

**Dividing the Pie:
Asymmetrically Informed Dealers
and Market Transparency**

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Abstract	We examine the consequences of transparency in an experimental multiple-dealer market with asymmetrically informed dealers. Five professional securities traders make a market for a single security. In each trading round, one of the dealers (the "insider") is told the security's true value. We vary both pre-trade and post-trade transparency by changing the way quote and trade information is published. The insider's profits are greatest when price efficiency is lowest. Price efficiency, in turn, is reduced by pre-trade transparency and increased by post-trade transparency. Market liquidity, measured by dealers' bid-ask spreads, is improved by pre-trade transparency and reduced by post-trade transparency.	
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Dividing the Pie: Asymmetrically Informed Dealers and Market Transparency

Abstract

We examine the consequences of transparency in an experimental multiple-dealer market with asymmetrically informed dealers. Five professional securities traders make a market for a single security. In each trading round, one of the dealers (the “insider”) is told the security’s true value. We vary both pre-trade and post-trade transparency by changing the way quote and trade information is published. The insider’s profits are greatest when price efficiency is lowest. Price efficiency, in turn, is reduced by pre-trade transparency and increased by post-trade transparency. Market liquidity, measured by dealers’ bid-ask spreads, is improved by pre-trade transparency and reduced by post-trade transparency.

Keywords

Financial markets, market microstructure, experimental economics, information asymmetry

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1. Introduction

Information is central to the structure and performance of financial markets. Indeed, a primary function of financial markets is to assemble and analyze information with the goal of accurate valuation of investment prospects. Asymmetric information is thus of obvious importance; the ability of financial markets to weigh and balance information from disparate sources and impound it in securities prices is basic to their function. The interactions among immediate participants – the brokers, dealers, market makers, and specialists directly involved in transacting on exchange floors and over-the-counter (OTC) networks – are crucial to a market’s ability to process information. We consider specifically the role of asymmetric information across dealers in an experimental multiple-dealer securities market. There are two broad issues at play here: the impact of asymmetric information on market performance and the impact of the institutional structure on information aggregation and dissemination.

Regarding the former, it is well documented that the presence of asymmetric information has substantial effects on the performance of financial markets. The literature has largely focused on asymmetries among investors outside the trading floor. An important topic has been “insider trading:” the use (or abuse) of proprietary information by corporate insiders. This is the traditional definition of insider trading. We distinguish sharply, however, between such traditional corporate insiders and securities dealers who are better informed than their peers in a multiple-dealer environment. Although both are clearly examples of asymmetric information, the nature and implications of the asymmetries will typically differ between these two cases, as detailed below.

The key issues regarding corporate insiders are fairness, price efficiency and market liquidity. For example, the Securities Exchange of 1934 in the U.S. effectively outlaws trading by corporate insiders as “unfair.” On the other hand, Leland (1992) argues that corporate insiders can bring new and relevant information into the market, making it more price-efficient and future prices less volatile, as prices reflect more information sooner. However, frequent trading by corporate insiders can reduce market liquidity, as uninformed and liquidity-motivated investors trade less, due to their informational disadvantage. Thus, separate from the issue of fairness, a trade-off between efficiency and liquidity exists. Significantly, this trade-off is not the same in different market microstructures. For example, Leland (1992, p. 883), Pagano and Röell (1996, p. 581) and Schnitzlein (1996, p. 613) all conclude that any discussion of whether insider trading helps or hurts markets should take place in the context of a specific market microstructure or trading mechanism. Specifically,

the opportunities for the better informed to hide and exploit their private information – and thus the size and allocation of private and public gains from insider trading – depend directly on the trading mechanism.¹

In contrast, we focus on a microstructure that is relatively neglected in the literature, namely multiple-dealer markets. The nature of interdealer informational asymmetries is fundamentally different from those generated by corporate insiders. Interdealer asymmetries typically arise from information – such as private order flow or the rumor mill – that should already be impounded in prices in a semi-strong-form efficient market. On the other hand, the information available to corporate insiders should only be impounded in prices if markets are fully strong-form efficient. For example, Copeland and Friedman (1991), using an experimental double-auction study, place this question in the context of the rational expectations modeling literature. They distinguish theoretically between no, full, and partial revelation of expectations (NRE, FRE, and PRE, respectively), where NRE corresponds essentially to semi-strong-form efficiency, and FRE corresponds to strong-form efficiency.

Their results are generally supportive of the PRE. Moreover, the potential social benefits of allowing insider trading – namely that it draws insiders into the market to reveal their information via trading – do not obtain as readily for dealers with insider information, since by definition dealers are already active in the market.

There is thus some question as to the benefits of interdealer trade. If markets are not already semi-strong-form efficient, then interdealer trading can impound information from dealers' private order flow, thus improving price quality. Moreover, in many markets, dealers may broker trades for corporate insiders, so that the dealer effectively becomes a surrogate corporate insider.² Because microstructural rules concerning the publication of quote and transaction details may affect the revelation and aggregation of material information, the interaction between such rules and interdealer information asymmetries becomes an interesting theoretical and practical issue. For example, market makers on the Stock Exchange Automated Quotation (SEAQ) system in London have argued for delayed publication of the details of trades, ostensibly to encourage the provision of liquidity to investors for large

¹ One example of a recent policy debate regarding asymmetries in this context involves the issue of “protected trading” on NASDAQ; see Franks and Schaefer (1995).

² Reviewing the extant evidence, Copeland and Friedman (1991, p. 265) note that, “all public information but probably not all private information is fully reflected in securities prices. The question then becomes *when and to what extent* private information becomes incorporated, or, from the opposite perspective, *what is the value* of private information to the investor?” (emphasis in the original). Notably, “private information” in their context would include private messages received by traders, analogous to interdealer information asymmetries.

transactions (see Flood, Huisman, Koedijk, and Röell (1997) – hereinafter FHKR (1997) – and Office of Fair Trading (1994)). Such publication delays create interdealer information asymmetries, allowing an affected dealer to unwind her resulting inventory before her competitors recognize her predicament. The informational question thus extends to issues of dealers' inventories, risk bearing, and capitalization.

In the present study, we consider the impact of rules concerning the publication of both transaction details (post-trade transparency) and live quotes (pre-trade transparency). These issues have been examined in other recent experimental work by Flood, Huisman, Koedijk, and Mahieu (1999) – hereinafter FHKM (1999) – Bloomfield and O'Hara (1999), Lamoureux and Schnitzlein (1997), and FHKR (1997), among others. As emphasized by Glosten (1999), the issues and results in this area can be complex and counterintuitive. (The main theoretical issues are considered by O'Hara (1995), and Pagano and Röell (1996). FHKM (1999), Bloomfield and O'Hara (1999), FHKR (1997), and Lamoureux and Schnitzlein (1997) consider the issues in an experimental context.) We focus here on the price discovery process. The obvious presumption would be that increased transparency should speed price discovery and therefore improve price efficiency. In the case of post-trade transparency, Bloomfield and O'Hara (1999) and FHKR (1997) find that this form of transparency (i.e., publication of transaction details via a public ticker or similar technology) indeed does speed price discovery. Notably, however, FHKM (1999) find that increased pre-trade transparency (i.e., the publication of live quotes) actually slows price discovery in a multiple-dealer market; their conclusion is that dealers in an opaque market will reprice more aggressively, to guarantee that they attract order flow. By contrast, in a fully pre-trade transparent market, in which all quotes are always public information, dealers can typically offer much smaller price improvements while nonetheless still guaranteeing that they are the best-price provider. Finally, Lamoureux and Schnitzlein (1997) find roughly that fully (pre- and post-trade) transparent markets are more price-efficient than fully non-transparent markets. We expect slower price discovery to benefit insiders at the expense of outsiders, as has been argued in the SEAQ case.

Other aspects of the microstructure can affect the nature and extent of the trade-offs involved. In a theoretical paper, Benveniste, Marcus, and Wilhelm (1992) examine relationships between specialists and floor brokers on major securities exchanges. Floor brokers occasionally broker trades from known corporate insiders, and may unilaterally hide or reveal this fact when they transact. Benveniste, Marcus, and Wilhelm (1992) conclude that

reputation effects and lack of anonymity induce floor brokers to reveal private information to the specialist in exchange for anticipated long-run benefits of discretionary services from the specialist (e.g., tighter spreads, or a willingness to fill the remainder of orders partially filled against the book). Such a system can produce a Pareto-dominant equilibrium in which floor brokers get better service, the specialist faces lower adverse-selection risks, and prices are more informative. Benveniste, Marcus, and Wilhelm (1992) suggest that non-specialist dealer markets such as NASDAQ are less likely to enjoy such benefits. Garfinkle and Nimalendran (1998) provide empirical support for this hypothesis. In the same vein, Madhavan and Cheng (1997) conclude that the “upstairs” market at the NYSE is used by traders who can credibly signal that they are liquidity motivated (and therefore do not have a special informational advantage), consistent with the theoretical predictions of Seppi (1990).

