Pre-trade transparency and informed trading: experimental evidence on undisclosed orders

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Abstract

I use experimental asset markets to analyze trading under different transparency and information settings. I find that both liquidity and informed traders use undisclosed orders to compete for liquidity provision. In opaque markets, traders increase aggressiveness to improve execution probability. Without information friction, market opacity enhances liquidity, especially toward the end of trading, and is beneficial for liquidity traders. Under informed trading, adverse selection drives market outcomes mainly around news announcements. Monopolistic insiders exploit opacity at the expense of large liquidity traders. Opacity does not affect informational efficiency with a monopolistic insider, but value discovery is faster when informational rents are shared.

(JEL classification: C91, C92, G28)

Keywords: Undisclosed orders, hidden liquidity, information asymmetry, market opacity, insider trading.

1 Introduction

In most modern trading platforms, orders posted to the limit order book (LOB) also include instructions specifying the degree of disclosure (Cheuvreux, 2012). Such orders, labeled as undisclosed (reserve or iceberg) orders, allow traders to limit the quantity exposure by concealing a portion of the order. This feature reduces the pre-trade transparency of the market, since traders do not observe the total depth available on the electronic LOB. Using laboratory markets, in this paper I address two related yet unresolved questions regarding the use of undisclosed orders. The first question inquires about the source of hidden liquidity and its impact on the trading strategies of market participants while the second is related to its implications on different dimensions of market quality.

Undisclosed orders account for a large proportion of trading activity in major exchanges, for example, more than 44% of the Euronext volume (Bessembinder, Panayides and Venkataraman, 2009), about 28% of the Australian Stock Exchange volume (Aitken, Berkman and Mak, 2001), 16% of executed shares on Xetra (Frey and Sandas, 2008), and 20% of executions in the NASDAQ (Yao, 2013).[1] However, the source of hidden liquidity is still controversial. Two separate viewpoints emerge regarding the types of traders and their motivation for submitting undisclosed orders. According to the first view, large liquidity traders enter markets for exogenous reasons and prefer undisclosed orders to compete with other liquidity suppliers and/or to protect their orders from fast traders (Buti and Rindi, 2009, 2013). If only large liquidity traders (Harris, 1997) opt for undisclosed orders, then the implications on market quality are mixed. While opacity improves depth at the top of the book, it widens the spread at the expense of small traders. On the other hand, in the second view, informed traders employ hidden liquidity to conceal private information and to minimize the price impact of large orders. If this is the underlying reason, then opacity introduced through undisclosed orders could harm the informational efficiency of

[1] Some exchanges, such as the NASDAQ, the NYSE, and alternative trading platforms, that is, dark pools, also offer completely hidden orders. However, my analysis is limited to partially disclosed orders following theoretical models on undisclosed orders (Moinas, 2010; Buti and Rindi, 2013).

financial markets. While the effect on market quality is positive due to increased trading volume (Moinas, 2010), this view also highlights the potential role of undisclosed orders as a tool to obscure insider trading. Boulatov and George (2013) suggest that hidden liquidity attracts informed traders to liquidity provision, hence improving liquidity and informational efficiency via intense competition. Overall, even though the stock exchanges are in a race to offer darker platforms, there is still no consensus in the academic literature on the virtues of concealing orders.

I design an asset market experiment to study market opacity introduced via undisclosed orders and its sensitivity to market friction induced by private information. I start with a baseline setting under symmetric information where I rule out the potential effects of adverse selection on hidden liquidity. I compare an opaque regime with a transparent alternative that excludes the possibility of undisclosed orders. In a second setting, I introduce a monopolistic insider in experimental asset markets, maintaining all other features. I also run additional sessions with two insiders. This design allows competition among informed traders (Boulatov and George, 2013). I analyze trading mechanisms under both symmetric and asymmetric information. My results contribute to the recent debate on dark trading and have important implications for market design.

I document several interesting findings from the experimental asset markets. My first observation is that both liquidity and informed traders compete for liquidity provision (Boulatov and George, 2013; Collin-Dufresne and Fos, 2015) and make use of undisclosed orders. In opaque markets, on average, about 20% of limit orders are replaced by undisclosed orders. Whenever traders reduce liquidity consumption to control for price risk, they provide liquidity more aggressively to increase execution probability, which in turn affects market liquidity. Both large liquidity and informed traders submit, on average, more undisclosed orders compared to other trader types, but there is substantial heterogeneity among informed traders: They either submit no undisclosed orders at all (nearly half of informed traders) or supply hidden liquidity in large quantities and at price levels further away from the midquote. Nonetheless, informed traders manage to pool with large liquidity traders in liquidity provision, exploit their informational advantage, and thus affect market outcomes.

Second, I show that large liquidity traders obtain higher trading profits in opaque markets under symmetric information, since liquidity consumption is cheaper. Once a monopolistic insider is introduced to the market, however, large liquidity traders are negatively affected by reduced transparency, because monopolistic insiders are better at extracting informational rents. In other words, under an opaque regime, a monopolistic insider is better off at the expense of large liquidity traders. However, once informational rents are shared by two insiders, then market transparency has a minor effect on the profits of liquidity traders. These results suggest that any welfare analysis of market transparency should control for the degree of adverse selection in the market.

Third, without an insider, reducing transparency contributes positively to market liquidity, especially toward the end of the trading period. Liquidity traders substitute part of the limit and marketable orders with undisclosed orders to reduce exposure to opportunistic traders and price risk but, at the same time, they increase limit order aggressiveness to compensate for the reduction in execution probability. This strategic behavior reduces both quoted bid-ask and realized spreads, that is, the temporary price impact of marketable orders. Under asymmetric information, however, the spread does not change overall under different transparency regimes. One exception is around public news announcements: Thanks to market opacity, informed traders do not have to rush to exploit their informational advantage and can afford to trade using less aggressive orders, that is, limit or undisclosed orders instead of marketable orders, but, to increase the execution probability, they submit liquidity more aggressively, which reduces quoted spreads immediately after information release. Increasing the degree of adverse selection with more insiders results in increased book depth in opaque markets without affecting quoted spreads, in line with empirical evidence from the Toronto Stock Exchange (Anand and Weaver, 2004). In the case of a monopolistic insider, transparency does not affect the informational efficiency of asset markets, but value discovery is faster in opaque markets when informational rents are shared between insiders (Boulatov and George, 2013). Bloomfield, O'Hara and Saar (BOS, 2015) also find that the depth dimension of liquidity improves due to opacity, but the authors do not document any effect on informational efficiency. However, their study has several differences in experimental design from mine, particularly regarding the quality of the private information held by informed traders.

There are few theoretical papers on hidden liquidity. My market design is closely linked to a paper by Buti and Rindi (2013), who study optimal order strategies in a dynamic LOB allowing undisclosed orders. In their model, risk-neutral traders make simultaneous strategic decisions on price, quantity, and exposure conditional on the state of the LOB and their private valuations of assets. Buti and Rindi's model extends the models of both Foucault (1999) and Parlour (1998), who abstract from private information. In equilibrium, large traders submit hidden liquidity to electronic LOB for two different motivations: to avoid competition for liquidity provision and/or to avoid being picked off by fast traders in case of a public information shock (Buti and Rindi, 2009). The former refers to a situation where a competitor undercuts a large limit buy (sell) order by sending a limit buy (sell) order at a slightly higher (lower) price (typically by the minimum tick size), thus gaining price priority. Undisclosed orders help prevent undercutting by hiding order quantity. In the latter case, supplying hidden liquidity would complicate the detection of mispriced orders (e.g., due to new information arrival) that are likely to be exploited by scalpers. In one of the earliest studies, Aitken, Berkman and Mak (2001) analyze the Australian Stock Exchange and conclude that uninformed liquidity suppliers use hidden quantity to reduce the option value of their limit orders (Copeland and Galai, 1983) and thus protect themselves from parasitic traders. Bessembinder, Panayides and Venkataraman (2009) and Pardo Tornero and Pascual (2011) show that traders use undisclosed orders to manage exposure and pick off risk. De Winne and D'Hondt, (2007) and Frey and Sandas (2008) fail to find any impact of private information on hidden liquidity provision.

Moinas (2010) proposes the first theoretical model with private information to analyze the effect of undisclosed orders on market performance and trader welfare. She builds a discrete sequential model of trading with incomplete information and concludes that hidden liquidity is part of the informed (insider) agent's equilibrium camouflage strategy. That analysis supports the idea that undisclosed orders are driven by informational concerns, that is, not revealing private information to the market through large orders that are likely to have a price impact. In a different setting, Boulatov and George (2013) also focus on hidden liquidity provision under asymmetric information. They predict that informed traders are more inclined to provide liquidity in opaque markets. Moinas (2010) and Boulatov and George (2013) suggest improved liquidity through reduced pre-trade transparency. Anand and Weaver (2004) show that informed traders use hidden liquidity to minimize price impacts if trading activity is high using data from the Toronto Stock Exchange. Belter (2007) and Kumar, Thirumalai and Yadav (2009) also provide evidence supporting the hypothesis that the use of undisclosed orders may be information driven.

Overall, the literature on undisclosed orders is far from conclusive. Given the controversy, experimental asset markets (e.g., Bloomfield and O'Hara, 1999; BOS, 2005, 2009, 2015; Perotti and Rindi, 2006) are instrumental when testing the main theoretical predictions on hidden liquidity, which is not always possible with empirical data. This paper is one of the first that attempts to fill this gap.

The paper proceeds as follows. In Section 2, I summarize the key theoretical predictions on undisclosed orders. In Section 3, I describe the experimental design. In Section 4, I present the statistical analysis and the findings. I conclude in Section 5.

2 Predictions on undisclosed orders

Before I describe the details of my experimental design, I briefly revisit the key predictions recent theories provide on the source of undisclosed orders and the impact of opacity on market quality.

Prediction 1*: Liquidity traders submit undisclosed orders to reduce the price impact of large orders (Esser and Mönch, 2007).*

Submitting an undisclosed order with a fixed peak size is a dominant order-splitting strategy as opposed to one splitting large limit orders because, given the time priority rule in the market, the visible part of the undisclosed order is automatically executed. If this is the underlying reason for hidden liquidity, I do not expect a significant change in market liquidity.

Prediction 2: *Liquidity traders submit undisclosed orders to avoid undercutting by other traders and to compete for liquidity provision (Buti and Rindi, 2013).*

If undisclosed orders are used to decrease price competition, the bid-ask spread widens because orders at the best prices are not subject to undercutting and submission of undisclosed orders to the second level of the book becomes optimal. While the depth at the top of the LOB increases, wider spreads reduce the surplus of marketable orders, which in turn reduces trading volume. Moreover, protection from undercutting results in higher trading profits for liquidity traders, especially when the tick size is large.

Prediction 3: *Informed traders contribute to market liquidity in opaque markets (Moinas, 2010). In the case of more than one informed trader, insiders compete for (hidden) liquidity provision (Boulatov and George, 2013).*

Informed liquidity suppliers often try to imitate the behavior of large liquidity traders to conceal their private information, and thanks to undisclosed orders, they can enjoy the informational advantage longer. According to Moinas's (2010) model, both informed and large liquidity suppliers benefit from opacity through an increase in depth and trading volume, but the author makes no prediction on spreads. However, one limitation of the model is that insiders can only supply liquidity and cannot take advantage of aggressive marketable orders. Boulatov and George (2013) conjecture that opacity through undisclosed orders attracts informed traders to supply liquidity and the competition among insiders leads to lower bid-ask spreads and more informationally efficient midquotes.

3 The experiment

The design of my asset market experiment takes into account recent theories on undisclosed orders and focuses on three dimensions: trader types, transparency, and information asymmetry. In a within-subject design, I control for three trader types and two transparency regimes. In the baseline setting, I test the effects of market opacity on both trading strategies and market quality under symmetric information. The analysis is extended by introducing informed trading. In this setting, there is an additional trader type, that is, an informed trader, which allows me to compare the transparency regimes under asymmetric information. Thus, using adverse selection, this experiment is used to separate market friction from pre-trade transparency.

Under symmetric information, trading is isolated from motives related to private information. The information structure is common knowledge; hence, there is no informational advantage across traders. In this setting, one should observe hidden liquidity as part of an order-splitting strategy (Esser and Mönch, 2007), due to competition for liquidity provision (Buti and Rindi, 2013) and/or protection from fast traders after public information release (Buti and Rindi, 2009). Under asymmetric information, adverse selection arises via a single insider with superior information. This setup is closer to the environment envisaged by Moinas's (2010) theory, which suggests informational concerns behind hidden liquidity. I refer to Moinas's model to convey the intuition in an environment with an informed trader. To test the sensitivity of the results to a single monopolistic insider, I run additional sessions with two informed traders, which allows competition among insiders (Boulatov and George, 2013).

3.1 Experimental asset markets

In this section, I describe the experimental design in detail and introduce main parameters of experimental markets (see online Appendix A for instructions). An experimental asset market is defined as a six-minute trading period. Traders in cohorts of six to eight traders attend a session under a particular treatment that consists of a series of experimental markets called replications. I introduce within-subject transparency manipulation: In all sessions, traders attend markets both under a transparent regime (three to four replications), with no undisclosed order option, and an opaque regime (three to four replications), with an undisclosed order option. The transparency treatment order is randomized; some cohorts start trading in transparent markets and others start in opaque markets. The market regime is explicitly announced before each trading period.

In each market, one asset is chosen from the distribution shown in Table 1. At the beginning of each trading period, the expected value of all securities is \$45 (experimental currency). In line with previous studies (e.g., BOS, 2005), the minimum tick size is fixed at \$1 in all experimental asset markets. Trading starts with an empty book. Traders are endowed with different amounts of cash and a number of securities, depending on the trader type, explained in the section below, but the expected values of the initial endowment of each trader type are the same. Cash and shares of the asset are given as a grant. In other words, the initial endowment is not subtracted from the final cash balances. This design allows no trading as a viable trading strategy. Unlike a dealership market, traders are not required to submit two-sided quotes. They can simply choose to provide or consume liquidity by taking one side of the trades. This feature reflects the electronic LOB mechanism common to many modern trading venues, such as Euronext.

