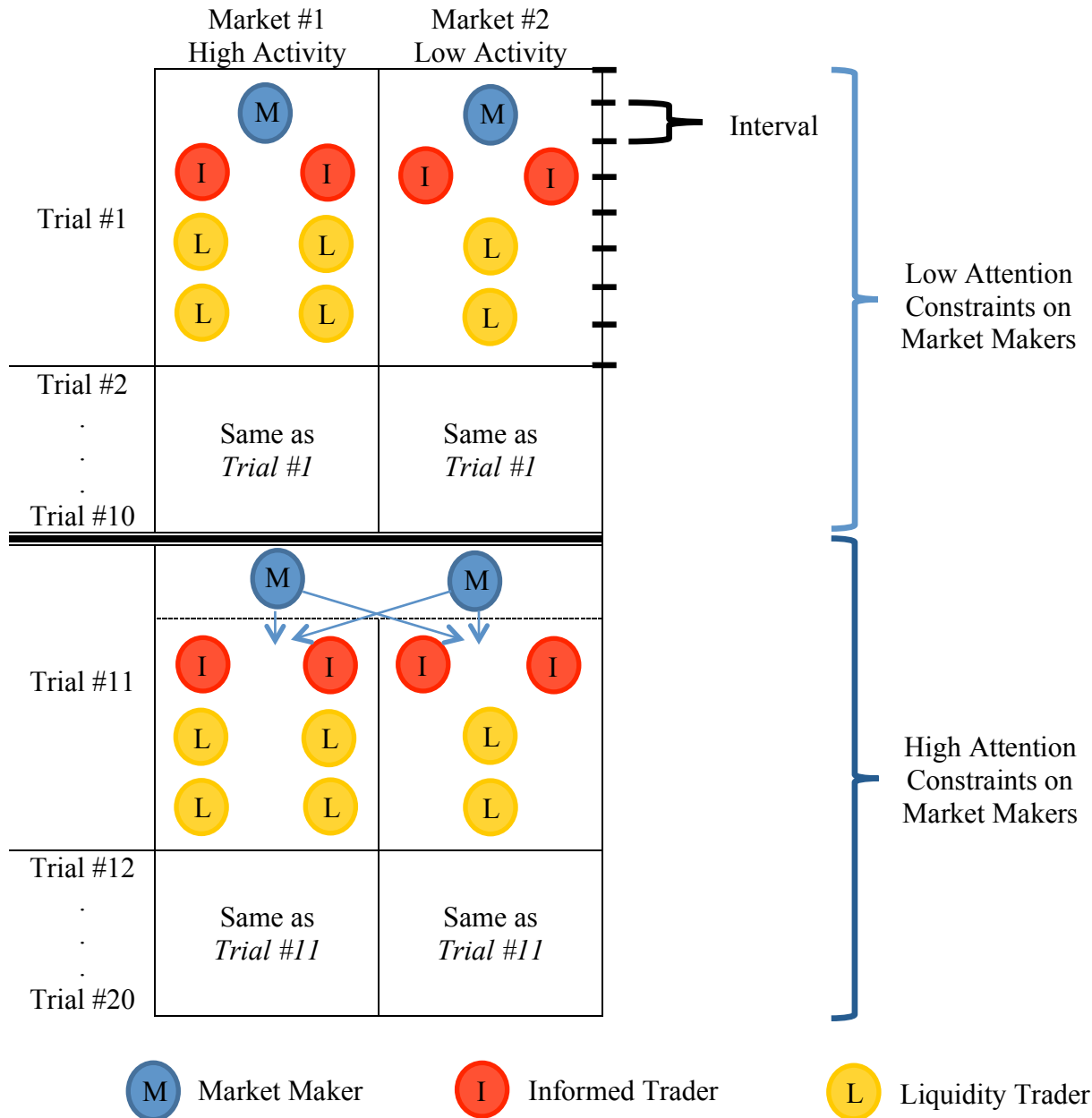


Table 1: Absolute deviations of security value from prior expected value of \$50

Trial #	Information Value	<i>Order 1</i>		<i>Order 2</i>	
		Low constraints first		High constraints first	
		<i>Stock 1</i>	<i>Stock 2</i>	<i>Stock 1</i>	<i>Stock 2</i>
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					
18	High	25	30	25	30
19	Low	24	29	24	29
20					