We consider the interaction between informational transparencies in the trading mechanism and informational asymmetries among market participants. It is difficult to study the impact of microstructure on the consequences of asymmetric information using empirical data. Even if it were possible to identify asymmetries, it would still hardly be feasible to isolate the effects of the trading mechanism. We therefore adopt an experimental methodology, which places our study in a longer tradition of experimental studies of securities markets. Sunder (1995, pp. 447-48) provides a useful three-part classification of such studies. He groups papers as those considering: (1) the dissemination of information from the ex-ante informed to the ex-ante uninformed; (2) the market-wide aggregation of diverse ex-ante information sets in the hands of individual traders; and (3) the simultaneous equilibrium in the markets for securities and information (in an environment where information is produced endogenously). This taxonomy is especially apt, since the present study focuses likewise on the interaction of institutions and asymmetric information. Our study falls into the first category, and we are concerned not so much with *whether* our markets disseminate insider information, but rather how effectively they do so. In our experimental markets, there is no endogenous information production, while information aggregation occurs rather quickly, in the sense that price consensus (all dealer spreads overlapping each other) is readily – if imperfectly – enforced by arbitrage.

Our study differs from most experimental double-auction studies (but not all; see, for example, Forsythe, Palfrey, and Plott (1982), and Plott and Sunder (1982)), in that our traders can *both* buy and sell the asset. Moreover, our dealers must act as market makers, providing

bid and ask quotes to other dealers at all times.³

Our market framework is based on Glosten and Milgrom's (1985) model; it is a quote-driven, continuous securities market in which five market makers trade a single imaginary security. We use three groups of professional securities dealers as experimental subjects.⁴

The market makers set quotes and trade with each other and with computerized external customers. The latter are either informed traders or noise traders. In each trading round, one of the market makers is randomly chosen to be the "insider." The insider knows the underlying value of the security. Since he is a market maker, he both trades and competes on price with the other market makers. In these experiments, we use the notion of pre-trade and post-trade transparency to distinguish between four different trading mechanisms. Following Pagano and Röell (1996), we define pre-trade transparency as the amount of quoted price information available to market makers, and post-trade transparency as the amount of transaction information available to market makers. We measure the relative private gains (in terms of insider profits) and public gains (in terms of speed of price discovery and size of dealer spreads) associated with various trading mechanisms when information asymmetries are present.

The contribution of this paper is three-fold. First, we consider four different trading mechanisms in which we explicitly distinguish between pre- and post-trade transparency in our analysis. (Other studies examining insider trading in different trading mechanisms use a quite general notion of transparency; see, e.g., Pagano and Röell (1996), and Schnitzlein

³ The use of market makers – who must quote upon demand – as opposed to non-market-making dealers (who can both buy and sell, but may refuse to quote when asked), is relatively rare in experimental studies, although they are a central feature of most decentralized dealer markets in the real world. There is a large literature on experimental securities markets, and a full discussion of the issues is well beyond the scope of the present paper. Surveys of the literature may be found in Davis and Holt (1993), Duxbury (1995), Friedman and Sunder (1994), Plott (1982), and Sunder (1995), among others.

⁴ Friedman and Sunder (1994, ch. 4) raise the possibility that student subjects may be preferable to professionals under some circumstances. Specifically, professional concerns, habits, and experiences may contradict trading procedures in the experimental market, and realistic payoffs (from the perspective of the research budget) may appear inconsequential to gainfully employed professionals. Although this is an important issue, we argue that does not significantly affect our current results. First, we have no indication, either from observing activity in the lab or during the formal post-experiment debriefing of the subjects, that our professional traders (who participated voluntarily) were not taking their task seriously or had failed to correctly understand their objectives and strategies in the experimental market. Moreover, in related research (essentially identical to the present study, but without an informed "insider" among the dealers), we conducted numerous student replications of our results from professional subjects. Although the students were clearly more likely than the professionals to request additional practice, to employ idiosyncratic trading tactics, and to ask basic questions about trading rules and procedures, the final results were always qualitatively the same. Regarding the magnitude of payoffs, our relatively small cash amounts are undoubtedly insufficient to induce the same sort of risk aversion that obtains in real securities markets. However, it is not clear that the use of student subjects would make the experiments more realistic in this regard.

(1996).) The distinction between price and transaction information is important, as the different types of information flows have different effects on market outcomes. It is also important in terms of inter-market competition, as competing exchanges worldwide implement trading mechanisms that indeed differ in the levels of both pre- and post-trade transparency.

Secondly, we use an experimental setting in which continuous trading is possible. This provides us with extensive time-series data: thousands of transactions and hundreds of quote settings for each of the trading mechanisms. Most experimental studies on microstructure have only a fraction of this available. Moreover, we use professional market makers as the subjects in our experiment. This is an important advantage over experiments using students as subjects.

Thirdly, we offer an alternative view of insider trading by giving the insider a different role than in most other studies (e.g., Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1992), and Schnitzlein (1996)). Generally, the insider is regarded as an external customer submitting orders to the financial market. Market makers then compete for the order via their quoted prices, and the order is typically executed against the best price. In contrast, our insider is a market maker, competing directly on price with other market makers. (Lyons (1996), for example, examines the role of private order flow as a source of interdealer information asymmetries in a multiple-dealer market.) Our setup is closest institutionally to multiple-dealer financial markets such as NASDAQ, the London Stock Exchange, or the foreign exchange market.

We find an inverse connection between insider profits and the price efficiency of the market. Slow price discovery allows insiders greater opportunities to accumulate speculative inventories at advantageous prices. At the same time, however, we find that post-trade transparency (i.e., a public ticker) improves price discovery, while pre-trade transparency reduces price discovery. Consequently, post-trade transparency reduces insider profits, while pre-trade transparency increases them. Meanwhile, increased pre-trade transparency reduces dealers' uncertainty and reduces market liquidity (as measured by bid-ask spreads), while post-trade transparency induces dealers to compete for private order flow, thus reducing spreads and increasing liquidity.

The paper is organized as follows. In section 2 we explain the experimental design and we introduce some terminology. Section 3 discusses the data obtained from the experiments and in section 4 we present some results. Section 5 summarizes the results and concludes.

2. Experimental Design and Terminology

This section briefly presents the experimental setup. Our goal is to investigate how the transparency mechanism affects the impact of asymmetric information on a financial market. More specifically, we examine price discovery (i.e., the convergence of dealer prices to the underlying true value), the distribution of profits, and bid-ask spreads. Our tests involve a computerized experimental securities market in which a number of human dealers (including one with an information advantage, referred to below as the “inside dealer” or simply the “insider”) trade continuously with each other and non-market-making customers. Trading is for a single imaginary security.

2.1 Market Design

Our experimental microstructure is essentially the continuous multiple-dealer version of the pure dealership market used by Glosten and Milgrom (1985). In their model, a specialist sets quotes and confronts investors who observe the quoted bid and ask prices and decide whether to trade (one unit at a time). The specialist is free to reset the bid and/or ask prices at any time. The investors represent both informed and liquidity traders and do not compete with the specialist, since they do not set limit orders in the market. Note that this market is quote-driven, in the sense that the specialist first sets quotes and then confronts orders from traders. This is the main difference between our experimental design and Kyle’s (1985) order-driven framework. In the latter model, the quantities traded by both informed and liquidity traders are first batched, and the market maker then determines a market-clearing price. (See Madhavan (1992) for an overview of the differences between quote-driven and order-driven markets. The Kyle model is the underlying framework of the experimental market used by Schnitzlein (1996).) Our experimental design is thus most similar to the quote-driven experimental markets used by Bloomfield and O’Hara (1999), FHKM (1999), and FHKR (1997). There are two significant differences here, compared with the experimental design of Bloomfield and O’Hara (1999). First, our market makers both set quotes (required) and initiate trades (voluntary), thereby allowing for interdealer trading. Interdealer trading is a significant component of a number of important markets, including futures and options exchanges, the OTC stock market, and the interbank foreign exchange and money markets. Second, our market is continuous rather than sequential, in the sense that the dealers may trade and revise their quotes at any time during the round. The most important difference with FHKM (1999) and FHKR (1997) is that in their experiments there is no strategic, price-competing insider

present. Moreover, we consider pre-trade and post-trade transparency simultaneously. FHKM (1999) analyze the effect of pre-trade transparency when post-trade transparency is low. FHKR (1997) examine the impact of post-trade transparency when pre-trade transparency is low.

2.2 The Role of the Dealers

A priori, the security's true (underlying) value is unknown to all human dealers but one. Before the start of each trading round all dealers receive a note. One of these notes has the true value printed on it, making the dealer who receives it the "inside dealer" or "insider;" the other notes have no information. The true value of the security can be seen as an *ex post* liquidation value as used in, among others, the Kyle (1985) and the Glosten and Milgrom (1985) model. Each participant is the insider in either two or three rounds. All dealers are informed that there is exactly one insider in every round. The true value is revealed publicly at the end of each trading round.

At the start of each round, each dealer is given an initial endowment of 1000 esquires (a fictional numeraire currency). Dealers are instructed to maximize their end-of-round wealth by trading on the security. Wealth is expressed in esquires. Dealers can gain or lose wealth during each round by buying and selling the security (i.e., by jobbing) and by building a long or short inventory of the security (speculating). Dealers are not instructed about possible trading strategies, neither when they are the insider nor when they are an "outsider." Each dealer trades according to his or her own expectations and predilections. If, at the end of the round, a dealer has a non-zero inventory position in the security, the trading software converts the inventory to cash (esquires) at the security's true value, thus realizing any capital gain or loss on the position.

The true value is set at random and differs in each practice and session round (the values appear in tables 1-6). The true value in any round is unrelated to the values in any other rounds. In effect, trading in every round can be regarded as trading for a new security. Dealers are told only that the true value is somewhere between a minimum of 1 and a maximum of 200. At the start of each round, the (non-insider) dealers do not have any prior information about the true value in that round, apart from the information that the price is uniformly distributed on the $[1, 200]$ range.