3.1.1 Information structure

There are three states in the world $\{L, M, H\}$: A single asset has either a high, middle, or low level of liquidation satisfying the following condition: $M - L \neq H - M$. Ex ante, each state is equally likely. A three-state design is used to simplify the already complicated trading mechanism (Plott and Sunder, 1988). The distribution of liquidation value is common knowledge to all traders and known before trading starts. One novel feature of my design is that an information event occurs in the middle of the trading period.[2] The experimenter releases the public information on the fundamental value of the security; the average value of liquidating dividends moves either up or down by 10 experimental currency units, that is,

$$E[v^a_{1,180}] = \$45 \overset{\text{public information}}{\Rightarrow} \begin{array}{l} E^u[v^a_{181,360}] = \$55 \\ E^d[v^a_{181,360}] = \$35 \end{array}$$

The information event changes the expected fundamental value of the asset. Initially, six realizations are possible, which reduces to three equally likely outcomes once the information event occurs. The information event exogenously widens the bid-ask spread during the trading period and renders some of the outstanding limit orders obsolete. Thus I test how traders adjust their strategies to changing market conditions under different transparency regimes and information settings.

3.1.2 Trading mechanism and the LOB

The trading mechanism is exactly the same under all treatments. Traders attend markets under both transparent and opaque regimes in a random order. In transparent markets, traders can post limit orders specifying the price, $p \in \{1, .., 90\}$, and the quantity, $q \in \{1, 2, ...9, 10\}$. Traders can submit block trades all at once, up to 10 shares. The submission of different order sizes is important in studying competition for liquidity provision (Easley and O'Hara, 1987; Buti and Rindi, 2009, 2013). Traders can also submit marketable orders stating only the quantity that hits the outstanding limit orders. Marketable orders above (below) the best ask (bid) are completely executed at different prices, given enough

[2] Even though the exact timing of the event is known to the market participants, the order revision cost, that is, the cost of canceling orders, differs across trader types, which still allows one to pick off stale orders.

depth at those price levels. However, a marketable order at or inside the best bid offer (BBO) does not walk up the book; that is, if the order quantity is greater than the quantity at the best limit ask (bid), the remaining quantity after execution remains on the same side of the book. This feature is similar to that of Euronext Paris. Limit orders reduce the price risk at the expense of execution probability, while marketable orders facilitate execution, introducing price risk. In these markets, first price and then time priority rules apply: orders that improve trading price, that is, buy (sell) orders submitted at higher (lower) prices, are executed first, regardless of arrival time, and if several orders are posted at the same price level, those that arrive first are executed first.

In opaque markets, traders can limit the quantity exposure by posting undisclosed orders, that is, they can choose to hide their orders, but a predefined portion of the order (peak size = 1) remains visible in the LOB. My design does not capture the trade-off between the optimal limit and the peak size of an undisclosed order, which is the focus of a continuous time model proposed by Esser and Mönch (2007). In opaque markets, first price and then visibility and finally time priority rules apply. Orders that improve trading price, that is, buy (sell) orders at higher (lower) prices, are executed first, regardless of arrival time, and if several orders are posted at the same price level, those that are visible are executed first, while the hidden part of undisclosed orders loses time priority against visible limit orders that arrive later in the book. The visible part of the undisclosed orders, which is equal to the peak size, does not lose time priority against other limit orders posted at the same price. Every time the visible part is executed, another unit equal to the peak size becomes visible, until the entire order is executed (see the example in online Appendix B).

In both markets, orders can be canceled any time during the trading period. All price levels are shown on the screen. All bids and ask prices are integers; hence, the tick size is one unit of experimental currency (BOS, 2005).[3] I impose short sale restrictions and bankruptcy conditions. However, traders are endowed with enough cash and securities and, hence, these

[3]Empirical evidence on the effects of relative tick size is mixed (O'Hara, Saar and Zhong, 2014). Online Appendix C shows whether the relative tick size has an impact on hidden liquidity submission.

conditions are rarely binding.[4]

3.1.3 Trader types

In each market, traders are randomly assigned to a trader type. Under symmetric information, there are three different types: traders with no exogenous trading motives, which I label *uninformed,* and traders with either small or large trading targets, that is, *small* and *large liquidity* traders (BOS, 2005, 2009). Unlike previous studies, trading targets are imposed per two-minute cycles, so there are three trading cycles in each market. Trading cycles over relatively long periods avoid situations in which traders immediately fulfill their targets and behave randomly. Small liquidity traders should either buy or sell eight shares per cycle. For large liquidity traders, the target is 20 shares per two-minute cycle. There are equal numbers of buy and sell targets. This symmetric design implies a zero aggregate net demand. The direction of the targets —buy or sell— remains the same during the six-minute trading periods. All traders are allowed to buy or sell, regardless of their targets, but liquidity traders are subject to a large penalty, $1,000 per unfulfilled target. The penalty is subtracted from the end-of-period payoffs.[5] I thus introduce heterogeneity among uninformed traders using trading obligations (Bloomfield and O'Hara, 1999; BOS, 2005). Liquidity traders transact for exogenous reasons related to the need to invest or to liquidate positions. Moreover, having liquidity traders with different trading obligations helps me test the effect of trading aggressiveness on market outcomes (Foucault, Kadan and Kandel, 2005).

Each trader starts trading with an initial endowment. The ex ante expected value of the initial endowments is $7,375 for all trader types. Uninformed traders start with $4,000 and 75 shares. Since these traders are given cash and shares as a grant, they do not have exogenous reasons to trade. The initial endowment composition of liquidity traders depends on the direction and magnitude of their targets. For example, traders with buy targets start

[4] Short-sale constraints are binding only for 3% of liquidity traders.

[5] I do not allow for the partial fulfillment of trading targets; the same penalty applies even if traders miss their targets by one share. Given the price grid, fulfilling the target is a dominant strategy (see online Appendix D).

with more cash and fewer shares (see Table 2).

In asymmetric information sessions, a monopolistic *insider* replaces one uninformed trader. The new trader type starts with the same initial endowment as the uninformed trader and has no trading obligation. On top of the dividend distribution, the monopolistic insider knows the true state of the world before each market starts. This gives the trader an informational advantage until the public information release when the trader learns the true value of the liquidating dividend. Adverse selection via a single informed trader allows me to investigate how the participation of an insider (Kyle, 1985; Collin-Dufresne and Fos, 2015) affects liquidity dynamics and trading strategies under different transparency regimes.[6] In further sessions, I analyze trading once there is competition among informed traders (Boulatov and George, 2013).

3.2 Participants and incentives

I run sessions with different incentive schemes. I first conduct paid pilot sessions with 24 Tilburg University students recruited through the CentER experimental laboratory. Pilot sessions lasted two and a half hours and the participants were paid on average €10 per hour. Questionnaires after the first pilot sessions revealed that participants had difficulty understanding the trading mechanism using undisclosed orders. Moreover, in these pilot sessions, the participants did not have enough training to develop trading strategies. To overcome this problem, I designed a longitudinal study with students who had a basic knowledge of the functioning of security exchanges.[7]

I ran the next sessions at Bocconi University with undergraduate students ($N = 72$, 11 cohorts) who attended a series of sessions as part of a market microstructure course requirement in 2009 ($N = 31$, five cohorts) and 2011 ($N = 41$, six cohorts). In 2009, I

[6] Insider trading is illegal in many countries, but in some countries such as in the United States, legal insider trading is allowed under strict filing requirements, such as SEC Form 4 or Schedule 13D filing (Collin-Dufresne and Fos, 2015) .

[7] I ran another two-month pilot study with PhD students ($N = 6$) who followed a market microstructure course. Their performance in the trading experiment determined 15% of their course grade.

presented the experiment as an opportunity to increase one's course grade by one to three points (up to 20%), based on trading performance. A total of 31 students committed themselves to attend a series of sessions for a month. The use of one's course grade as an incentive scheme is controversial in experimental economics and finance; however, given the longitudinal nature of the experiment, grades provide a good scheme to guarantee commitment for an extended period. Moreover, this incentive mechanism has the advantage of introducing the possibility of loss, that is, obtaining no points after attending one month of trading sessions (Kroll and Levy, 1992). In 2011, I repeated the same experiment, but this time introducing an average payment of €12.5 per hour on top of the course grade incentive. I report the aggregate results of both experiments below.[8]

Participants first attended a lab session for the presentation of instructions and trading rules. The training session lasted 90 minutes and participants had extensive interactive training with the trading interface. They attended a second online training session to improve their familiarity with the trading rules and to develop trading strategies. In the last three online sessions, participants traded under three different settings, that is, under symmetric information, asymmetric information, and either with auctions for private information (2009) or under asymmetric information with multiple insiders (2011).[9] In each session, participants are randomly assigned to a different cohort, but against traders with the same experience level.

All participants start with some cash and a security endowment as explained above and the interest rate is zero. Trading gains from one period are not transferred to other periods but are recorded to calculate cumulative payoffs. Participants' earnings in each market are the liquidation value of the assets they hold at the end of the trading period plus the capital gains (losses) obtained through trading assets minus the fixed penalty for not fulfilling each trading target. All price and values are denominated in the laboratory currency. In the

[8] Separate analyses of the data reveal that the lack of monetary incentives did not change the participants' behavior in such a way that would impair our inferences (results available upon request).

[9] I discuss the results on auctions for private information in online Appendix E.

training sessions, I provided the participants with the explicit formula used to compute the payoffs. This ensured that they unambiguously understood the incentives and how they related to trading. Participants' grades and monetary payoffs depended on their cumulative performance in all trading (except training) sessions.

4 Results

The statistical analysis is conducted at both the market and individual subject levels. Each of the eleven cohorts is a single independent data point averaged over different replications under the same market design, that is, opaque versus transparent. At the market level, I compare the within-cohort differences of market quality measures (within-subjects design). I report the Wilcoxon signed-rank p-values for the paired samples. At the individual level, for each participant, dependent variables are aggregated under a relevant cell, that is, trader type$\times$transparency, and the trading strategies of the same participant are compared under different trading roles. This design allows me to control for individual differences across participants. The results of an analysis of variance (ANOVA) are used to determine the effects of market structure on trading profits under different information settings.

To calculate market quality measures, an algorithm merges orders from the LOB with transaction data from the transaction book. All submitted limit, marketable, and undisclosed orders are collected on a tick-by-tick basis. I reconstruct the LOB for outstanding orders and obtain snapshots of the LOB for each second, which permits calculation of all depth-related measures at all price levels of the electronic order book.

I compute liquidity, depth, and volatility measures separately to assess the impact of market transparency and informational friction on market quality. As a liquidity measure, I proxy for *message traffic* using the total number of limit and marketable orders (and undisclosed orders under an opaque regime) submitted to the LOB. I also report the total *transacted volume* in shares and the number of shares per trade. The quoted bid-ask spread and effective spread reflect implicit transaction costs and the price impact of marketable orders. The latter is measured by $P_t - M_t$ $(M_t - P_t)$ for a buy (sell) order, where P_t and M_t are the transaction price and the midquote (BOS, 2009). I decompose the effective spread into temporary and permanent price impacts. The former is also known as the realized spread and is measured by the distance between the transaction price and the midquote prevailing after five trades, while the latter is the difference between the midquote and the midquote prevailing after five trades. The (visible) depth is the total number of (visible) shares both at the BBO and at all price levels of the LOB, labeled *book depth*. Finally, volatility is the sample estimate of the standard deviation of prices using both the transaction price and the midquote.

4.1 Overview: order types

Figure 1 exhibits the time evolution of submitted shares of different order types under symmetric (Panel A) and asymmetric information (Panel B). The data are aggregated over 30-second intervals across different replications and cohorts.

Since trading starts with an empty book, there is a large accumulation of limit orders at the beginning of each market. Limit shares show a downward trend during the trading period, exhibiting cyclical spikes coinciding with trading targets. Marketable orders, on the other hand, do not show any trend during the trading period. However, both limit and marketable shares move together around trading cycles, that is, at the second and fourth minutes, reflecting both exogenous trading targets and endogenous reactions to trading opportunities (Foucault, Kadan and Kandel, 2005, 2013). Liquidity provision decreases just before a public information release. This reduction is similar to the evidence on anticipated news in equity (e.g., Graham, Koski and Loewenstein, 2006; So and Wang, 2014) and bond markets (e.g., Green, 2004; Engle et al., 2012). The sudden spike in marketable orders after a public information release shows that traders respond very rapidly to news and adjust to new fundamentals. The features are common under both symmetric and asymmetric information.

Undisclosed orders exhibit a downward sloping pattern, which is consistent with the fact that they lose time priority in execution. At the beginning of the trading period, when the book builds, spreads are typically larger, with higher price volatility, and this is when I expect to see more extensive use of undisclosed orders (Bessembinder, Panayides and Venkataraman, 2009). Traders are also more likely to submit undisclosed orders before public information release to avoid the risk of picking off stale orders, but the use of undisclosed orders should increase as the time to news announcement decreases (Buti and Rindi, 2009).[10] In Panel A of Figure 2, I compare the number of undisclosed orders submitted in the first and second halves of trading. The number decreases, on average, from 45 shares to 23 shares (p-value $< .000$) under symmetric information and from 55 shares to 34 shares (p-value $< .000$) under asymmetric information. However, when I compare undisclosed orders right before and after an information release, the decrease is less pronounced. An increase in undisclosed orders under asymmetric information that persists through the last trading cycle hints at informational motives behind hidden liquidity provision (Chakrabarty and Shaw, 2008). To explore this notion further, I analyze trading strategies in Section 4.2.