2.3 Quoting, Trading, and Pre-trade Transparency

At the start of each round, each dealer is obliged to enter a quote (that is, a bid price and an ask price) within 10 seconds. Dealers who fail to enter an initial quote within the first 10 seconds are penalized at the rate of 10 esquires per second after that, until an initial quote is entered. Thereafter, every dealer always has a quote outstanding, at which the other market makers and the external customer can trade. (We use the terms “external customer” and “robot” interchangeably.) The maximum individual spread is limited to 30 esquires.⁵

The primary parameters in our experiments are the level of pre-trade transparency and the level of post-trade transparency. These parameters define our trading mechanisms. Both variables can assume one of two values: high or low. When the level of pre-trade transparency is high (we also refer to this as “full quote disclosure”), all outstanding price quotes appear continuously on the trading screen of each market maker. Bid and ask prices appear in separate queues in the center of the screen. Best prices are at the top of the queue; that is, bid (ask) prices are ranked from the top of the screen down in decreasing (increasing) order. Next to every price, the identity of the dealer who quoted this price appears, with the letters “A” through “E” indicating the five market makers, and “R” denoting the (non market making) robot. If at any time the bid (ask) price of several dealers is the same, then the most recently quoted price is at the top (i.e., strict price-and-time priority holds). An example of the trading screen appears in figure 1. A financial markets analogy is the basic NASDAQ retail trading screen. When a dealer opts to buy (sell), he automatically does so at the lowest (highest) quoted ask (bid) price.

When the level of pre-trade transparency is low (this situation is also referred to as “no quote disclosure”), no price information is publicly available. Instead, prices and transactions are communicated on a strictly bilateral basis. Dealers call each other to obtain price quotes. The dealer who receives a call does not respond actively. She does not even notice that she is being called; instead, her most recently quoted bid and ask prices automatically appear on the caller’s screen. Then, the caller has the option to buy, sell, or do nothing. The size of a trade is always equal to one.

⁵ This restriction is imposed to prevent dealers from effectively exiting the market by quoting infinite spreads. In practice, it was never binding.

2.4 Transaction Information and Post-trade Transparency

A high level of post-trade transparency implies that there is full and immediate trade disclosure. That is, every dealer receives information about all transactions that have occurred. A financial markets analogy is a public stock ticker that reports the details of the day's trades. The information appears in a transaction history window on the trading screen and consists of the identities of the buyer and seller, the transaction size (which always equals one share in our setup) and the price at which the transaction cleared. When the level of post-trade transparency is low, only transactions in which a particular dealer was involved are listed in his window. There is no delay in trade disclosure.

2.5 Robot Behavior

As mentioned above, the experiment involves two types of subjects. In addition to the five human dealers, there is a computerized (robot) trader in our market. This robot does not set quotes and cannot be called by the market makers. The robot represents an external customer of the securities market. The robot is programmed to trade every 7 seconds against the best prices in the market. Prior to each robot transaction, it is determined by chance whether the trade is an informed or an uninformed one. The noise level – i.e., the *a priori* probability, α , that a trade is informed – equals 0.5 in all rounds. At the start of the experiment, the dealers are told this probability. The dealers can therefore expect about half of the robot trades to be informed. Note that the market makers are never told whether a particular robot trade was informed or uninformed. However, given their knowledge of the probability that a robot is informed (α), dealers may be able to filter relevant price information by observing robot transactions.

If the robot initiates an informed trade, it buys (sells) if the lowest ask price (highest bid price) at that time is below (above) the true value of the security. The robot does not trade if quoted bid-ask spreads surround the true value. Note that the robot maximizes its expected profits only at the trade level; there is no dynamic strategy. Over the whole round the robot is restricted to trading only at multiples of 7 seconds. Since informed robot trades depend on the true value, these transactions contain direct information about the true value. If a robot initiates an uninformed trade, a binomial random draw (with probability one half) determines whether the robot sells or buys; if it sells (buys), it does so against the highest bid price (lowest ask price) available. Details of robot transactions follow the same post-trade transparency rules as interdealer transactions. As the identity of the robot is denoted with the

letter “R,” a robot trade that appears in the transaction history window is distinguishable from interdealer trades.

2.6 Rounds and Parameters

Together, the two experimental parameters – the level of pre-trade transparency (high or low) and the level of post-trade transparency (high or low) – are combined in a full-factorial design (i.e., using all four possible combinations). In addition, there are two nuisance parameters, namely the true value of the security, which changes each round, and the particular sequence in which the experimental variables are implemented.

We ran the experiments with three groups of human subjects. Each group of subjects traded in two “sessions” consisting of six five-minute trading rounds per session. To control for possible learning effects, the first group started with a session with no quote disclosure, and then moved on to a session of full quote disclosure; the second group, on the other hand, followed the opposite sequence. The third group followed the same sequence as the first (except that they completed only four rounds with each pre-trade transparency treatment). Within each session, post-trade transparency alternated between low and high from round to round. Each trading session followed two five-minute practice rounds, one in which the level of post-trade transparency was low and the other in which it was high. The practice rounds acquaint the subjects with the trading system and provide a chance to ask questions. In the “real” (i.e., the non-practice) rounds, subjects were paid for their results. The data reported here come from the real sessions.

At the end of each round, all dealers learn their final wealth. Esquires are translated into Dutch guilders according to the following payment scheme, which is explained to the dealers before the start of the experiment (1 USD \approx 1.75 NLG). In every round, 15 guilders are divided among all market makers, making this a fixed-sum game. Because the true value strongly influences the insider’s speculative profits, and because the insider has an overwhelming informational advantage, we adjust the final guilder payments so that they do not depend linearly on the insider’s esquire wealth, but rather on his wealth compared with other dealers. Specifically, if the insider fails to earn the highest esquire wealth, his guilder payoff is zero. Otherwise, he receives 6 guilders if his esquire wealth is more than three times that of the best outsider; 5 guilders if his esquire wealth is between two and three times that of the best outsider; and 4 guilders when his esquire wealth is between one and two times that of

the best outsider.⁶ What is left after the insider has been paid is divided among the other market makers according to their esquire wealth.

3. Data

The data were collected from experiments held at the laboratory of the Center for Research in Experimental Economics and Political Decision Making (CREED) at the University of Amsterdam. The subjects in the first experiment, conducted on 27 January 1997, are five professional option traders from Optiver. In the second experiment, conducted on 3 February 1997, five professional equity traders from ABN Amro Bank, de Generale Bank, and Oudhoff Effecten participated. These subjects acted as market makers in 12 independent rounds, divided into two six-round sessions. The third replication, involving five professional options traders from Amsterdam Options Traders, was conducted on 21 April 1999. Unfortunately, an operating system failure at the CREED lab forced us to abandon this set of replications before we were done. Eight rounds of usable data were produced, however.

Tables 1-6 present the settings in each round and some basic summary statistics. In the trading mode without quote disclosure we obtain, on average, 45 quote settings, 130 transactions in which only outsiders (i.e., the four dealers who did not receive inside information) are involved, 180 transactions between the insider and an outsider, and 37 transactions initiated by the robot. Disclosing quotes leads to more activity in the market. In the trading mode where quotes are disclosed there were, on average, 65 quote settings, 197 transactions in which only outsiders are involved, 291 transactions between the insider and an outsider and 35 transactions initiated by the robot. These averages are taken over all three subject groups.

⁶ The purpose of this admittedly complex payoff scheme is to cap payoffs to the insider, to prevent the game from becoming a winner-take-all contest (which would disrupt risk-sharing among the dealers). Because the insider begins trading with such an extreme informational advantage, guilder payoffs to the four outsiders under a traditional linear payoff scheme would typically be minuscule. This creates incentives for risk-seeking behavior by the outsiders (e.g., speculating as heavily as possible on a random guess about the true value, in hopes of keeping pace with the insider); similar effects were revealed in pretests of the experimental software using student subjects. The three payoff buckets for the insider are intended to maintain an incentive for active trading at the margin. Note that this payoff scheme is not a classic “beat-the-market” tournament, in the sense of James and Isaac (2000). First, only the insider is singled out for a relative payoff rule. Second and more importantly, there is not a fixed exogenous distribution for the true value. Rather, the true value is non-random, and dealers are able to learn it in the course of trading, so that persistent price bubbles (rational deviations of quoted prices from the true value) are extremely unlikely, and indeed do not occur in our data. Lastly, we are comforted by the fact that our results appear to conform closely to the earlier results of FHKR (1997) and FHKM (1999), who use an affine payment scheme.

4. Results

The following analysis examines the speed of price discovery, the level of insider profitability, and bid-ask spreads (as measures of efficiency, unfairness, and liquidity, respectively). We regard them as functions of pre-trade and post-trade transparency, and we consider the full-factorial 2x2 matrix of transparency arrangements. We adopt a two-letter notational shorthand, in which the first letter indicates the pre-trade transparency treatment and the second letter indicates post-trade transparency. For example, “HL” indicates a high pre-trade and low post-trade transparency regime. The summary statistics aggregated for each transparency regime appear in table 7, and offer a preview of the more detailed results discussed below. Our results are consistent with the earlier work of FHKR (1997), Bloomfield and O’Hara (1999), Madhavan (1995), and FHKM (1999), who also examine price discovery in multiple-dealer experimental markets. However, neither of these earlier papers considers all four transparency combinations examined here, and neither includes an asymmetrically informed dealer.