Panel B in Figure 2 shows the percentage of executed volume that consists of undisclosed orders. The figure reveals that 17.8% to 19.5% of the executed volume in the experimental asset markets is undisclosed, which is similar to the evidence documented in empirical studies (e.g., Frey and Sandas, 2008; Yao, 2013). While the ex ante probability of execution is lower for undisclosed orders, it seems that undisclosed orders are submitted aggressively to the LOB and more so under symmetric information (Frey and Sandas, 2008; Hasbrouck and Saar, 2009).

4.2 Trading strategies

In Table 3, I report the average number of shares of limit, marketable, and undisclosed orders submitted by each trader type under symmetric information. The focus is on

[10] On the contrary, Jiang, Lo and Verdelhan (2011) document the withdrawal of hidden depth before news announcement in U.S. Treasury bond markets.

competition for liquidity provision and trader aggressiveness. I report four different measures: i) the number of limit orders submitted inside the bid-ask spread that improves the best price, ii) the number of limit orders submitted at the BBO, iii) the average distance of limit orders to the prevailing midquote, and iv) the average distance of undisclosed orders to the prevailing midquote conditional on submission (Bessembinder, Panayides and Venkataraman, 2009).

In my asset markets, exogenous trading targets constrain liquidity traders' behavior. In principle, liquidity traders should be more active in trading by participating not only in liquidity demand but also in liquidity provision. This is what I observe in Table 3 under both transparent and opaque regimes. Since liquidity traders, especially large ones, have exogenous trading motives, they also trade faster and provide liquidity more aggressively at the top levels of the book. The difference between transparent and opaque regimes is that traders also have the option to provide liquidity using undisclosed orders. Large liquidity traders use this option and shift about 20% of liquidity supply to undisclosed orders. It seems that they follow a mixed strategy of using both limit and undisclosed orders for liquidity provision, together with marketable orders to satify their liquidity needs and guarantee execution. Undisclosed orders allow liquidity traders to reduce order exposure and to control price risk and therefore complement both limit and marketable orders. However, at the same time, they reduce the execution probability due to the visibility priority rule. Large liquidity traders act strategically and improve execution probability by submitting limit orders more aggressively, rather than demanding more liquidity through marketable orders.

Traditionally, informed traders are associated with short-lived information and are hence perceived as impatient traders who would like to exploit informational advantages as quickly as possible by consuming liquidity. However, researchers (BOS, 2005; Kaniel and Liu, 2006; Rindi, 2008; Boulatov and George, 2013) suggest that informed traders contribute substantially to liquidity provision, particularly when the information is sufficiently persistent. If used strategically, undisclosed orders may increase the life of private information by concealing trading motives (Moinas, 2010). The results reported in Table 4 under asymmetric information suggest that informed traders indeed act strategically and pool with large liquidity traders in both liquidity provision and consumption under a transparent regime. In terms of submitted shares, I do not observe significant differences between large liquidity and informed traders. In other words, informed traders are as active as large liquidity traders in liquidity provision (Menkhoff, Osler and Schmeling, 2010). This evidence suggests fierce competition, that is, a race to trade (Boulatov and George, 2013) between two trader types for liquidity provision. Notably, under an opaque regime, informed traders are less active in liquidity provision through visible limit orders and act less aggressively: They submit fewer limit orders that improve prices (inside spread) so that they can exploit their informational advantage as long as possible. They also exploit undisclosed orders to provide liquidity. However, I observe substantial heterogeneity among insiders (e.g., Cohen, Malloy and Pomorski, 2012), and some informed traders do not use undisclosed orders at all. Once submitted, however, informed traders use undisclosed orders in larger quantities, further from the prevailing midquote.

4.3 Trading profits

The general conclusion that can be drawn from current models is that opacity via undisclosed orders improves the welfare of the market participants. In the absence of informed traders, Buti and Rindi (2013) predict that liquidity traders, especially large ones, benefit from opaque markets. Models under adverse selection (Moinas, 2010; Boulatov and George, 2013) make a similar prediction for both informed and uninformed traders.

I measure trading profits at the individual subject level for each trader type and compute profits as the final payoff net of the initial endowment.[11] Panel A in Figure 3 exhibits the trading profits in markets under symmetric information and compares profits across transparent and opaque regimes. Liquidity traders, especially large ones, are better off in

[11] I elicit traders' risk preferences following Holt and Laury's (2002) procedure. The average number of safe choices (n=69) is 4.74, which suggests slightly risk-averse behavior. Therefore, I believe that trading profit is a good approximation for measuring subjects' utility.

opaque markets at the expense of uninformed traders. The increase in trading profits for large liquidity traders is in line with Buti and Rindi's (2013) prediction, but the mechanism generating differences in profits seems to be different. In online Appendix F.1, I decompose the trading profits into "make and take" profits, that is, profits through limit orders versus marketable orders, respectively. I see that market making for uninformed traders is less profitable under an opaque regime, which leads to the difference in total profits across the two transparency regimes. On the other hand, large liquidity traders suffer losses, on average, through limit orders under both transparent and opaque regimes. While the make losses are more pronounced under an opaque regime, liquidity consumption is more profitable. Differences in trading profits across transparency regimes are likely to arise due to differences in implicit transaction costs across regimes. Therefore, in the next section, I compare different measures of liquidity across transparency regimes.

As a formal analysis, I run an ANOVA to test the effects of market design on trading profits under symmetric information. The dependent variable is the trader's payoff relative to the average market payoff normalized by the unconditional expected payoff ($7,375). The independent variables include *trader type* —uninformed, small liquidity (buy/sell), large liquidity (buy/sell)—, *opacity* (transparent vs. opaque), and *extremity* (whether the state is extreme or not), and four interaction terms. An asset is classified as extreme if the liquidating dividend is more than 20% from the unconditional mean (BOS, 2005). The results are shown in Table 5. Neither trader type nor market opacity alone affects trader profits. It is also not surprising that the extremity variable is not significant, since none of the traders have superior information in these markets. The only significant variable is the interaction term, *type*×*opacity*, suggesting that market opacity has different implications for different trader types, consistent with the evidence above.

I repeat the same analysis under asymmetric information. Panel B in Figure 3 shows that informed traders, on average, earn more than the other trader types. This result is expected, since in my experimental markets informed traders have a clear informational advantage and they seem to be able to extract an informational rent. Interestingly though, they are, on average, better off under an opaque regime at the expense of large liquidity traders. The decomposition in online Appendix Table F.2 also shows that opacity adversely affects both the make and take profits of large liquidity traders. Hence, unlike markets under symmetric information, once information friction is introduced, large liquidity traders are worse off due to reduced transparency, which is in contrast with Moinas's (2010) prediction. The ANOVA results in Table 6 indicate that trader type, particularly an informed one, clearly affects trading profits under asymmetric information. The significant interaction term $type \times extremity$ shows that a monopolistic insider can better exploit his or her informational advantage, especially when the information is more valuable.

4.4 Market quality

An important regulatory concern is how a reduction in pre-trade transparency of the financial markets affects market quality (e.g., Madhavan, Porter and Weaver, 2005; Foucault, Pagano and Röell, 2010; Gozluklu, 2013). In light of the theoretical predictions summarized in Section 2, I now turn to the analysis of changes in market quality due to pre-trade opacity introduced via undisclosed orders. Market quality is measured along different dimensions, that is, liquidity, depth, and volatility, as defined in Section 4.

Table 7 reports both the mean and median values of different market quality measures under transparent and opaque regimes and symmetric information. Trading activity and volatility measures are not sensitive to market transparency. Book depth, on average, is higher (yet not significant) in opaque markets, while visible book depth is lower, reflecting the reduction in market transparency. The average trade size is similar across transparency regimes, suggesting that order splitting cannot be the main motive (Prediction 1) behind hidden liquidity. The main change induced by opacity is the reduction of quoted spreads (by almost a quarter tick, on average) and, in particular, the realized spread, capturing the temporary price impact of marketable orders (p-value=0.087). Improved liquidity is broadly in line with the increased market participation of liquidity traders with undisclosed orders to avoid the risk of being picked off. However, the risk of being picked off cannot alone explain the reduction in spreads. First, traders have other means of avoiding exposure risk, via order cancellation. Second, there is no significant increase in undisclosed orders before information release. Finally, online Appendix Table G.1 also shows the displayed and undisclosed fill rates of submitted orders for both the entire trading period and one minute after information release. While the fill rates are lower for displayed orders for the entire trading period, I do not observe a significant decrease in fill rates right after information release.

A reduction in spreads is in contrast with Prediction 2, which suggests an increase in spreads due to price competition via undisclosed orders. Given the balanced nature of the trading targets, that is, equal numbers of buy and sell targets, liquidity traders in these markets coordinate to satify their liquidity needs rather than compete; hence, there is no increase in the bid-ask spread as predicted by Buti and Rindi (2013). Further inspection into the dynamic evolution of liquidity shows that the reduction in spreads in opaque markets is mainly concentrated around the deadlines of trading targets, especially at the end of the trading period (p-value=0.005). In the next section, I analyze dynamic trading strategies to see how they affect aggregate market outcomes.

Under asymmetric information, most of the market outcomes are insensitive to the transparency regime (see Table 8). Only the average trade size decreases significantly (p-value= 0.087), reflecting the participation of both liquidity and informed traders in hidden liquidity provision. Since both large liquidity and informed traders join the race for liquidity provision, there is an increase in book depth (Prediction 3), but this result is only statistically significant when there is more than one informed trader (discussed later in Section 4.6). Importantly, I do not detect a decrease in spreads, either in quoted or in the realized spreads, over the entire trading period, except the period around a public information announcement. Spreads around the information event are lower, on average, by more than one tick under an opaque regime. This is the period when liquidity traders are exposed to more adverse selection risk. The fill rates in online Appendix Table G.2 show that uninformed and liquidity traders exploit undisclosed orders to protect themselves against adverse selection. On the other hand, the monopolistic insider can exploit the informational rent longer in opaque markets, thanks to the undisclosed orders. Rather than acting aggressively using marketable orders to benefit from the informational advantage, the insider can pool with liquidity traders and provide liquidity more aggressively. The insider can thus increase the execution probability without revealing private information. I can thereby observe the reduction in spreads around the release of public information. Overall, the results indicate that informational friction is an important dimension in the transparency debate.[12]

4.5 From trading to market outcomes

Unlike the experimental evidence provided by BOS (2015), I observe not only the sensitivity of trading strategies to transparency regimes, but also that some of the market outcomes are driven by both the transparency regime and informational friction. However, it is important to highlight the differences in experimental design between the BOS (2015) study and mine. First, the composition of traders is not the same: BOS's (2015) design includes only two types of traders: liquidity and informed. Second, the information structure is different. In BOS's (2015) experiment, the informed traders participate in all markets, hence there is no symmetric information setting. Third, informed traders are not insiders but receive an imprecise signal about the fundamental value of the asset. Last but not least, in BOS's (2015) study markets are open for three minutes, without a public information release in the middle of trading.

To see how aggregate trading affects market outcomes, I report liquidity make and

[12] In online Appendix H, I show that how insider trading increases adverse selection costs, that is, an increase in volatility and bid-ask spread, regardless of the transparency regime.

take measures that reflect the aggregate order choice. Liquidity make is proxied by the submission rate, which is the sum of submitted limit orders (and undisclosed orders in opaque markets) over total orders. The take rate, on the other hand, is the sum of submitted marketable orders over limit orders (and undisclosed orders in opaque markets). Limit order aggressiveness captures the impatience of the average market participant (Foucault, Kadan and Kandel, 2005). It is measured by the average distance between the limit order price and the prevailing midquote at the time of order submission. While aggressive liquidity provision reduces spreads, liquidity consumption has the opposite effect on market liquidity.

In Figure 4, I compare order submission strategies in transparent and opaque markets under symmetric information over one-minute time intervals. The vertical line indicates the time of the public information release about the final dividend distribution. The submission rates are very similar across transparency regimes. The significant reduction in spreads toward the end of two-minute cycles in opaque markets (see Table 7) coincides with the period when traders supply liquidity more aggressively rather than switch to marketable orders. There is a reduction in spreads when traders try to increase the execution probability of limit orders by submission to the top of the book. Right after information release, the mispricing of stale orders is corrected. In opaque markets, due to the greater accumulation of limit orders before the announcement, limit orders are submitted less aggressively after the information release, but more orders are picked off with marketable orders. The overall effect is a larger (but insignificant) spread in opaque markets right after the release of public information. This implies that, in the absence of information asymmetry, opacity affects market outcomes mainly through the strategic choice of order aggressiveness. Dynamic strategies reflect the trade-off between waiting costs and the cost of immediacy, that is, bid-ask spreads, and confirm the intuition that mainly aggressive limit orders drive the evolution of spreads (Foucault, Kadan and Kandel, 2005).

Figure 5 shows dynamic order submission strategies in transparent and opaque markets under asymmetric information. It also separately shows the strategies of informed traders (lines with star symbols). First, I see that informed traders act differently from all the other market participants: They are very active in liquidity provision, especially around the information event, but they do not necessarily supply liquidity aggressively. Monopolistic insiders also engage heavily in liquidity consumption right after the information release to exploit their informational advantage, but they manage to pool with large liquidity traders and increase the execution probability of their informed orders by submitting more aggressive limit orders in opaque markets, rather than exploiting marketable orders. Hence, there is a significant decrease in bid-ask spreads after the release of public information under asymmetric information.[13]

Outstanding limit orders can also be revised through order cancellation. Figure 6 shows cancel-to-make rate under symmetric and asymmetric information. The figure shows that traders cancel more orders in opaque markets regardless of the information setting, especially in the second half of trading. In other words, cancel-to-make rate provides further evidence that market opacity helps traders reduce exposure costs.

4.6 Competition between insiders

The results reported so far rely on a monopolistic informed trader. As a robustness test, I run additional session with two insiders. One can argue that competition among informed traders could lead to different market outcomes that would not arise in a market with a single informed trader (Boulatov and George, 2013). To alleviate this concern, I repeat the analysis in Section 4.4, analyzing the implication of opacity on market quality under asymmetric information with two insiders.

The results in Table 9 are broadly in line with those in Table 8. One difference, however, is that increasing the degree of adverse selection results in increased book depth in opaque markets (p-value=0.016) without much affecting the spreads. This result is consistent with the previous empirical evidence from the Toronto Stock Exchange (Anand and Weaver, 2004)

[13] I do not observe a significant effect on spreads in the first trading cycle, because until the informed traders become insiders, trading strategies vary greatly.

and the experimental findings of BOS (2015). Under an opaque regime, quoted spreads are lower, on average, by half a tick (but not statistically significantly) and, unlike markets with a monopolistic insider, spreads are similar around public news releases across transparency regimes. However, opacity has a significant impact on effective spreads, mainly through the reduction of a permanent price impact. It seems that fierce competition for liquidity provision among insiders accelerates the incorporation of information into prices under an opaque regime.

4.7 Informational efficiency

An important function of efficient markets is to aggregate information and reflect the true fundamental value of traded assets. Undisclosed orders could hinder value discovery if they are predominantly used by informed traders to conceal their informed trades. However, if all market participants opt for hidden liquidity, then the effect on information efficiency will not be clear. In fact, the evidence so far is mixed (Ye, 2012; Zhu, 2014; BOS, 2015; Comerton-Forde and Putnins, 2015).

The public news announcement in the experimental design allows me to test how information is incorporated into prices through trading under different transparency regimes. The informational efficiency of the markets is proxied by the average deviation of midquotes from the fundamental asset value once the news is made public. The deviation is measured as the absolute difference between the midquote and the true dividend normalized by the range of the dividend distribution.

In the presence of a monopolistic insider, midquotes converge monotonically to the true liquidating dividend after the information event. Panel A of Figure 7 reveals that market transparency does not affect the informational efficiency of the markets. The monopolistic insider competes with other large liquidity traders and follows pooling strategies to maximize the informational advantage. The use of undisclosed orders at lower levels of the book does not help with the value discovery. The situation is different when there is competition among insiders for liquidity provision. Panel B of Figure 7 shows that value discovery is faster under opaque markets with shared informational rents, where competition for liquidity provision is more intense (Boulatov and George, 2013). Market opacity induces informed traders to provide liquidity more aggressively, which leads to more informative transaction prices.[14]

5 Conclusion

In my experimental asset markets, traders exploit undisclosed orders to enrich their strategy set. Undisclosed orders not only help liquidity traders reduce order exposure but also control the price risk. Hence they complement both limit and marketable orders. In opaque markets, liquidity traders improve execution probabilities by managing limit order aggressiveness. Under asymmetric information, monopolistic insiders compete with large liquidity traders for liquidity provision and, even though a subset of informed traders rely on hidden liquidity, opaque markets help insiders trade less aggressively.

The market transparency increases the trading profits of large liquidity traders in opaque markets under symmetric information. While a liquidity trader submits directional orders in line with her trading target, an uninformed trader operates on both sides of the LOB. The reduced cost of immediacy via lower spreads in opaque markets helps liquidity traders and is detrimental for uninformed ones. On the contrary, under adverse selection, large liquidity traders are worse off from reduced transparency, especially if the information is owned by a single insider. An insider is better at exploiting her informational advantage in an opaque market.

My results show that the effect of undisclosed orders on market quality largely depends on informational friction. Without an insider, a reduction in transparency contributes positively to market liquidity by reducing spreads, especially toward the end of trading. On the other hand, under asymmetric information, the effect of market opacity on liquidity

[14] This result regarding informational efficiency differs from that of BOS (2015). The difference may be due to the fact that, in my setting, insider traders know the fundamental value of the asset, as opposed to informed traders who receive a signal about the true value, as in BOS's study (2015).

is mostly visible around the release of public news. Increasing the degree of adverse selection also results in increased book depth in opaque markets. Limiting pre-trade transparency can be beneficial for securities that are less exposed to private information, for example, large firms and bonds; however, in markets with a potential for asymmetric information, for example, higher institutional participation or small firms, undisclosed orders do not necessarily improve market quality, except around information-sensitive periods, unless there is fierce competition among informed traders.

Finally, I show that the value discovery is also sensitive to the degree of asymmetric information. In the case of a monopolistic insider, the market transparency does not change the informational efficiency of the markets, while value discovery is faster under opaque markets when informational rents are shared between insiders.

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Figure 1

Order submission

Figure 1 shows the dynamic evolution of limit, marketable, and undisclosed order submission in shares. The data are aggregated over markets under symmetric and asymmetric information, and I report average values per market over 30-second intervals. The vertical line indicates the time of the public information release about the final dividend distribution.

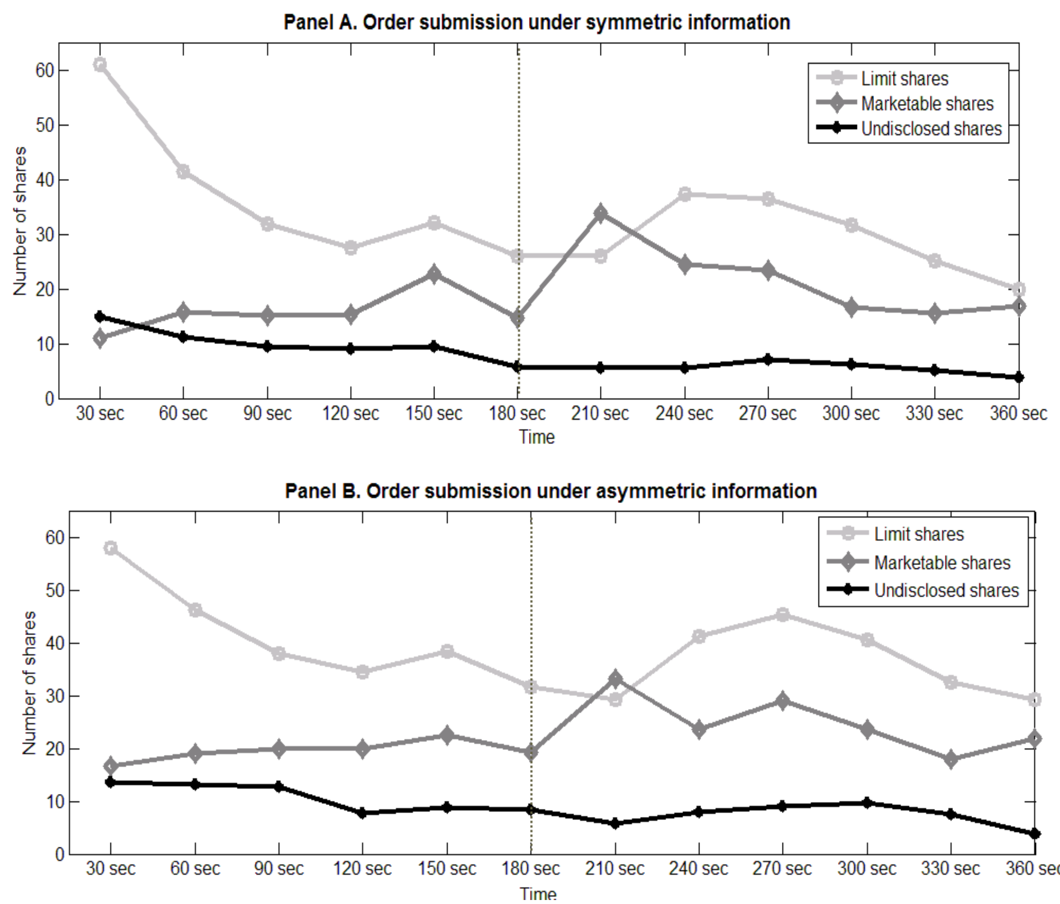


Figure 2
Undisclosed orders

Panel A shows the number of undisclosed orders submitted in different time periods during trading: first half and second half of trading, one minute before and after the public information release. Panel B shows the mean and median percentage of executed volume that consists of undisclosed orders both in markets under symmetric and asymmetric information.

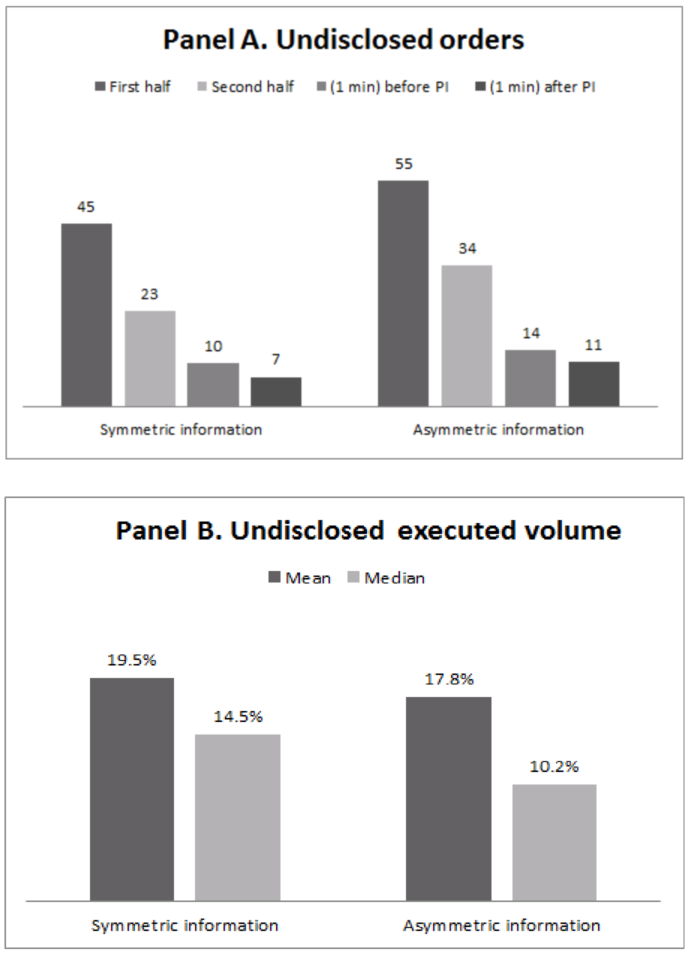
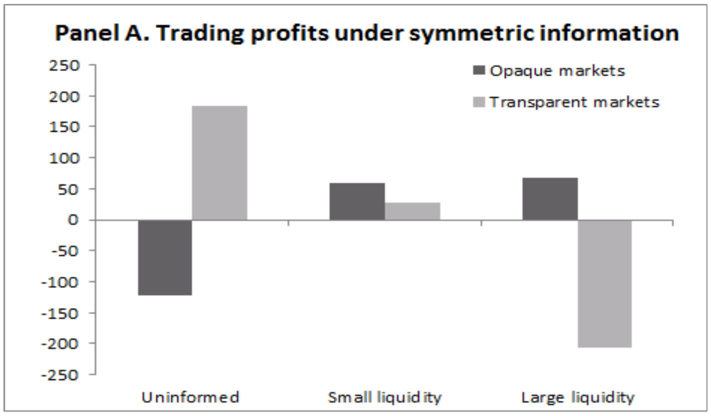


Figure 3
Trading profits

This figure shows the average trading profits of each trader type. The trading profit is the final payoff net of the initial endowment. Panel A exhibits the trading profits in markets under symmetric information, that is, no insider trader, and I compare profits across transparent and opaque markets. Panel B exhibits trading profits in markets under asymmetric information, that is, with one insider, and I compare profits across transparent and opaque markets.



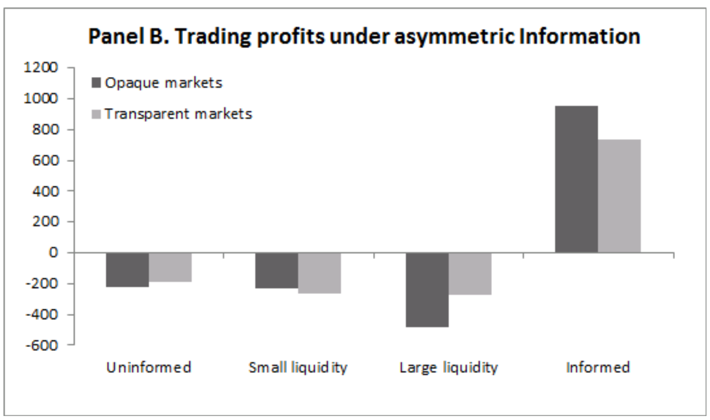


Figure 4
Aggregate trading strategies under symmetric information

In this figure, I compare the average (median) liquidity make, take, and aggressiveness in transparent and opaque markets under symmetric information. Liquidity make is proxied by the submission rate, that is, the sum of submitted limit orders (plus undisclosed orders in opaque markets) over total orders. The take rate is the sum of submitted marketable orders over limit orders (plus undisclosed orders in opaque markets). The limit order aggressiveness is the average distance between the limit order price and the prevailing midquote at the time of order submission. The data are aggregated over 60-second time intervals. The vertical line indicates the time of the public information release about the final dividend distribution. The dashed (solid) line shows the transparent (opaque) markets.