4.1 Price Efficiency

In this section we concentrate on the effect of pre- and post-trade transparency on the informational efficiency of prices. In our experiments, information about the true value of the security is brought into the market via transactions of the informed robot trader and the market maker with inside information. As the expected flow of informed robot transactions is constant over the different trading regimes, differences in price efficiency should reflect differences in the transparency regime. As we show in the next subsection, these differences in price discovery have important implications for insider profitability: insiders profit more when price discovery is slow.

Following Bloomfield and O’Hara (1999), FHKR (1997), FHKM (1999) and Schnitzlein (1997), we use price errors to measure the efficiency of the market. Our hypothesis on the effect of transparency on price efficiency is based on the results of, among others, Bloomfield and O’Hara (1999), FHKR (1997), and Pagano and Röell (1996). These studies find that increasing post-trade transparency leads to greater efficiency. The presumption would be that it is relatively hard for insiders to hide private information when transaction information is widely available to the non-insider market makers. In contrast, FHKM (1999) find a search-cost effect that causes increased pre-trade transparency to reduce efficiency in a multiple-dealer market. For simplicity, we state our null hypothesis to apply

equally to both pre- and post-trade transparency:

H1: The decline of the price errors is faster in (pre- and/or post-trade) transparent markets than in less (pre- and/or post-trade) transparent markets,

while acknowledging that low pre-trade transparency may behave counter intuitively.

Figure 2 shows the average price error time path for each of the four trading mechanisms. We define price errors as the absolute difference between the average midpoint of all outstanding quotes and the underlying value of the security. Since the only *ex ante* information uninformed market makers have about the underlying value is that it lies between 1 and 200, their best initial guess should be that the underlying value is around 100. This guess is reflected in the value of the price error at the beginning of each round, which is generally close to the absolute difference between the true value and 100. As shown in figure 2 and the last panel of table 7, price errors clearly move towards zero after the first 20 seconds, a pattern observed in all four trading mechanisms.

Price errors decline as more information about the underlying value of the security is brought into the market. By definition, the better the market's ability to transmit information, the faster price errors decline. While the average price error paths in figure 2 disguise considerable round-to-round variation in initial errors and convergence rates, the most and least transparent cases (HH and LL) appear to perform well relative to the others.

This supposition is borne out by a more controlled statistical analysis. In table 8, we average price errors across all three groups and all rounds with a common transparency regime. Averages of dealer spread midpoints are taken at 50-second intervals throughout the trading round (plus an early reading after the first 20 seconds of trading), and are normalized by the starting error for the round. (The starting error is defined as $\text{abs}(100 - \text{TrueValue})$, since the expected starting quote for the uninformed dealers is 100.) Normalization compensates for differences in the true value of the security across rounds, allowing meaningful averages and comparisons. The bulk of price discovery occurs during the first 150 seconds of trading, and the HH and LL regimes clearly outperform HL and LH over this interval. After 150 seconds, average price errors are over twice as large for HL (38%) and LH (36%) as they are for either HH (17%) or LL (15%).

More formally, we estimate an individual effects panel model to examine the price efficiency in each of the four different trading mechanisms used in the experiments. (For details on estimating fixed individual effects panel models, see Baltagi (1995).) Thus, we

regress the price errors obtained in all 32 rounds on a constant, 32 individual-round dummies and four trend dummies. The dummy variables are included in order to isolate the effects of transparency. The estimated equation is:

$$|P_{tr} - TrueValue_r| = \mathbf{b}_0 + \sum_{i=1}^{32} \mathbf{b}_i \mathbf{I}(r = i) + \sum_{k=LL, LH, HL, HH} \mathbf{b}_k \mathbf{I}(r = k)t + \mathbf{e}_{tr} \quad (1)$$

where t denotes time in seconds and r the trading round, P_{tr} is the average midpoint over all bid and ask quotes at time t , $\mathbf{I}(\cdot)$ is a dummy variable for trading round and trading mechanism, and \mathbf{e}_{tr} is an i.i.d. error term. Since dealers' behavior changes after price discovery is achieved – trends in prices typically level off abruptly at this point – we discard observations after the point in time at which price errors have converged to a value less than or equal to five. Moreover, we omit the transactions completed in the first twenty seconds of each trading round in order to ensure that all market makers have submitted bid and ask quotes. OLS estimates for equation (1) are presented in table 9a. The third column shows the estimate of the intercept, while the estimates of the trading mechanism dummies are depicted in the fourth column. Larger negative values for the slope coefficient imply faster price discovery. The estimates of the 32 individual-round dummies represent differences in the underlying value in each round and the identity of the insider. They are omitted to conserve space. The coefficients for the dummies are generally significantly different from zero, indicating that the underlying value and the personal characteristics of the insider may influence market outcomes.

Table 9a generally confirms the conclusions from table 8, with the exception that the LL regime does not perform relatively as well in the regression analysis as it did in the more straightforward comparison of table 8. Table 9 thus largely supports hypothesis *H1*, that efficiency is greater when transparency is higher. The results show a clear ranking of the different trading mechanisms, although estimates of the slope coefficients in table 9a are not

significantly different from one another at a 5% level, as revealed in table 9b.⁷ The notable exception to the notion that more transparency is better is the least transparent microstructure (i.e., LL), in which efficiency is better than in the case with high pre-trade and low post-trade transparency (HL); this difference is marginally statistically significant. This result confirms the earlier work of FHKM (1999), who find that price discovery is faster under LL than HL; they argue that search costs can explain this counterintuitive result, as high pre-trade transparency sharply reduces the incentives for aggressive price improvements. The results of table 9 also confirm the conclusions of FHKR (1997), who find that price discovery is faster under LH than LL. Neither FHKR (1997) nor FHKM (1999) include an asymmetrically informed dealer in their experiments.

Lastly, we consider the implications of conditioning on only one of the transparency variables at a time. Row A of table 10 reports the results of estimating a modified version of equation (1), in which there are only two transparency dummies, based on the degree of pre-trade transparency. In other words, the HL and HH rounds are pooled, as are the LL and LH rounds. The difference across coefficients for the pooled groups is marginally significant, and the search cost effect described by FHKM (1999) appears to dominate: price discovery is faster when pre-trade transparency is low. Similarly, row B pools the HL and LL rounds (as well as the LH and HH rounds) to examine the impact of post-trade transparency. In this case, the transparency effect described by FHKR (1997) seems to dominate, as price discovery is faster when post-trade transparency is high. This difference is also marginally statistically significant.

4.2 Insider Profits

The profits for the inside dealer are closely related to price efficiency in that round. A slow

⁷ Estimating equation (1) with transaction data rather than average spread midpoints yields larger (that is, more negative) slope coefficients for the low pre-trade transparency cases, and smaller coefficients for the high pre-trade cases. Using transaction price data, the estimated slopes are: LL (-0.243), LH (-0.302), HL (-0.129), and HH (-0.232). The seemingly faster price discovery for the LL and LH cases is due to the fact that a significant minority of trades are made at off-market prices (a result of incomplete search by the dealer hitting the quote). Note that price trends become apparent in early trading, so that when prices trend upward (downward), the preponderance of dealers hit the asks (bids) of their peers. Meanwhile, we conjecture that the seemingly slower price discovery for the HL and HH cases reveals skewness in the typical distribution of quoted prices at a particular point in time. Recall that purchase (sale) orders go automatically to the best ask (bid) under high pre-trade transparency. Thus, if prices are trending upward (downward), quoting dealers are more aggressive about keeping their ask (bid) off the market to avoid being hit. The result is greater dispersion in ask (bid) prices, creating a gap between mean and median prices overall.

convergence of price errors indicates that the propagation of information is slow. Although the insider's speculative inventory strategy is essentially unchanged by faster price discovery, his ability to acquire inventory at advantageous prices diminishes more quickly. Hence insider profits should be relatively large when efficiency is weak, and vice versa. In the preceding subsection we found evidence favoring our hypothesis that the speed of price discovery is positively dependent on market transparency, with the exception that the least transparent regime (LL) performs relatively well in this regard, consistent with the search-cost effect reported by FHKM (1999). With this exception, then, we expect a generally inverse relationship between insider profits and transparency, since insider profitability should be inversely related to the speed of price discovery. This expectation is consistent with the conclusions of Bloomfield and O'Hara (1999) and Pagano and Röell (1996). Hence, we formulate the following hypothesis:

H2: Insider profits are lower in (pre- and/or post-trade) transparent markets than in less (pre- and/or post-trade) transparent markets.

As with hypothesis *H1*, however, we acknowledge the caveat that increased pre-trade transparency (relative to the LL regime) may increase insider profits by reducing price efficiency.

In comparing insider profits across transparency regimes, we adjust the profits for the underlying value in the trading round. When the true value is extreme (i.e., far from 100), insiders are likely to make larger profits than when it is moderate. As this effect is not due to transparency differences, we normalize total insider profits by the absolute difference between the true value and 100 in each round. Moreover, we look at both average insider profits and average insider profits per transaction. Although it does not affect our conclusions, we regard the latter number as more meaningful, as the number of transactions differs substantially across trading mechanisms (search costs impose a logistical obstacle that reduces transaction rates substantially in the LL case). The penultimate section of table 7 presents insider profits (and average outsider losses) under each trading mechanism, averaged across all rounds. Unsurprisingly, outsider losses are closely related to insider profits. More importantly, insider profits are smallest in the most transparent market (HH), which was also the market in which price discovery occurred most quickly. Interestingly, however, the least transparent market (LL) shows similarly small insider profits, a fact consistent with its relatively speedy price discovery, established in the preceding subsection.