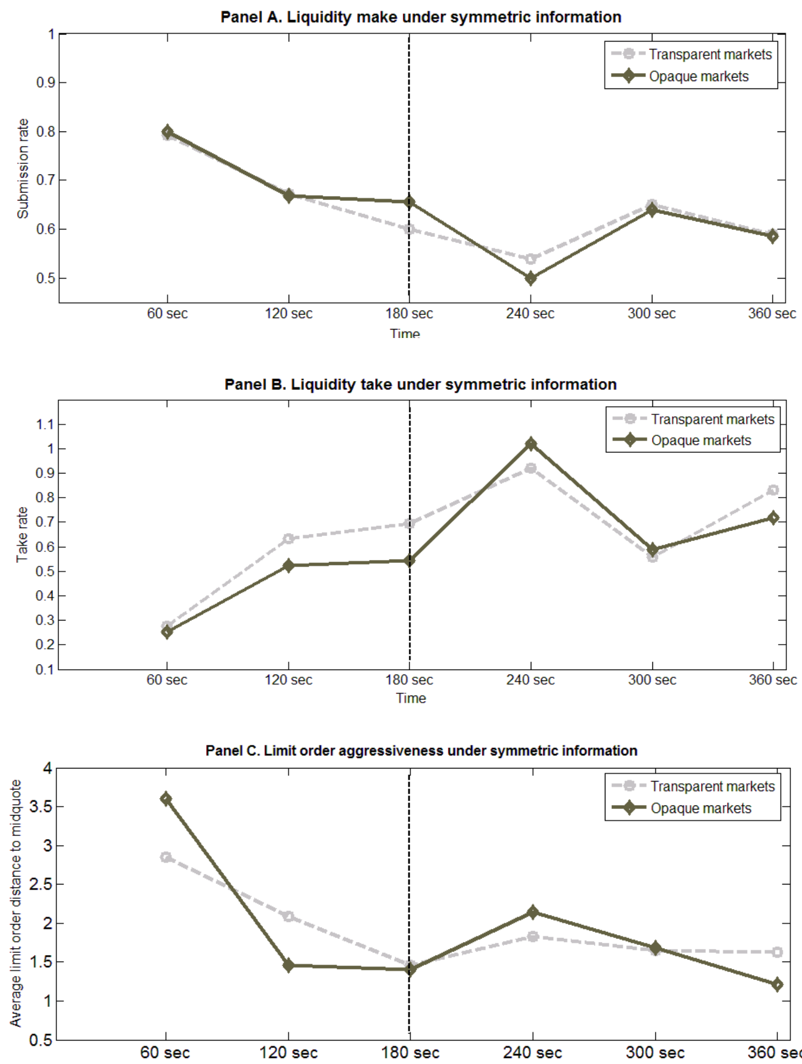


Figure 5
Aggregate trading strategies under asymmetric information

In this figure, I compare the average (median) liquidity make, take, and aggressiveness in transparent, and opaque markets under asymmetric information. Liquidity make is proxied by the submission rate, that is, the sum of submitted limit orders (plus undisclosed orders in opaque markets) over total orders. The take rate is the sum of submitted marketable orders over limit orders (plus undisclosed orders in opaque markets). The limit order aggressiveness is the average distance between the limit order price and the prevailing midquote at the time of order submission. The data are aggregated over 60-second time intervals. The vertical line indicates the time of the public information release about the final dividend distribution. The dashed (solid) line shows the transparent (opaque) markets. The lines with stars show the trading strategies of informed traders.

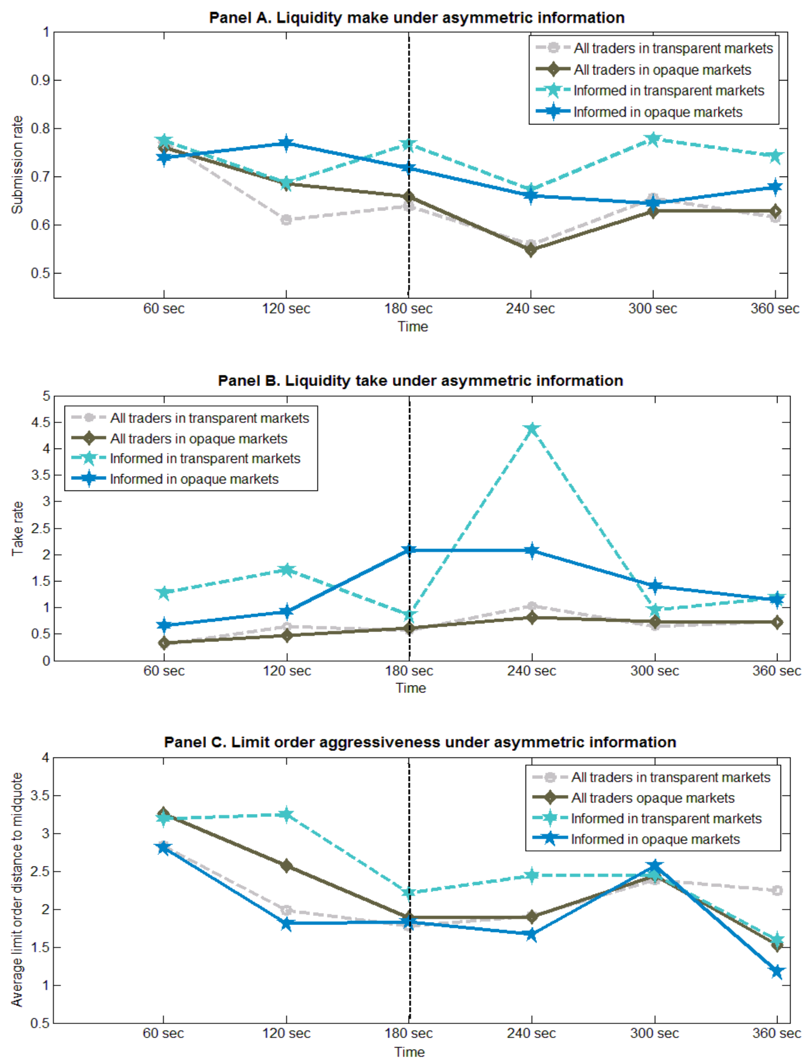


Figure 6
Order cancellation

In this figure, I compare the order cancellation rates in transparent and opaque markets under symmetric and asymmetric information. The cancel to make rate is the proportion of limit orders (plus undisclosed orders in opaque markets) that are canceled. The bars show the cancel-to-make rate both for the entire period, and for the period after the public information release, that is, the last three minutes of trading.

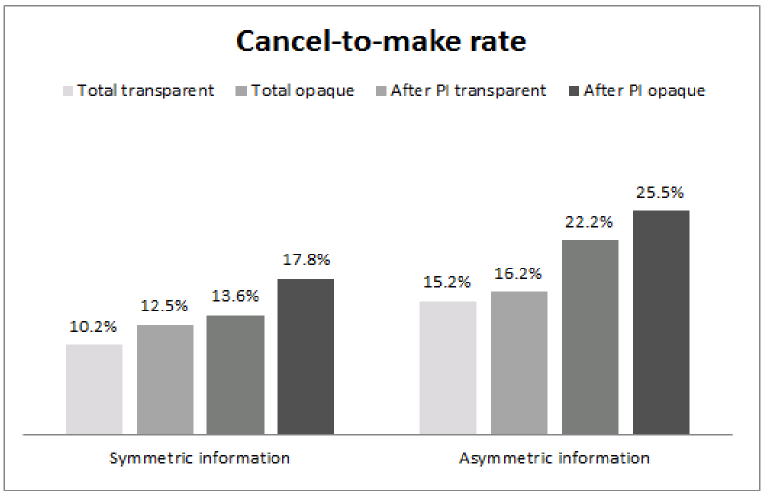


Figure 7
Value discovery

This figure shows the average deviation of midquotes from the fundamental asset value after the public information release. The deviation is the absolute difference between the midquote in each second, and true dividend normalized by the range of dividend distribution Panel A shows the data under asymmetric information with a monopolistic insider. Panel B shows the data under asymmetric information with two insiders. The data are aggregated over 30-second time intervals.

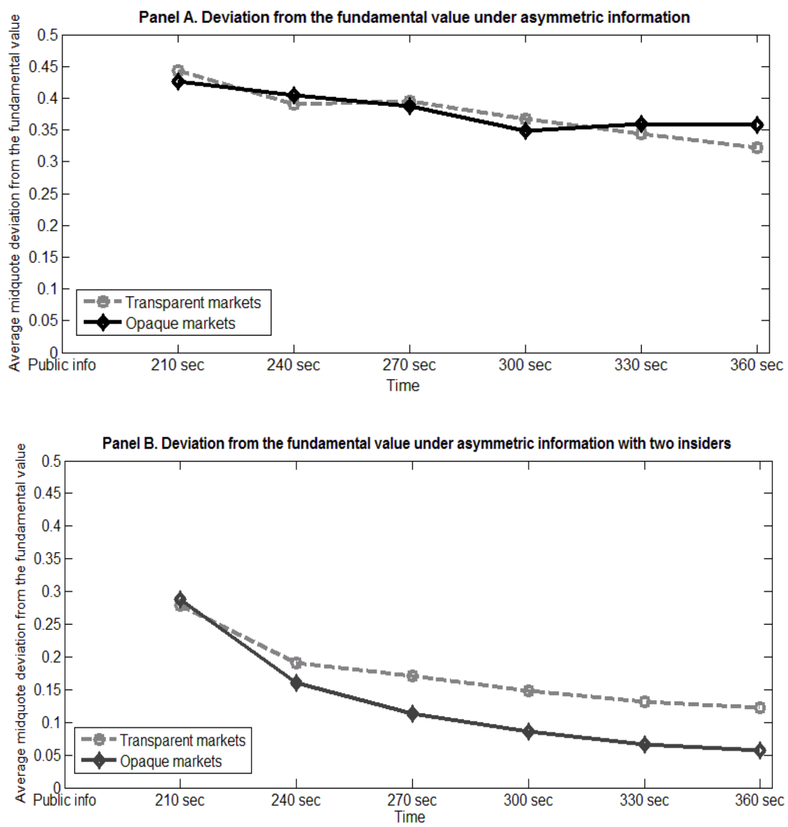


Table 1
Liquidating dividend distribution

This table shows the liquidating dividend distribution of the assets traded in experimental markets. For each market, an asset from this pool is selected. The columns 1-3 correspond to the initial values of the dividends until the public information arrival at the third minute. The other columns show the distribution under the good news (columns 4-6), that is, \$10 increase in unconditional expected value, and bad news (columns 7-9), that is, \$10 decrease in unconditional expected value.

	Initial states			**Good news**			**Bad news**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Asset	L	M	H	L	M	H	L	M	H
1	30	41	64	40	51	74	20	31	54
2	29	41	65	39	51	75	19	31	55
3	28	41	66	38	51	76	18	31	56
4	27	41	67	37	51	77	17	31	57
5	26	41	68	36	51	78	16	31	58
6	25	41	69	35	51	79	15	31	59
7	26	49	60	36	59	70	16	39	50
8	25	49	61	35	59	71	15	39	51
9	24	49	62	34	59	72	14	39	52
10	23	49	63	33	59	73	13	39	53
11	22	49	64	32	59	74	12	39	54
12	21	49	65	31	59	75	11	39	55

Table 2
Experimental design

This table shows the parameter choices for different trader types. The initial endowment in each market is the sum of the cash in experimental units and shares given to each trader type. For each trader type, the unconditional expected value of the initial endowments is the same: the initial cash plus the number of shares times \$45, that is, \$7,375. Trading targets are defined per two-minute cycles, and remain the same during the six-minute trading period. Missing a target is penalized by subtracting \$1,000 per unfulfilled target from the final payoff at the end of each market. The dividend distribution is common knowledge to all trader types. Informed traders know the true state before trading starts.

Trader Type	**Endowments**		**Targets**		**Asset**
	Cash	**Share**	**per 2 min.**	**Penalty**	**info**
1 or 2 uninformed	\$4,000	75	no target	no penalty	distribution
1 small liquidity (buy)	\$5,125	50	8 shares	\$1,000	distribution
1 small liquidity (sell)	\$2,875	1000	8 shares	\$1,000	distribution
1 large liquidity (buy)	\$6,700	15	20 shares	\$1,000	distribution
1 large liquidity (sell)	\$1,300	135	20 shares	\$1,000	distribution
0, 1 or 2 informed	\$4,000	75	no target	no penalty	true state

Table 3
Trading strategies under symmetric information

This table reports the differences in trading strategies across trader types, that is, uninformed with no target, small and large liquidity traders under symmetric information. Panel A and Panel B show the results for transparent and opaque markets, respectively. The columns 1-3 show the average shares submitted per trader using limit, marketable, and undisclosed orders. The columns 4-6 report measures of trader aggressiveness and competition in the following order: the number of limit orders submitted inside spread, at the BBO, and the average distance of limit orders to the prevailing midquote. The last column reports the average distance of undisclosed orders to the prevailing midquote conditional on submission. The values in parentheses are the standard deviations. The table also reports one-sided Wilcoxon signed-ranked results of two consecutive rows in the same column. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	LO	**MO**	**HLO**	**Inside**	**BBO**	**LO Agg.**	**HLO Agg.**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Transparent markets							
Trader type	mean (std)	mean (std)	mean (std)	mean (std)	mean (std)	mean (std)	$\overline{\text{mean}}$ (std)
Uninformed	57.84 (57.05)	23.66 (27.61)	– (–)	2.04 (2.24)	11.61 (11.76)	2.89 (1.98)	– (–)
Small liquidity	63.81 (65.20)*	32.43 (27.43)***	– (–)	2.76 (2.19)**	15.42 (11.87)***	2.37 (2.20)***	– (–)
Large liquidity	70.38 (37.12)***	56.27 (31.39)***	– (–)	3.53 (2.13)***	16.87 (9.28)***	1.98 (1.36)*	– (–)
Panel B. Opaque markets							
Trader type	mean (std)	mean (std)	mean (std)	mean (std)	mean (std)	mean (std)	$\overline{\text{mean}}$ (std)
Uninformed	48.21 (57.25)	19.73 (23.56)	11.69 (21.06)	1.56 (2.04)	9.87 (11.44)	2.70 (2.23)	2.63 (2.63)
Small Liquidity	56.84 (58.80)**	29.28 (21.92)***	9.80 (17.79)	2.40 (1.96)***	14.06 (13.07)***	2.29 (3.62)**	2.84 (1.90)
Large Liquidity	57.36 (46.85)	48.57 (31.48)***	15.41 (29.41)***	3.36 (2.64)***	16.66 (14.23)**	1.65 (1.53)***	1.58 (1.36)

Table 4
Trading strategies under asymmetric information

This table reports the differences in trading strategies across traders types, that is, uninformed with no target, small and large liquidity traders, and informed trader under asymmetric information. Panel A and Panel B show the results for transparent and opaque markets, respectively. The columns 1-3 show the average shares submitted per trader using limit, marketable, and undisclosed orders. The columns 4-6 report measures of trader aggressiveness and competition in the following order: the number of limit orders submitted inside spread, at the BBO and the average distance of limit orders to the prevailing midquote. The last column reports the average distance of undisclosed orders to the prevailing midquote conditional on submission. The values in parentheses are the standard deviations. The table also reports one-sided Wilcoxon signed-ranked results of two consecutive rows in the same column. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	LO	**MO**	**HLO**	**Inside**	**BBO**	**LO Agg.**	**HLO Agg.**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Transparent markets							
Trader type	mean (std)	mean (std)	mean (std)	mean (std)	mean (std)	mean (std)	$\overline{\text{mean}}$ (std)
Uninformed	72.45 (58.17)	26.35 (27.89)	– (–)	2.35 (1.95)	9.99 (8.80)	3.38 (2.92)	– (–)
Small liquidity	76.91 (56.31)	41.00 (48.89)**	– (–)	3.54 (2.08)*	15.90 (10.61)***	2.55 (2.00)***	– (–)
Large liquidity	80.50 (51.15)***	52.25 (50.82)***	– (–)	4.25 (2.91)**	19.44 (15.45)	2.38 (1.84)	– (–)
Informed	77.31 (71.76)	52.54 (51.45)*	– (–)	3.54 (3.78)	16.14 (14.15)	3.90 (4.60)	– (–)
Panel B. Opaque markets							
Trader type	*mean* (*std*)	*mean* (*std*)	*mean* (*std*)	*mean* (*std*)	*mean* (*std*)	*mean* (*std*)	$\overline{mean}$ (*std*)
Uninformed	57.85 (57.88)	27.42 (35.39)	9.70 (18.99)	2.35 (2.98)	9.55 (9.40)	3.89 (4.01)	3.74 (3.86)
Small liquidity	60.98 (51.87)	37.25 (42.34)**	9.11 (18.35)	3.27 (2.68)***	13.21 (11.22)*	2.84 (2.09)**	4.04 (3.78)
Large liquidity	74.10 (66.00)***	45.84 (30.24)	16.52 (34.79)**	3.84 (2.98)**	15.08 (11.75)**	2.28 (1.84)	2.80 (2.40)
Informed	59.88 (51.19)**	45.00 (56.92)*	24.82 (53.85)	2.97 (3.07)**	13.09 (9.59)**	2.60 (2.06)	3.60 (3.15)**

Table 5
ANOVA results under symmetric markets

This table presents the results of an ANOVA to test the effects of market structure on trading profits under symmetric information. The dependent variable is the trader's payoff relative to the average market payoff normalized by the unconditional expected payoff ($7,375). The independent variables include trader type —uninformed trader, small liquidity (buy/sell), large liquidity (buy/sell)—, opacity (transparent versus opaque), extremity (whether the state is extreme or not), and interaction terms. An asset is classified as extreme if the liquidating dividend is more than 20% from the unconditional mean. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Source	df	Sum of Squares	F-statistics	p-value
Trader type	4	0.019	0.92	0.454
Opacity	1	0.001	0.16	0.678
Extremity	1	0.000	0.07	0.794
Interaction (type, opacity)	4	0.052	2.48	0.043**
Interaction (type, extremity)	4	0.026	1.25	0.290
Interaction (opacity, extremity)	1	0.000	0.03	0.873
Interaction (type, opacity, extremity)	4	0.017	0.79	0.530
Error	494	2.541		

Table 6
ANOVA results under asymmetric markets

This table presents the results of an ANOVA to test the effects of market structure on trading profits under asymmetric information. The dependent variable is the trader's payoff relative to the average market payoff normalized by the unconditional expected payoff ($7,375). The independent variables include trader type —uninformed trader, small liquidity (buy/sell), large liquidity (buy/sell) and informed traders—, opacity (transparent versus opaque), extremity (whether the state is extreme or not), and interaction terms. An asset is classified as extreme if the liquidating dividend is more than 20% from the unconditional mean. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Source	**df**	**Sum of Squares**	**F-statistics**	***p*-value**
Trader type	5	0.622	9.50	0.000***
Opacity	1	0.000	0.02	0.875
Extremity	1	0.006	0.45	0.502
Interaction (type, opacity)	5	0.072	1.10	0.362
Interaction (type, extremity)	5	0.247	3.77	0.002***
Interaction (opacity, extremity)	1	0.000	0.00	0.965
Interaction (type, opacity, extremity)	5	0.099	1.52	0.181
Error	431	5.646		

Table 7
Pre-trade transparency under symmetric information

This table reports the mean and median values for various market quality measures under symmetric information. I compare transparent and opaque markets using a paired sample analysis (11 cohorts) and report one sided Wilcoxon signed-rank p-values. I compute message traffic as the sum of limit, marketable, and undislosed orders (in case of opaque markets) submitted to the LOB, the total transacted volume in shares, and the number of shares per trade. I report quoted bid-ask spread for the entire trading period, for each trading cycle, and each minute. Cycle 1, 2, and 3 refer to the trading period between 1-120 secs, 121-240 secs, and 241-360 secs, respectively. The effective (realized) spread is the distance between the transaction price and the midquote (prevailing after five trades). The permanent price impact is the difference between the midquote and the midquote prevailing after five trades. (Visible) BBO depth refers to the (visible) shares at the BBO, while (visible) book depth consists of the (visible) shares at all levels of the LOB. Price (midquote) volatility is the standard deviation of transaction prices (midquotes). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Transparent		**Opaque**		
Panel A. Liquidity	mean	median	mean	median	p-value
Message traffic	354	287	334	274	0.449
Transacted volume	215	204	208	216	0.310
Shares per trade	1.85	1.78	2.23	1.77	0.120
Bid-ask spread	1.87	1.74	1.64	1.60	0.120
Cycle 1	2.20	1.97	1.82	1.73	0.074*
1-min	2.78	2.48	2.42	2.03	0.139
2-min	1.67	1.66	1.28	1.18	0.010***
Cycle 2	1.67	1.33	1.57	1.67	0.449
3-min	1.43	1.26	1.25	1.27	0.160
4-min	1.91	1.23	1.89	1.90	0.319
Cycle 3	1.65	1.47	1.57	1.37	0.483
5-min	1.53	1.48	1.76	1.32	0.319
6-min	1.81	1.33	1.38	1.20	0.005***
Effective spread	0.60	0.57	0.54	0.48	0.260
Realized spread	0.45	0.34	0.29	0.27	0.087*
Permanent price impact	0.15	0.12	0.25	0.19	0.449
Panel B. Depth	mean	median	mean	median	p-value
BBO depth	20.93	19.85	24.97	20.59	0.232
Visible BBO depth	20.93	19.85	19.57	17.67	0.319
Book depth	124.53	123.73	135.98	135.36	0.120
Visible book depth	124.53	123.73	105.56	98.63	0.074*
Panel C. Volatility	mean	median	mean	median	p-value
Midquote volatility	4.97	4.83	4.66	4.15	0.160
Price volatility	3.00	3.12	3.01	2.40	0.500

Table 8
Pre-trade transparency under asymmetric information

This table reports the mean and median values for various market quality measures under asymmetric information. I compare transparent and opaque markets using a paired sample analysis (11 cohorts) and report one sided Wilcoxon signed-rank p-values. I compute message traffic as the sum of limit, marketable, and undisclosed orders (in case of opaque markets) submitted to the LOB, the total transacted volume in shares, and the number of shares per trade. I report quoted bid-ask spread for the entire trading period, for each trading cycle and each minute. Cycle 1, 2, and 3 refer to the trading period between 1-120 secs, 121-240 secs, and 241-360 secs, respectively. The effective (realized) spread is the distance between the transaction price and the midquote (prevailing after five trades). The permanent price impact is the difference between the midquote and the midquote prevailing after five trades. (Visible) BBO depth refers to (visible))shares at the BBO, while (visible) book depth consists of the (visible) shares at all levels of the LOB. Price (midquote) volatility is the standard deviation of transaction prices (midquotes). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Transparent		**Opaque**		
Panel A. Liquidity	mean	median	mean	median	p-value
Message traffic	336	294	334	318	0.483
Transacted volume	240	261	226	190	0.207
Shares per trade	2.16	2.01	1.93	1.78	0.087*
Bid-ask spread	3.05	2.59	2.81	2.88	0.483
Cycle 1	2.93	2.16	3.57	2.48	0.183
1-min	3.56	3.21	4.09	3.48	0.139
2-min	2.36	1.86	3.13	2.27	0.207
Cycle 2	3.20	2.04	1.76	1.48	0.012**
3-min	2.94	1.93	1.62	1.43	0.062*
4-min	3.40	2.15	1.86	1.44	0.012**
Cycle 3	3.07	2.64	3.12	2.07	0.483
5-min	3.54	2.73	2.73	2.45	0.289
6-min	2.73	1.68	3.53	1.70	0.416
Effective spread	1.02	0.87	0.79	0.88	0.260
Realized spread	0.67	0.60	0.48	0.70	0.449
Permanent price impact	0.34	0.44	0.31	0.31	0.382
Panel B. Depth	mean	median	mean	median	p-value
BBO depth	16.69	16.22	18.82	18.71	0.289
Visible BBO depth	16.69	16.22	15.18	12.41	0.120
Book depth	132.60	120.52	149.61	152.43	0.382
Visible book depth	132.60	120.52	113.35	107.51	0.120
Panel C. Volatility	mean	median	mean	median	p-value
Midquote volatility	6.60	6.78	6.84	7.07	0.350
Price volatility	4.97	5.41	4.91	4.07	0.500

Table 9
Pre-trade transparency under asymmetric information (two insiders)

This table reports the mean and median values for various market quality measures under asymmetric information with two insiders. I compare transparent and opaque markets using a paired sample analysis (six cohorts) and report one-sided Wilcoxon signed-rank p-values. I compute message traffic as the sum of limit, marketable, and undisclosed orders (in case of opaque markets) submitted to the LOB, the total transacted volume in shares, and the number of shares per trade. I report quoted bid-ask spread for the entire trading period, for each trading cycle and each minute. Cycle 1, 2, and 3 refer to the trading period between 1-120 secs, 121-240 secs, and 241-360 secs, respectively. The effective (realized) spread is the distance between the transaction price and the midquote (prevailing after five trades). The permanent price impact is the difference between the midquote and the midquote prevailing after five trades. BBO depth refers to shares at Best Bid Offer (BBO), while (visible) book depth are the (visible) shares at all levels of the LOB. Price (midquote) volatility is the standard deviation of transaction prices (midquotes). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Transparent		**Opaque**		
Panel A. Liquidity	mean	median	mean	median	p-value
Message traffic	371	352	395	415	0.219
Transacted volume	230	232	223	203	0.423
Shares per trade	1.98	1.76	1.70	1.38	0.156
Bid-ask spread	2.87	2.54	2.35	2.04	0.500
Cycle 1	3.82	2.55	2.85	2.48	0.500
1-min	3.59	2.67	2.91	2.68	0.500
2-min	4.10	2.70	3.08	2.78	0.422
Cycle 2	2.73	1.83	2.00	1.86	0.219
3-min	2.52	1.94	2.03	1.69	0.344
4-min	3.06	2.31	2.16	2.19	0.281
Cycle 3	2.35	2.29	2.02	1.84	0.344
5-min	2.82	3.17	2.42	2.10	0.344
6-min	2.40	1.55	1.71	1.54	0.359
Effective spread	2.46	3.23	0.54	0.16	0.078*
Realized spread	0.33	0.13	1.43	2.14	0.219
Permanent price impact	2.12	1.31	-0.89	-0.50	0.031**
Panel B. Depth	mean	median	mean	median	p-value
BBO depth	17.96	16.16	19.94	19.46	0.219
Visible BBO depth	17.96	16.16	16.26	15.59	0.281
Book depth	133.08	123.53	159.00	154.16	0.016**
Visible book depth	133.08	123.53	120.28	120.92	0.281
Panel C. Volatility	mean	median	mean	median	p-value
Midquote volatility	8.09	8.08	8.00	7.77	0.500
Price volatility	6.81	5.64	7.19	7.02	0.500

Internet appendix to "pre-trade transparency and informed trading: experimental evidence on undisclosed orders"

(For online publication)

A. Experiment instructions

Please read the instructions carefully before joining the experimental asset markets. Make sure that you understand the trading mechanism and feel free to ask questions in case of any doubts.

Rule 1: Please do not talk to other traders during trading. If you have any question, please raise your hand and the experimenter will come to your trading desk.

Trading interface

To join the experimental asset markets, you will have to open an internet browser and connect to the website announced by the experimenter. After you sign up, you will be asked to log into the markets, and you will be connected to the jMarkets server. After everybody has logged in, a markets interface will appear. Once the trading is closed in the market, close your browser and the trading window. Upon experimenter's request, you will have to login with the same signup information to enter a new market.

1. Active markets

The *Active markets* panel is renewed each period. In this panel, you will see a scroll-down column. This column corresponds to a market for the security. The security name is indicated on top. The time left in a market is indicated on the right hand side above the Active Markets panel. At the top of the column, on the left hand side you find your trading target, remaining target and remaining time for the target (if you have one!). In the middle, you find your current holdings of the security. Your current cash holdings are given on the right hand side above the Active Markets panel below the time remaining for trading period.

The column consists of a number of price levels at which you and others enter offers to trade. Current offers to sell are indicated in red; offers to buy are indicated in blue. When pressing the *Highest Buy/Lowest Sell* buttons on top of a column, you will be positioned in the best offer to buy (that is, the highest price at which somebody offers to buy) and the best offer to sell (that is, the lowest price that anybody offers to sell at).