To test *H2* more formally, we again estimate a fixed effects panel model in which we regress total profits per transaction in each of 32 rounds on four trading mechanism dummies. The model is given in equation (2):

$$\frac{\mathbf{p}_r}{|100 - TrueValue_r|} = \sum_{i=1}^{32} \mathbf{b}_i \mathbf{I}(r = i) + \sum_{k=LL, LH, HL, HH} \mathbf{b}_k \mathbf{I}(r = k) + \mathbf{e}_{ir} \quad (2)$$

where r denotes the trading round, \mathbf{p}_r is the average insider profit (either normalized by the number of transactions or non-normalized) in round r , $\mathbf{I}(\cdot)$ is a dummy variable for trading mechanism and \mathbf{e}_r is an i.i.d. error term. OLS estimates of equation (2) appear in table 11. Estimates of the 32 individual-round dummies are omitted from the table to conserve space. Again, we see that insider profits are lowest in the most transparent (HH) and least transparent (LL) cases. On the other hand, insiders are best off in the mixed-transparency cases (HL and LH). The pairwise differences in regression slope coefficients between the HH case and each of the two mixed-transparency cases (i.e., HH vs. HL, and HH vs. LH) are marginally significant. We conclude that insider profitability is inversely and causally related to the speed of price discovery in the market.

As with price discovery, we also consider the implications of conditioning on only one transparency variable at a time. Table 12 reports insider profits averaged across each subsample of rounds. Row A of table 12 pools results based on pre-trade transparency, with the pooled LL and LH results in the first column, and the pooled HL and HH results in the second column. Row B similarly pools LL and HL (LH and HH) in the first (second) column. Although the standard errors are too large for either of the inter-column differences to be statistically significant, the pattern in the calculated averages fits neatly with the results in table 10. For the same two subsamples for which price discovery was relatively fast (i.e., low pre-trade and high post-trade; see table 10), we find here that insider profitability is relatively low. We confirm our conclusion that price discovery is the determining factor for our insider profitability results.

In summary, the results for insider profits show a clear negative relationship between insider profits and the speed of price discovery, as anticipated. However, because the relationship between price discovery and transparency is a non-linear one, the relationship between insider profits and transparency is similarly non-linear. Specifically, although the highest-transparency regime has higher price efficiency and correspondingly lower insider profits than either of the mixed-transparency mechanisms (HL or LH), the least transparent regime (LL) also stands out with relatively high price efficiency and low insider profits. Thus,

the connection between transparency and insider profitability is not immediate, but rather makes its impact via the price discovery process.

4.3 Spreads

The spread between market makers' bid and ask quotes is generally assumed to consist of three different components: order-processing costs, inventory-holding costs, and adverse-selection costs. The first two components are nominally equal to zero in our experiments, and we focus on the latter.⁸ The standard adverse-selection component represents compensation to the dealer for losses to informed investors. However, a number of papers (e.g., Madhavan (1995)) argue that dealers in a multiple-dealer market should narrow their spreads in an effort to "purchase" informative order flow, with the goal of exploiting the resulting information in subsequent trading, a tactic that should be enforced by interdealer competition. Thus, adverse-selection costs subsume both the degree of uncertainty in the market and the degree of (imperfect) competition. The existing literature also indicates that an explicit distinction between pre-trade and post-trade transparency is necessary when examining the relation between transparency and bid-ask spreads. Pagano and Röell (1996) find that the spread size decreases when more price information is available in the market. The argument is that uncertainty decreases when market makers know more about each other's quotes. On the other hand, Bloomfield and O'Hara (1999) find that spreads increase when more transaction information becomes available in the market. Madhavan's (1995) model concludes that market makers compete more fiercely when they cannot observe other market makers' transactions, since in this case they must attract transactions to themselves to gain the information implicit in the order flow. We thus conjecture that reduced pricing uncertainty under pre-trade transparency should reduce spreads, while reduced competition under post-trade transparency should increase them. We formulate our hypothesis as follows:

H3: Bid-ask spreads are smaller in pre-trade transparent markets than in less pre-trade transparent markets. However, bid-ask spreads are larger in post-trade transparent markets than in less post-trade transparent markets.

⁸ Although there is no nominal inventory-financing cost in our experiments, dealer risk-aversion creates an implicit cost. However, the overriding source of risk for a (non-insider) dealer in our experiments is the adverse-selection risk of a trade with an informed robot or dealer. Note also that a recent working paper by Flood, Huisman, Koedijk, and Lyons (1999) argues that search costs in multiple-dealer markets represent a fourth spread component that has not been fully recognized in the literature.

Figure 3 shows the average spread size in each of the trading mechanisms, measured as the average bid-ask spread of all outside dealers in the relevant trading rounds.⁹ The initial spreads are high and similar in each trading mechanism, but spreads decrease as information is brought into the market over time. The spreads are nearly uniformly consistent with $H3$, which translates to the following four conditions:

1. $S_{LL} > S_{HL}$
2. $S_{LH} > S_{HH}$
3. $S_{HH} > S_{HL}$
4. $S_{LH} > S_{LL}$

where S_k is the average spread size under trading regime k . For at least the first 230 seconds of trading, the average spread size is lowest when pre-trade transparency is high and post-trade transparency is low, indicating that uncertainty is relatively low and competition relatively severe. The reverse holds for the LH market, in which spreads are relatively large. The other predictions of $H3$ similarly hold in the data.

In order to buttress the evidence in figure 3, table 13 presents the average outsider spreads pooled for all trading rounds with the specified transparency treatment. For example, row A of table 13 presents in the first (second) column the average outsider spread for all LL and LH (HL and HH) rounds. As predicted, increased pre-trade transparency narrows dealer spreads. Similarly, in row B, we see that increased post-trade transparency increases spreads. The predictions of $H3$ continue to hold under a finer-grained analysis. Thus, on average, $S_{LL} = 23.9$, $S_{LH} = 25.1$, $S_{HL} = 20.1$, and $S_{HH} = 21.1$.¹⁰ Although neither of the inter-column differences in table 13 is statistically significant at the 5% level, hypothesis $H3$ is nonetheless clearly supported by the available evidence.

⁹ A naïve conjecture is that insider's spread should differ systematically from those of the outsiders, since the adverse-selection incentives apply differently to the insider. However, the insider recognizes the obvious importance of concealing her identity. None of our spread results is changed markedly by including or excluding the insider.

¹⁰ Moreover, insider spreads are not appreciably different from those presented in table 13. Recalculating the table with insider spreads, we get in row A (row B) $S_{L^*} = 24.1$ and $S_{H^*} = 20.0$ ($S_{*L} = 22.1$ and $S_{*H} = 22.9$), respectively.

5. Summary and Conclusion

In recent years, market regulators and academic researchers worldwide have debated intensively about the implication and effects of asymmetric information on financial markets. Regulators have been particularly concerned with policies on insider trading, including both traditional corporate insiders as well as asymmetrically informed securities dealers. Numerous studies have investigated the costs and benefits of informational asymmetries for financial markets. In general terms, new information should enter the market as quickly as possible to improve the efficiency of market prices. On the other hand, the strategic use in trading of such an informational advantage can drive away the uninformed, and may therefore reduce market liquidity and the overall demand for securities.

In this paper, we follow the recommendations of Leland (1992), Pagano and Röell (1996), and Schnitzlein (1996), to examine the extent to which market microstructure affects the impact of asymmetric information on market performance. Specifically, we consider a multiple-dealer market in which one of the dealers begins with fundamental information unavailable to the other dealers. We vary two standard transparency rules as experimental variables: the pre-trade publication of dealer quotes (private information or broadcast) and the post-trade publication of transactions (public ticker or private information). The characteristics of the trading mechanism affect how difficult it is for uninformed dealers to detect an insider and infer his strategies; conversely, they affect the ability of the insider to exploit his informational advantage.

As it is extremely difficult to study insider trading empirically, we obtain our results from an experimental financial market, in which three groups of five professional securities traders act as market makers for a single imaginary security. The dealers set quotes and trade with each other and with both informed and liquidity-motivated clients. In each 5-minute experimental trading round, one of the dealers receives (inside) information about the true value of the security. We create four different trading mechanisms by varying the two transparency rules. An important innovation is that we model the insider as a market maker in a multiple-dealer market, while most other studies consider an informed external investor. This is relevant, since dealers in multiple-dealer markets will typically have inside information via their private order flow, if not from other sources as well. Moreover, when a limit order book is present, external customers are also able to compete on price to a limited degree.

We obtained our data from a series of 5-minute trading rounds for three groups of

subjects. Our results clearly indicate an inverse connection between insider profits and the price efficiency of the market. Slow price discovery allows insiders greater opportunities to accumulate speculative inventories at advantageous prices. However, the connection between insider profitability and transparency is somewhat more complex, because the connection between transparency and price efficiency is non-linear. Post-trade transparency (i.e., a public ticker) improves efficiency. Conversely, however, and consistent with the earlier work of FHKM (1999), pre-trade transparency in our multiple-dealer market slows price discovery, thus increasing insider profitability. Market liquidity, measured by average dealer bid-ask spreads, behaves consistently with theoretical predictions. Increased pre-trade transparency reduces dealers' uncertainty and reduces spreads. On the other hand, eliminating post-trade transparency creates an incentive for dealers to compete for private order flow, thus reducing spreads.

References

- Baltagi, B.H., 1995, *Econometric Analysis of Panel Data*, John Wiley & Sons.
- Benveniste, L., A. Marcus, and W. Wilhelm, 1992, "What's Special about the Specialist?," *Journal of Financial Economics*, 32, 61-86.
- Bloomfield, R., and M. O'Hara, 1999, "Market Transparency: Who Wins and Who Loses?," *Review of Financial Studies*, 12(1), 5-35.
- Copeland, T., and D. Friedman, 1991, "Partial Revelation of Information in Experimental Asset Markets," *Journal of Finance*, 46, 265-295.
- Easley, D., and M. O'Hara, 1992, "Time and the Process of Security Price Adjustment," *Journal of Finance*, 69-90.
- Flood, M.D., R. Huisman, C.G. Koedijk, and R.K. Lyons, 1999, "Search Costs: The Neglected Spread Component," working paper, Office of Thrift Supervision.
- Flood, M.D., R. Huisman, C.G. Koedijk, and R.J. Mahieu (FHKM), 1999, "Quote Disclosure and Price Discovery in Multiple Dealer Financial Markets," *Review of Financial Studies*, 12(1), 37-59.
- Flood, M.D., R. Huisman, C.G. Koedijk, and A.A. Röell (FHKR), 1997, "Post-trade Transparency in Multiple Dealer Financial Markets," working paper, Erasmus University Rotterdam.
- Forsythe, R., T.R. Palfrey, and C.R. Plott, 1982, "Asset Valuation in an Experimental Market," *Econometrica*, 50, 537-82.
- Franks, J., and S. Schaefer, 1995, "Equity Market Transparency on the London Stock Exchange," *Journal of Applied Corporate Finance*, 8(1), 70-77.
- Friedman, D., and S. Sunder, 1994, *Experimental Methods: A Primer for Economists*, Cambridge University Press.
- Garfinkel, J., and M. Nimalendran, 1998, "Market Structure and Trader Anonymity: An Analysis of Insider Trading," working paper, Securities and Exchange Commission, June.
- Glosten, L., 1999, "Introductory Comments: Bloomfield and O'Hara, and Flood, Huisman, Koedijk, and Mahieu," *Review of Financial Studies*, 12(1), 1-3.
- Glosten, L.R., and P.R. Milgrom, 1985, "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders," *Journal of Financial Economics*, 14, 71-100.
- James, D., and R.M. Isaac, 2000, "Asset Markets: How They are Affected by Tournament Incentives for Individuals", *American Economic Review*, 90, 995-1004

- Kyle, A.S., 1985, "Continuous Auctions and Insider Trading," *Econometrica*, 53(6), 1315-35.
- Lamoureux, G.L., and C.R. Schnitzlein, 1997, "Herd Through the Grapevine: Winner's Curse in a Fragmented Asset Market," working paper, University of Arizona.
- Leland, H.E., 1992, "Insider Trading: Should It Be Prohibited?," *Journal of Political Economy*, 100(4), 859-87.
- Lyons, R.K. , 1996, "Foreign Exchange Volume: Sound and Fury Signifying Nothing?," in: J. Frankel, G. Galli, and A. Giovannini, eds., *The Microstructure of Foreign Exchange Markets*, University of Chicago Press, 183-201.
- Madhavan, A., 1992, "Trading Mechanisms in Securities Markets," *Journal of Finance*, 47, 607-641.
- Madhavan, A., 1995, "Consolidation, Fragmentation, and the Disclosure of Trading Information," *Review of Financial Studies*, 8, 579-603.
- Madhavan, A., and M. Cheng, 1997, "In Search of Liquidity: Block Trades in the Upstairs and Downstairs Markets," *Review of Financial Studies*, 10(1), 175-203.
- Office of Fair Trading, 1994, "Trade Publication Rules and the London Stock Exchange," *A report to the Chancellor of the Exchequer by the Director General of Fair Trading under the Financial Services Act 1986*, United Kingdom, November.
- O'Hara, M., 1995, *Microstructure Theory*, Basil Blackwell, Cambridge, Mass.
- Pagano, M. and A. Röell, 1996, "Transparency and Liquidity: A Comparison of Auction and Dealer Markets with Informed Trading," *Journal of Finance*, 51(2), 579-611.
- Plott, C.R., 1982, "Industrial Organization Theory and Experimental Economics," *Journal of Economic Literature*, 20, 1485-1527.
- Plott, C.R. and S. Sunder, 1982, "Efficiency of Experimental Security Markets with Insider Information: An Application of Rational-Expectations Models," *Journal of Political Economy*, 90, 663-98.
- Schnitzlein, C.R., 1996, "Call and Continuous Trading Mechanisms Under Asymmetric Information: An Experimental Investigation," *Journal of Finance*, 51(2), 613-36.
- Schnitzlein, C.R., 1997, "The Importance of Common Knowledge Assumptions in Models of Insider Trading: An Experimental Investigation," working paper, University of Arizona.
- Seppi, D., 1990, "Equilibrium Block Trading and Asymmetric Information," *Journal of Finance*, 45(1), 73-94.
- Sunder, S., 1995, "Experimental Asset Markets: A Survey," in: J. Kagel and A. Roth, eds., *The Handbook of Experimental Economics*, Princeton University Press, 445-500.

Table 1
Summary Statistics

This table contains summary statistics of the trading rounds without quote disclosure for the first group of subjects.

Group 1						
session 1: no quote disclosure						
<i>Round no.</i>	1	2	3	4	5	6
<i>Settings</i>						
Post-trade transparency	L	H	L	H	L	H
α	0.5	0.5	0.5	0.5	0.5	0.5
True value	61	44	152	186	19	151
<i>Results</i>						
# Quotes set	38	35	50	61	69	40
# Trades						
Total	315	442	121	199	279	328
Outsiders ¹	149	180	44	53	125	80
Insider ²	132	220	44	105	116	215
Robot	34	42	33	41	38	33
Avg. dealer spreads						
Outsiders	29	26	26	27	23	27
Insider	24	30	22	25	24	23
<i>Average end-of-round capital</i> ³						
<i>Dealers</i>						
Outsiders	-430	-945	-95	-1265	-1175	-451
– Std. deviation	(870)	(2401)	(450)	(1938)	(2283)	(179)
Insider	1733	3410	203	4408	4085	1848

¹ Trades in which only (human) outsiders are involved.

² Trades in which the insider is involved.

³ Expressed in esquires and excluding the initial amount of capital.

Table 2
Summary Statistics

This table contains summary statistics of trading rounds with quote disclosure for the first group of subjects.

Group 1 session 2: quote disclosure						
<i>Round no.</i>	1	2	3	4	5	6
<i>Settings</i>						
Level of post-trade transparency	L	H	L	H	L	H
α	0.5	0.5	0.5	0.5	0.5	0.5
True value	186	81	134	64	49	165
<i>Results</i>						
# Quotes set	91	74	87	78	98	61
# Trades						
Total	673	518	638	816	664	652
Outsiders ¹	351	252	247	322	213	165
Insider ²	280	238	363	453	412	449
Robot	42	28	28	41	39	38
Avg. dealer spreads						
Outsiders	15	17	13	25	21	18
Insider	30	12	23	19	26	12
<i>Average end-of-round capital</i> ³						
<i>Dealers</i>						
Outsiders	-4089	-133	-417	708	-2431	-660
– Std. deviation	(3740)	(134)	(484)	(3173)	(3577)	(1543)
Insider	15041	504	1719	-3124	8789	2557

¹ Trades in which only (human) outsiders are involved.

² Trades in which the insider is involved.

³ Expressed in esquires and excluding the initial amount of capital.

Table 3
Summary Statistics

This table contains summary statistics of trading rounds without quote disclosure for the second group of subjects.

Group 2						
session 2: no quote disclosure						
<i>Round no.</i>	1	2	3	4	5	6
<i>Settings</i>						
Level of post-trade transparency	L	H	L	H	L	H
α	0.5	0.5	0.5	0.5	0.5	0.5
True value	61	44	152	186	19	151
<i>Results</i>						
# Quotes set	38	42	41	36	45	44
# Trades						
Total	289	551	330	558	324	337
Outsiders ¹	121	228	154	306	114	104
Insider ²	134	281	141	210	169	202
Robot	34	42	35	42	41	31
Avg. dealer spreads						
Outsiders	22	23	23	27	26	24
Insider	15	30	23	27	28	23
<i>Average end-of-round capital</i> ³						
Dealers						
Outsiders	-324	-1961	-549	-3764	-1003	-594
– Std. deviation	(949)	(4406)	(1673)	(12243)	(1722)	(1679)
Insider	1358	7698	2015	13118	3521	2139

¹ Trades in which only (human) outsiders are involved.

² Trades in which the insider is involved.

³ Expressed in esquires and excluding the initial amount of capital.

Table 4
Summary Statistics

This table contains summary statistics of trading rounds with quote disclosure for the second group of subjects.