When you move your cursor to a particular price level box, you get specifics about the available offers. On top, at the left hand side, you'll see the number of units requested for purchase. Each time you click on it, you send an order to buy one unit yourself. On top, at the right hand side, the number of units offered for sale is given. You send an order to sell one unit each time you yourself click on it. At the bottom, you'll see how many units you offered. (Your offers are also listed under Current Orders to the right of the Active Markets panel.)

If you click on the price level, a small window appears that allows you to offer multiple units to buy or to sell.

2. Order book

Order book lists the all the orders made during the trading period that are not yet transacted. The sell orders are listed on top of the buy orders in a descending order. In each row, you can see the price and trade direction, that is, buy or sell, and the units.

3. History

The *History* panel shows a chart of past transaction prices for the security. Like the Active Markets panel, it refreshes in every market.

4. Transaction history

The *Transaction history* table shows your past transactions in the market. In each row, you see the Price (Transaction price), standing price and units. Transaction price is the price that is offered by the buyer or the seller and the standing price is the best, that is, the lowest (highest) sell (buy) price standing price in the order book.

5. Earning history

The *Earnings history* table shows, for each period, your final holdings for the security shares and cash, as well as the resulting market earnings (net of penalty).

Experimental asset markets

The experiment consists of a sequence of asset markets. Before entering the market, you will be given a fresh supply of shares of a single security and cash. Once markets open you are free to trade the shares of the security. You buy shares with cash and you get cash if you sell shares. Do not feel compelled to trade; make sure that trading is to your best interest!

Trader types

As a trader you might have trading targets while the market is open. Traders' target will be either to sell 20 shares (alternatively 8 shares) each 2 minutes or to buy 20 shares (alternatively 8 shares) each 2 minutes. But, there are also traders in the market without trading targets. In each market, there will be two traders without trading targets, one with 20 sell, one with 20 buy, one with 8 sell and one with 8 buy targets.

Traders will have different targets in different markets. If you have a target, it will be stated clearly on your screen. At the end of trading, you will be assessed a penalty for each unfulfilled target. This penalty is large enough that it is worth trading at any price, no matter how unfavorable, to hit your target. The goal of a target trader is to meet his or her goal at the most favorable prices possible. Once they hit their targets, target traders can buy or sell as many shares as they please without penalty.

The security

At the beginning of each market, you will be given a fresh supply of shares of a security along with cash. At the end of the periods, the security pays a liquidating dividend (per share) that is determined by the drawing of a state. The possible states State 1, State 2 or State 3 are equally likely. The security pays a different dividend in each state.

Information structure

All traders attending the experimental asset markets will have access to the same information regarding the value of the security. The dividends paid in each state will be announced to all traders at the beginning of the trading period. But, the actual state at the end of the market will be unknown until market closes. There will be a public information release in the middle of the trading period regarding the dividends paid by the security. Public information will reveal either a uniform upward or uniform downward shift of dividends in all states.

The table below is an example of how the dividends depend on each state.

Security A	State 1	State 2	State 3
Dividends	30	41	64
Chance	1/3	1/3	1/3
True State	?	?	?
Dividends After Public Information			
uniform downward Shift	20	31	54
uniform upward Shift	40	51	74

How to be the best trader?

You start each market with a number of shares and amount of cash. Your initial endowment will be clearly stated on your trading interface.

Bankruptcy rules apply in the markets; that is, you cannot buy shares if you do not have money to pay for them, and you cannot sell shares you do not own.

Each security and cash expires at the end of the market, which means that you do not carry them over to the next market. At that point, the securities pay a liquidating dividend (per share) as specified above. The dividends, together with your cash balance (net of target penalty), constitute your market earnings.

Your aim as a trader is to maximize your end-of trading wealth. Traders' earnings in each market is the liquidation value of the security you hold at the end of the trading in each market, plus the capital gains (losses) obtained through trading of the asset minus the penalty (1,000 experimental currency) for each unfulfilled trading target.

An example: You make money every time you buy a share for less than true value or sell a share for more than true value. For example, buying a share worth \$45 at a price of \$30 creates a gain of \$15 (Experimental Units). Selling that share at that price creates a loss of \$15 (Experimental Units).

Trading mechanism and the rules

Whenever you enter an offer to sell at a price below or equal to that of the best available buy order, a sale takes place. You receive the price of the buy order in cash. Whenever you enter an offer to buy at a price above or equal to that of the best available sell order, a purchase takes place. You will be charged the price of the sell order. You can cancel your orders.

The system imposes strict price-time priority[15]: It means that among buy orders those at higher prices will be executed first, and if there are several buy orders at the same price level, the oldest orders in the book will be executed first. Analogously, among sell orders those at low prices will be executed first, and if there are several sell orders at a given price level, the oldest ones will be executed first.

[15] In practice sessions, I explained how the priority rules change under an opaque regime. See online Appendix B for details.

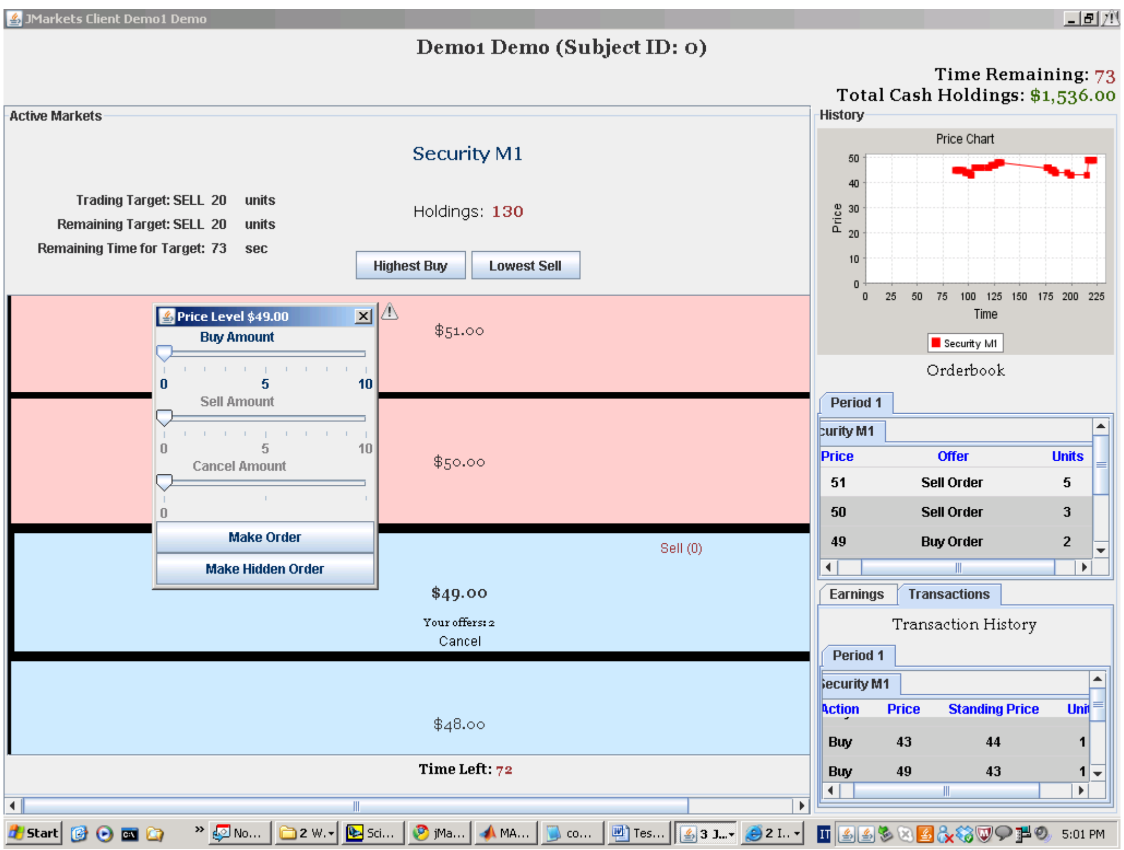
Notice that you cannot trade with yourself. If you try to take an order you entered, your request will be rejected. You can never enter a buy at a price greater than your own sell, or a sell at a price less than your own buy. Doing so would be like trying to trade with yourself.

Before you send in an offer, jMarkets will check two things: the cash constraint, and the bankruptcy constraint.

The cash constraint concerns whether you have enough cash to buy securities. If you send in an offer to buy, you need to have enough cash.

The bankruptcy constraint concerns your ability to deliver on promises that you implicitly make by trading securities. We may not allow you to trade to holdings that generate losses in some state(s). A message appears if that is the case and your order will not go through. Enjoy trading!

A.1 Trading interface[16]



[16] I thank Yomi Kastro and Vahit Hanoglu for their help with the modification of the jMarkets to incorporate undisclosed orders.

B. Description of an electronic limit order book (LOB)

In this section, I explain peculiar features of electronic limit order books (LOB). LOBs are commonly used in many exchanges around the world. An electronic LOB is a centralized automated market where agents submit buy and sell orders to a computerized system. In this paper, I focus on order-driven markets which are based on traders' direct interaction as opposed to quote-driven markets where intermediaries such as specialists or dealers are active. In these continuous double auction markets, traders supply liquidity by posting limit orders and demand liquidity via marketable orders. A limit order specifies both the quantity and the price (maximum price for limit buy or minimum price for limit sell) for execution. Marketable orders only specify the quantity and are executed at best price (highest bid/lowest ask) available. Marketable orders are executed immediately, but are subject to price risk. Since the trader does not specify the price, execution at the prevailing best price might be unfavorable. On the contrary, limit orders limit the price risk by the specified price, but immediate execution is not guaranteed, that is, there is execution risk associated with limit orders. Below we show a simple illustration of a LOB once several limit orders have been posted;

Ask / Bid	**Price**	**Visible depth**	**Actual depth**
A_3	54.00	30	30
A_2	52.00	40	40
A_1	51.00	10	10
B_1	49.00	20	20
B_2	47.00	30	30
B_3	46.00	15	15

In this illustration, I focus on the best three ask and bid prices. The tick size is \$1 and in its current state the bid-ask spread is \$2. The rows in bold show the current best bid-offer (BBO). In transparent markets, where undisclosed orders are not available, the visible quantity (depth) is equal to actual quantity in all price levels. In opaque markets, traders are also allowed to specify their exposure, by stating the portion of the quantity to they are willing to hide. In most of the markets there is a minimum quantity (peak size) for hidden orders that cannot be hidden (a.k.a. undisclosed orders). In opaque markets, on the other hand, the peak size is equal to zero. In these markets visible depth might be equal or smaller than actual depth.

To give an example, assume that an undisclosed order HLO^{A}_{10} of 10 shares @50.00 arrives in the ask side at time t-2 and the peak size is 1.

Ask / Bid	**Price**	**Visible depth**	**Actual depth**
A_3	52.00	40	40
A_2	51.00	10	10
A_1	50.00	1	10
B_1	49.00	20	20
B_2	47.00	30	30
B_3	46.00	15	15

The best ask price A_1 becomes \$50.00 decreasing the bid-ask spread to \$1. Since the peak size is 1, only one share is visible at the best ask, while the actual depth is 10 shares. The bid side of the book remains unaffected.

I further assume that a limit order LO_{10}^{A} of 10 shares @50.00 arrives in the ask side at time t-1. The visible depth at the best ask (@50.00) increases to 11 shares while the actual depth is 20 shares.

Ask / bid	**Price**	**Visible depth**	**Actual depth**
A_3	52.00	40	40
A_2	51.00	10	10
A_1	50.00	11	20
B_1	49.00	20	20
B_2	47.00	30	30
B_3	46.00	15	15

LOBs are governed by order precedence rules for matching orders. In most of the exchanges, first price priority, that is, orders at best prices are executed first, then visibility priority; the visible quantity has precedence over hidden quantity and finally time priority is applied, that is, in case of price and visibility match, orders that enter the book first will be executed first. In transparent markets, only price and time priority rules apply. To see how the precedence rules work, assume that a market bid $\mathrm{MO}_{10}^{\mathrm{B}}$ of 10 shares arrives at time t. Since the visible part of $\mathrm{HLO}_{10}^{\mathrm{A}}$ has time priority over the $\mathrm{LO}_{10}^{\mathrm{A}}$, but the hidden part loses visibility priority against $\mathrm{LO}_{10}^{\mathrm{A}}$, only the visible unit from $\mathrm{HLO}_{10}^{\mathrm{A}}$ and 9 units from $\mathrm{LO}_{10}^{\mathrm{A}}$ are executed, decreasing the actual depth from 20 to 10 shares. Since the minimum visible unit from the undisclosed order must be 1, another unit from $\mathrm{HLO}_{10}^{\mathrm{A}}$ becomes visible, and thus the visible depth becomes two shares: one visible unit from $\mathrm{HLO}_{10}^{\mathrm{A}}$ and the unexecuted part of $\mathrm{LO}_{10}^{\mathrm{A}}$.

Ask / bid	**Price**	**Visible depth**	**Actual depth**
A_3	52.00	40	40
A_2	51.00	10	10
A_1	50.00	2	10
B_1	49.00	20	20
B_2	47.00	30	30
B_3	46.00	15	15

C. Relative Tick Size

In order to address the potential impact of relative tick size on trading strategies, I run an ANOVA to test the effect of relative tick size on hidden liquidity provision under asymmetric information. The dependent variable is the submitted undisclosed order volume. The independent variables include trader type —uninformed, small liquidity (buy/sell), large liquidity (buy/sell), informed— and relative tick size (low, medium, high) based on the terciles of liquidating dividend values, and the interaction term.

Table C.1. ANOVA results: relative tick size

Source	df	Sum of squares	F-statistics	p-value
Trader type	5	8,732	1.49	0.194
Relative tick size	2	1,181	0.5	0.605
Interaction (type, tick size)	10	12,462	1.07	0.391
Error	206	241,033		

As the results above suggest, neither the trader type nor the relative tick size seems to affect the decision on hidden liquidity provision. Panel B in Table 4 shows that there are no significant differences in hidden liquidity submission between large liquidity and informed traders. Yet, being informed may still be an important dimension of this decision. Next, I run another ANOVA where I replace the trader type with a binary variable of being informed. I see that while being informed is important in hidden liquidity provision, the relative tick size still does not affect informed traders' decisions to submit undisclosed orders.