Group 2 session 1: quote disclosure						
<i>Round no.</i>	1	2	3	4	5	6
<i>Settings</i>						
Level of post-trade transparency	L	H	L	H	L	H
α	0.5	0.5	0.5	0.5	0.5	0.5
True value	186	81	134	64	49	165
<i>Results</i>						
# Quotes set	39	57	56	40	45	52
# Trades						
Total	580	501	398	514	449	748
Outsiders ¹	178	265	135	155	163	283
Insider ²	359	205	237	326	248	426
Robot	43	31	26	33	38	39
Avg. dealer spreads						
Outsiders	23	25	24	25	22	20
Insider	26	23	17	16	14	29
<i>Average end-of-round capital</i> ³						
<i>Dealers</i>						
Outsiders	-6334	-371	-365	-733	-543	-1376
– Std. deviation	(10157)	(976)	(561)	(753)	(1045)	(4146)
Insider	24902	1565	1539	2834	2127	5239

¹ Trades in which only (human) outsiders are involved.

² Trades in which the insider is involved.

³ Expressed in esquires and excluding the initial amount of capital.

Table 5
Summary Statistics

This table contains summary statistics of trading rounds without quote disclosure for the third group of subjects.

Group 3				
session 1: no quote disclosure				
<i>Round no.</i>	1	2	3	4
<i>Settings</i>				
Level of post-trade transparency	L	H	L	H
α	0.5	0.5	0.5	0.5
True value	61	44	152	186
<i>Results</i>				
# Quotes set	48	47	49	45
# Trades				
Total	118	513	209	638
Outsiders ¹	67	137	96	116
Insider ²	24	334	72	486
Robot	27	42	41	36
Avg. dealer spreads				
Outsiders	21	23	21	24
Insider	10	27	28	26
<i>Average end-of-round capital</i> ³				
<i>Dealers</i>				
Outsiders	-59	-1572	-510	-3348
– Std. deviation	(250)	(2773)	(1145)	(2038)
Insider	205	5742	1578	12530

¹ Trades in which only (human) outsiders are involved.

² Trades in which the insider is involved.

³ Expressed in esquires and excluding the initial amount of capital.

Table 6
Summary Statistics

This table contains summary statistics of trading rounds with quote disclosure for the third group of subjects.

Group 3 session 2: quote disclosure				
<i>Round no.</i>	1	2	3	4
<i>Settings</i>				
Level of post-trade transparency	L	H	L	H
α	0.5	0.5	0.5	0.5
True value	186	81	134	64
<i>Results</i>				
# Quotes set	49	72	72	65
# Trades				
Total	371	179	458	200
Outsiders ¹	159	86	83	91
Insider ²	182	66	340	69
Robot	30	27	35	40
Avg. dealer spreads				
Outsiders	20	18	23	21
Insider	21	18	25	9
<i>Average end-of-round capital</i> ³				
<i>Dealers</i>				
Outsiders	-1169	-216	-848	-88
– Std. deviation	(2346)	(267)	(1373)	(532)
Insider	4367	853	3296	275

¹ Trades in which only (human) outsiders are involved.

² Trades in which the insider is involved.

³ Expressed in esquires and excluding the initial amount of capital.

Table 7
Summary Statistics for Each Trading Mechanism

In this table, the summary statistics for individual rounds depicted in tables 3.1 through 3.6 are averaged over all three groups and eight rounds to obtain summary statistics for the four trading mechanisms.

Variable	LL	LH	HL	HH
<i>Number of quotes set</i>	47.3	43.8	67.2	62.4
<i>Number of trades</i>				
Total	248.1	445.8	528.9	516.0
Outsiders	108.8	150.5	191.1	202.4
Insider	104.0	256.6	302.6	279.0
Robot	35.4	38.6	35.1	34.6
<i>Average dealer spreads</i>				
Outsiders	23.9	25.1	20.1	21.1
Insider	21.8	26.4	22.8	17.3
<i>Average end-of-round capital</i>				
Outsiders	- 518.1	- 1737.5	- 2024.5	- 358.6
Insider	1837.3	6361.6	7722.5	1337.9
<i>Price discovery</i>				
Time to convergence ¹	185.8	241.3	138.6	105.5
Percentage price error ²				
after 100 seconds	0.39	0.57	0.39	0.32
after 200 seconds	0.12	0.23	0.32	0.15
after 300 seconds	0.06	0.09	0.18	0.14

¹ Average number of seconds until the average quote midpoint for all dealers has converged to less than 5 esquires away from the underlying true value.

² Average price error after t seconds, divided by the average price error after 20 seconds.

Table 8
Normalized Price Errors in Different Trading Mechanisms

This table presents normalized price errors for four different transparency regimes. The normalized price errors are based on the absolute difference between the true value of the security in each round and the average midpoint of all outstanding quotes. These errors are then averaged over eight rounds in order to obtain the average price errors for each different trading mechanism. The resulting numbers are corrected for the average initial price error in each transparency regime, to obtain price errors that are directly comparable across trading mechanisms. The initial price error is defined as $\text{abs}(100 - \text{TrueValue})$.

Time (in seconds)	LL	LH	HL	HH
50	0.58	0.78	0.65	0.48
100	0.33	0.56	0.44	0.25
150	0.15	0.36	0.38	0.17
200	0.11	0.22	0.35	0.13
250	0.08	0.13	0.27	0.14
300	0.05	0.08	0.22	0.11

Table 9a
Price Efficiency

This table presents the estimated intercept and the coefficients of the trading mechanism dummies from the fixed effects panel model depicted in equation (3.1). Robust standard errors are presented in parentheses. Significance at the 5% level is denoted by *. The number of data points is 4535. The R-squared of the regression is equal to 0.756.

	Pre-Trade Transparency	Post-Trade Transparency	Estimated Intercept	Estimated Slope Coefficient
LL	low	low	$\beta_0: 57.72^*$ (2.449)	- 0.207* (0.030)
LH	low	high		- 0.228* (0.034)
HL	high	low		- 0.138* (0.021)
HH	high	high		- 0.317* (0.141)

Table 9b

Matched Pair Tests of Transparency Effect on Price Efficiency

This table presents the implications of changing the level of pre-trade and post-trade transparency on the price efficiency in the market. The effects of pre-trade and post-trade transparency on price efficiency are computed using the coefficients for the trading mechanism dummies in equation (3.1). The standard errors depicted in this table are robust to heteroskedasticity. None of the effects is statistically different from zero at the 95% confidence level.

Invariable Transparency	Transparency Effect	Trading Mechanisms	Effect on Estimated Slope
low post-trade transparency	pre-trade	LL vs. HL	0.069 (0.038)
high post-trade transparency	pre-trade	LH vs. HH	- 0.089 (0.145)
low pre-trade transparency	post-trade	LL vs. LH	- 0.021 (0.041)
high pre-trade transparency	post-trade	HL vs. HH	- 0.179 (0.141)

Table 10

Pooled Effects of Pre-Trade and Post-Trade Transparency on Efficiency

In the fixed effects panel model depicted in the first row (case A) of this table, LL and LH rounds are pooled (first column), as are HL and HH (second column), to examine the effect of conditioning solely on pre-trade transparency. In the second row (case B), LL and HL are pooled, as are LH and HH for a similar analysis of the effect post-trade transparency. Robust standard errors are in parentheses. Significance at the 5% level is denoted by *. The differences between low-transparency and high-transparency estimates are not significantly different from zero at the 95% confidence level in either case A or B. The number of data points is 4535. The R-squared of regression A (B) is equal to 0.748 (0.750).

Regression	Estimated Intercept	Slope Estimate Low Transparency	Slope Estimate High Transparency
A: pre-trade transparency	57.053* (2.162)	- 0.221* (0.023)	- 0.160* (0.026)
B: post-trade transparency	57.146* (2.400)	- 0.170* (0.021)	- 0.235* (0.033)

Table 11a
Insider Profits

This table depicts the fixed effects panel coefficients for the trading mechanism dummies in equation (3.2). For the first column, π_r is the coefficient on total insider profits; for the second column, π_r is the coefficient on total insider profits divided by the total number of insider transactions. The data is pooled over 32 rounds. Robust standard errors appear in parentheses. Significance at the 5% level is denoted by *. The number of observations is equal to 32. The R-squared amounts to 0.301 for the raw profits and 0.119 for the profits per transaction.

Pre-Trade Transparency	Post-Trade Transparency	Raw Profits	Profits per Transaction
low	low	31.43* (20.84)	0.2657* (0.0704)
low	high	91.07* (20.84)	0.3608* (0.0704)
high	low	115.25* (20.84)	0.3554* (0.0704)
high	high	34.16* (20.84)	0.1957* (0.0704)

Table 11b

Matched-Pair Tests of the Effect of Transparency on Insider Profits

This table presents the implications of changing the level of pre-trade and post-trade transparency on the insider profits. The effects of pre-trade and post-trade transparency on insider profits per transaction are computed using the coefficients for the trading mechanism dummies in equation (3.2). The standard errors depicted in this table are robust to heteroskedasticity. None of the effects is statistically different from zero at the 5% level.

Invariable Transparency	Transparency Effect	Trading Mechanisms	Effect on Estimated Intercept
low post-trade transparency	pre-trade	LL vs. HL	0.090 (0.100)
high post-trade transparency	pre-trade	LH vs. HH	- 0.165 (0.100)
low pre-trade transparency	post-trade	LL vs. LH	0.095 (0.100)
high pre-trade transparency	post-trade	HL vs. HH	- 0.160 (0.100)

Table 12

Effects of Pre-Trade and Post-Trade Transparency on Average Profits

This table presents the effect of transparency on insider profits by averaging the insider profits over two different transparency regimes. In the first row (case A), average insider profits in LL and LH rounds are computed (first column), as are HL and HH (second column), to examine the effect of conditioning solely on pre-trade transparency. In the second row (case B), average insider profits in LL and HL are calculated, as are LH and HH for a similar analysis of the effect post-trade transparency. Standard deviations are in parentheses.

Transparency Variable	Average Low Transparency	Average High Transparency
A: pre-trade transparency	4099 (3933)	4530 (6784)
B: post-trade transparency	4780 (6524)	3850 (4309)

Table 13

Effects of Pre and Post-Trade Transparency on Average Spreads

This table presents the effect of transparency on dealer spreads by averaging the spreads over two different transparency regimes. In the first row (case A), average outsider spreads in LL and LH rounds are computed (first column), as are HL and HH (second column), to examine the effect of conditioning solely on pre-trade transparency. In the second row (case B), average outsider spreads in LL and HL are calculated, as are LH and HH for a similar analysis of the effect post-trade transparency. Standard deviations are in parentheses.

Transparency Variable	Average Low Transparency	Average High Transparency
A: pre-trade transparency	24.5 (2.39)	20.6 (3.65)
B: post-trade transparency	22.0 (3.88)	23.1 (3.36)

Figure 1
Trading Screen

This figure depicts an example of a trading screen in the market without quote disclosure. Each dealer has her own trading screen. The window on the left presents the cash balance (790 esquires), this dealer's inventory (2 shares long), this dealer's outstanding quote of (90 - 110), and this dealer's approximate profit, based on the price of the last transaction in which she was involved (1010 esquires). The window also shows the time remaining in this round. When this dealer calls another dealer, bid and ask quotes appear in the center window. In the heading of this window, "ID" denotes the identity of the quoting dealer, "Sell" denotes the quoted bid (at which this dealer can sell), and "Buy" denotes the quoted ask (at which this dealer can buy). In the market with full quote disclosure where all quotes are disclosed publicly, all bids are presented below "Sell" ranked from highest to lowest and all asks are presented below "Buy" ranked from lowest to highest. Information on past transactions appears at the right of the trading screen. By default, it displays the details of the last 20 transactions; the dealer can scroll through the list with the PageUp and PageDown keys. For all transactions, the identities of the buying (under heading "buy") and the selling ("sel") dealer are displayed, along with the number of shares traded and the transaction price. For example, the first row indicates that this dealer (his identity is depicted by *) bought one share for 100 esquires from dealer B. The five dealers' identities are denoted by letter ranging from "A" through "E". The robot is denoted with the letter "R". The fourth transaction is thus an example of a trade in which the robot sold one share to this dealer for 110 esquires.

Your Position		Price Quotes				Transactions				
Money	: 790.00	ID	Sell	Buy	ID	#	buy	sel	units	price
LIFE Shares :	2					1	*	B	1	100.00
Your quote :						2	D	*	1	110.00
bid :	90.00 ask : 110.00					3	*	A	1	110.00
Approximate wealth						4	*	R	1	110.00
based on last price :										
1010.00 esquires										
Time remaining :	158 sec									

PageUp/PageDown = scroll

Figure 2
Price Errors

This figure shows the average price errors for each combination of transparency variables; e.g. “low, high” refers to low pre-trade and high post-trade transparency. Price errors are defined as the absolute difference between the true value of the security and the average midpoint of outstanding quotes. The price errors are averaged across all rounds with the specified combination of transparency variables. The first 20 seconds of each round are omitted, to allow time for all dealers to submit their first quotes.

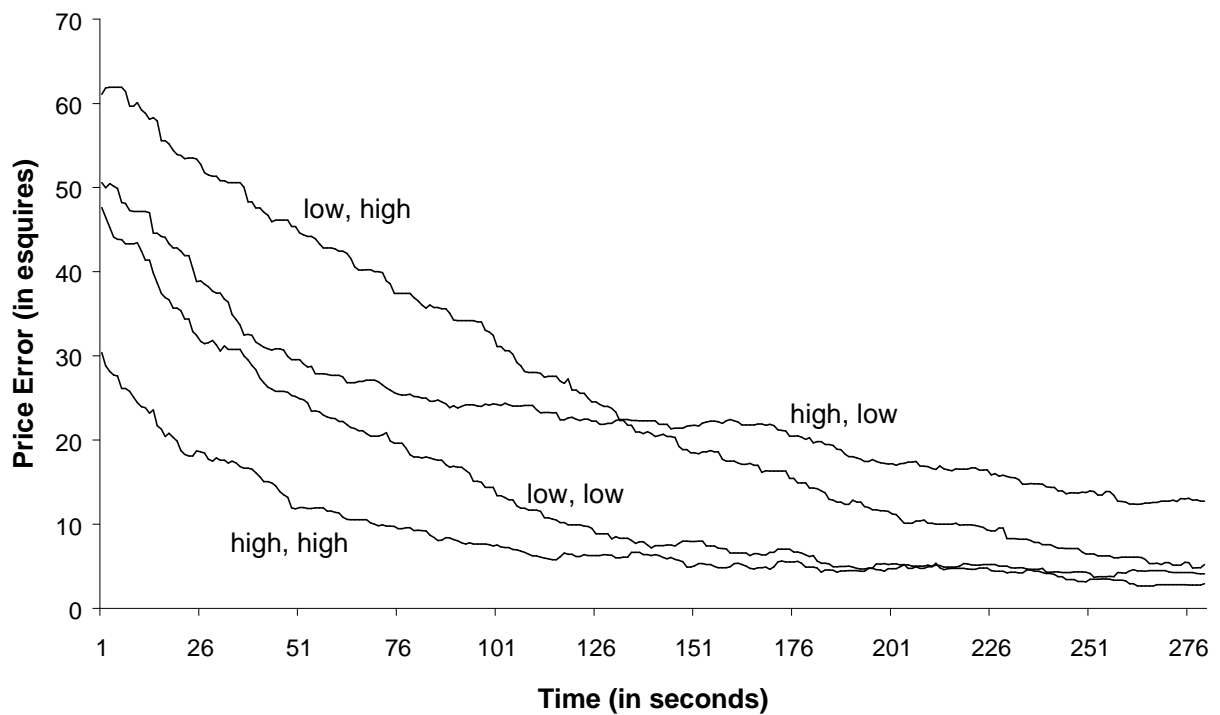
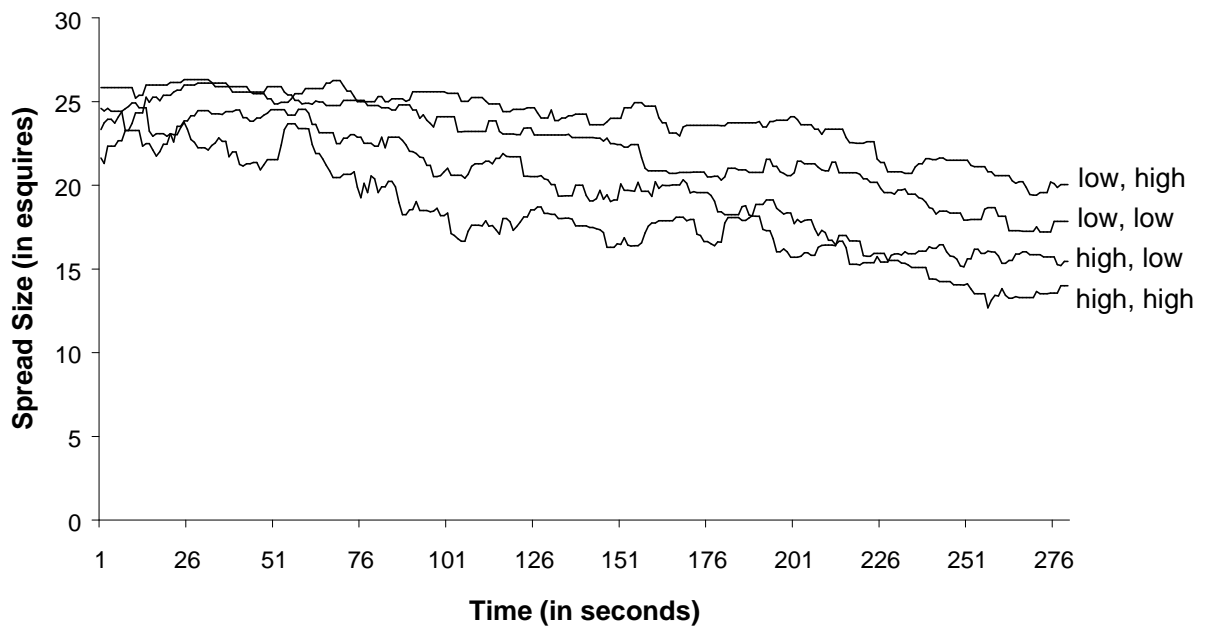


Figure 3
Dealer Spreads

This figure shows the average outsider spreads in the four different microstructures for all three groups of subjects. The average spread in each trading round is defined as the average size of the spread between the bid and ask quotes of all market makers. The lines in this graph were constructed by averaging the spreads of 8 individual rounds with the same trading mechanism. The first 20 seconds of each trading round were omitted from the calculation, as dealers used this time period to enter their first bid and ask quotes.



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