Table C.2. ANOVA results: relative tick size

Source	df	Sum of squares	F-statistics	p-value
Informed	1	3,804	3.27	0.0718*
Relative tick size	2	2,296	0.99	0.3741
Interaction (informed, tick size)	2	4,569	1.97	0.1426
Error	218	253,398		

D. Trading Targets

Consider a liquidity trader who must buy L shares (L=8 (20) for small (large) liquidity traders) every two-minute cycle, and incurs a fixed penalty of $1,000 experimental currency if the target is not reached. Then her expected profit, if she reaches the target by buying the asset at p is:

$$E[\pi] = L(E[\beta_t v^a] - p_t),$$

where $E_t[v^a]$ is the expected value of the liquidating dividend, and β_t is the unobservable private evaluation of the asset (Parlour, 1998; Buti and Rindi, 2013).[17] However, if she executes only $x\% <1$ of the target, then her expected profit is:

$$E[\pi] = xL(E[\beta_t v^a] - p_t) - 1,000,$$

Note that not fulfilling the target is more profitable only if:

$$\begin{aligned} xL(E[\beta_t v^a] - p_t) - 1,000 &> L(E[\beta_t v^a] - p_t) \\ for \text{ large traders} &: p_t > E[\beta_t v^a] + \frac{50}{(1-x)} \\ for \text{ small traders} &: p_t > E[\beta_t v^a] + \frac{125}{(1-x)} \end{aligned}$$

Given that the price grid is limited to $1-$90 and $E[v^a]$=$45, fulfilling the target is a dominant strategy for small liquidity traders regardless of the private evaluation of the asset and the portion x of the target. For large liquidity traders, on the other hand, not fulfilling the target can only be a dominant strategy if they are the most eager sellers with very low β_t. However, there is no a priori reason why a trader with a large buying (selling) target should be an eager seller (buyer).[18]

[17] Buti and Rindi (2013) assume a β drawn from the uniform distribution that is symmetric around 1. Extreme values of β indicate higher willingness to trade, while a β close to one represents lowest willingness to trade.

[18] In fact there was only one trader out of 292 cases where a large seller did not fulfill the target, and had more shares than initial endowment at the end of the trading period.

E. Auction for private information

As a direct test on the relative importance of undisclosed orders in the presence of private information, I also run additional sessions (2009 experiment) where markets under asymmetric information are preceded by a second-price sealed bid (Vickrey) auction for insider information. Before markets open, participants are informed about the market design, and each participant sends a sealed bid to the experimenter, that is, an amount in experimental currency unit, to be the informed trader. The trader who submits the highest bid becomes the informed trader in the next market, that is, ex-ante she knows the true state of the world, and pays (subtracted from her/his trading account) the second highest bid. Under such an auction mechanism traders are induced to reveal their true valuation for private information.[19] For the sake of illustration, assume that there are two traders: t_1(she) and t_2(he). Suppose that t_1 bids below her valuation $v_{t_1} > b_{t_1}$, if t_2 bids higher than her valuation $b_{t_2} > v_{t_1}$, then she will not be the insider so bidding up to her valuation v_{t_1} will not harm her. If her bid is higher $b_{t_2} < b_{t_1}$, then she will be the insider, and again bidding up to her valuation will not change anything since she pays b_{t_2}. However, if $b_{t_1} < b_{t_2} < v_{t_1}$, then by bidding lower than her valuation, she cannot be the insider whereas by bidding the true valuation $b_{t_1} = v_{t_1}$, she becomes the insider by paying b_{t_2}. On the other hand, bidding more than the private valuation, $b_{t_1} > v_{t_1}$ is never a good strategy, especially if $b_{t_1} > b_{t_2} > v_{t_1}$, where trader 1 ends up paying higher than her valuation. Submitted auction bids measure the relative price of private information under both transparent and opaque regimes.

My aim is to measure the relative valuation of private information without relying on trading data. If undisclosed orders are primarily used for hiding private information, I would expect a higher valuation for private information in opaque markets. Bids are averaged over replications at the individual level (N=31, 2009 experiment) and we obtain two average bids per trader for both opaque and transparent markets. I conduct a paired sample Wilcoxon signed-rank test to see differences in personal valuation under both regimes. The average value paid for private information in opaque markets is, on average, 12 percent higher compared to that in transparent markets, $\mu^{PIbid}_{opaque} = \$1182 > \mu^{PIbid}_{transparent} = \$1056$; however, this difference is not statistically significant (Wilcoxon p-value=0.231). Therefore, indirect evidence from private information auctions fails to strongly support for information-based arguments behind undisclosed orders.

[19] I implicitly assume that traders have private valuations (and know it precisely) for being the insider. This might well not be the case. But, since I am interested in relative valuations under both opaque and transparent regimes, this assumption is innocuous.

F. Trading profits

Table F.1

Trading profits under symmetric information

This table reports differences in trading profits across traders types -uninformed traders with no target, small and large liquidity- and transparency regimes under symmetric information (Table F.1) and under asymmetric information (Table F.2). The trading profit is measured as the difference between the fundamental value and the purchase price for buy orders and the difference between sale price and the fundamental value for sell orders. I report both profits during the entire trading period, and profits one minute after the public information release. Profits are aggregated in each cohort, and the table reports the average values across 11 cohorts. Trading profits are decomposed into make, that is, limit order (and undisclosed orders under an opaque regime) and take, that is, marketable order, profits. In opaque markets, the values in parenthesis indicate the average make profits obtained through undisclosed orders. The table reports one-sided Wilcoxon signed-ranked p-values of two consecutive rows (transparent vs. opaque) in the same column. Asterisks above profits indicate whether the values are statistically different from 0. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Total profits			**1-min after public info**		
Panel A. Uninformed	Make	Take	Total	Make	Take	Total
Transparent	87.2	96.8	183.9*	20.7	93.4***	114.1***
Opaque	−228.5**	105.7*	−122.8	−160.4***	122.7***	−37.8
(Undisclosed)	(−26.8**)			(−25.2***)		
(p-value)	(0.009***)	(0.350)	(0.027**)	(0.021**)	(0.289)	(0.034**)
Panel B. Small liquidity	Make	Take	Total	Make	Take	Total
Transparent	−5.6	33.6	28.0	−8.6	−16.9	−25.5
Opaque	−145.7***	203.9**	58.2	−114.0***	159.5***	45.5
(Undisclosed)	(−23.4***)			(−13.0***)		
(p-value)	(0.016**)	(0.035**)	(0.483)	(0.007***)	(0.003***)	(0.074*)
Panel C. Large liquidity	Make	Take	Total	Make	Take	Total
Transparent	−111.8	−95.4*	−207.3***	−60.1**	−26.4*	−86.5**
Opaque	−182.7**	251.1**	68.4	−160.2***	154.0***	−6.3
(Undisclosed)	(−55.4*)			(−49.2***)		
(p-value)	(0.319)	(0.042**)	(0.012**)	(0.037**)	(0.027**)	(0.074*)

Table F.2

Trading profits under asymmetric information

This table reports differences in trading profits across traders types -uninformed with no target, small and large liquidity traders, and informed trader- and transparency regimes under asymmetric information. The trading profit is the difference between the fundamental value and the purchase price for buy orders and the difference between sale price and the fundamental value for sell orders. I report both profits during the entire trading period and profits one minute after the public information release. Profits are aggregated in each cohort, and the table reports the average values across 11 cohorts. The trading profits are decomposed into make, that is, limit order (and undisclosed orders) and take, that is, marketable order, profits. In opaque markets, the values in parenthesis indicate the average make profits obtained through undisclosed orders. The table reports one-sided Wilcoxon signed-ranked p-values of two consecutive rows (transparent vs. opaque) in the same column. Asterisks above profits indicate whether the values are statistically different from 0. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Total profits			1-min after public info		
Panel A. Uninformed	Make	Take	Total	Make	Take	Total
Transparent	-137.4^{*}	-54.7^{*}	-192.1	-73.7^{*}	42.7	-31.0
Opaque (Undisclosed)	-227.4^{***} (-47.3^{***})	0.74	-226.7^{**}	-189.4^{***} (-31.1^{***})	-28.0	-217.4^{***}
(p-value)	(0.260)	(0.160)	(0.483)	(0.087^{*})	(0.416)	(0.074^{*})
Panel B. Small Liquidity	Make	Take	Total	Make	Take	Total
Transparent	-182.4	-78.1	-260.5^{*}	-39.7	49.9^{*}	10.2
Opaque (Undisclosed)	-179.4 (-39.3)	-55.5	-234.9	-4.7^{*} (0.36)	145.7^{***}	141.0^{*}
(p-value)	(0.483)	(0.449)	(0.416)	(0.382)	(0.103)	(0.139)
Panel C. Large Liquidity	Make	Take	Total	Make	Take	Total
Transparent	-206.9^{*}	-64.9	-171.9^{**}	-116.4^{***}	-5.2	-111.2^{**}
Opaque (Undisclosed)	-293.9^{**} (-31.6^{*})	-190.5	-484.4^{***}	-169.5^{***} (-43.8^{**})	70.6^{*}	-98.8^{*}
(p-value)	(0.207)	(0.183)	(0.062^{*})	(0.183)	(0.087^{*})	(0.449)
Panel D. Informed	Make	Take	Total	Make	Take	Total
Transparent	292.4^{***}	442.4^{***}	734.9^{***}	18.6	114.7^{***}	133.3^{***}
Opaque (Undisclosed)	346.6^{***} (80.4^{**})	606.7^{***}	953.3^{***}	28.1^{*} (18.5^{*})	146.9^{***}	175.0^{**}
(p-value)	(0.500)	(0.120)	(0.139)	(0.500)	(0.449)	(0.449)

G. Fill Rates

Table G.1

Fill rates under symmetric information

The table below reports differences in fill rates of limit (undisclosed) orders across traders types -uninformed with no target, small and large liquidity traders-, and transparency regimes under symmetric information. I report the disclosed fill rate (DFR), the undisclosed fill rate (UFR) and the total fill rate (TFR). The former is the ratio of executed limit shares over submitted limit (and undisclosed) shares. The UFR is the ratio of executed undisclosed orders over over submitted limit (and undisclosed) shares. The TFR is the sum of the DFT and the UFR. I report all fill rates both for the entire trading period, and one minute after public information release. The fill rates are aggregated in each cohort, and the table reports the average values across 11 cohorts. The table reports one-sided Wilcoxon signed-ranked p-values of two consecutive rows (transparent vs. opaque) in the same column. Asterisks above p-values indicate whether the difference is statistically significant. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Whole period			**1-min after public info**		
Panel A. Uninformed	DFR	UFR	TFR	DFR	UFR	TFR
Transparent	0.448	-	0.448	0.917	-	0.917
Opaque	0.370	0.085	0.454	0.706	0.190	0.896
(p-value)	(0.042**)	(-)	(0.416)	(0.138)	(-)	(0.278)
Panel B. Small liquidity	DFR	UFR	TFR	DFR	UFR	TFR
Transparent	0.517	-	0.517	1.001	-	1.008
Opaque	0.401	0.055	0.456	0.692	0.089	0.746
(p-value)	(0.016**)	(-)	(0.139)	(0.371)	(-)	(0.472)
Panel C. Large Liquidity	DFR	UFR	TFR	DFR	UFR	TFR
Transparent	0.568	-	0.568	1.939	-	1.939
Opaque	0.458	0.105	0.563	1.530	0.224	1.801
(p-value)	(0.021**)	(-)	(0.382)	(0.423)	(-)	(0.385)

Table G.2

Fill rates under asymmetric information

This table reports differences in fill rates of limit (undisclosed) orders across traders types -uninformed with no target, small and large liquidity, and informed trader- and transparency regimes under asymmetric information. I report the disclosed fill rate (DFR), the undisclosed fill rate (UFR) and the total fill rate (TFR). The former is the ratio of executed limit shares over submitted limit (and undisclosed) shares. The UFR is the ratio of executed undisclosed orders over submitted limit (and undisclosed) shares. The TFR is the sum of the DFT and the UFR. I report all fill rates both for the entire trading period, and one minute after public information release. The fill rates are aggregated in each cohort, and the table reports the average values across 11 cohorts. The table reports one-sided Wilcoxon signed-ranked p-values of two consecutive rows (transparent vs. opaque) in the same column. Asterisks above p-values indicate whether the difference is statistically significant. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Whole period			**1-min after public info**		
Panel A. Uninformed	DFR	UFR	TFR	DFR	UFR	TFR
Transparent	0.481	-	0.481	1.496	-	1.496
Opaque	0.250	0.096	0.346	0.869	0.116	0.985
(p-value)	(0.005***)	(-)	(0.012**)	(0.139)	(-)	(0.160)
Panel B. Small liquidity	DFR	UFR	TFR	DFR	UFR	TFR
Transparent	0.489	-	0.489	0.869	-	0.870
Opaque	0.410	0.067	0.477	3.240	0.147	3.387
(p-value)	(0.051*)	(-)	(0.416)	(0.382)	(-)	(0.449)
Panel C. Large liquidity	DFR	UFR	TFR	DFR	UFR	TFR
Transparent	0.582	-	0.582	1.088	-	1.088
Opaque	0.461	0.084	0.546	1.021	0.096	1.126
(p-value)	(0.051*)	(-)	(0.350)	(0.053*)	(-)	(0.348)
Panel D. Informed	DFR	UFR	TFR	DFR	UFR	TFR
Transparent	0.378	-	0.378	1.254	-	1.254
Opaque	0.326	0.067	0.393	0.273	0.148	0.456
(p-value)	(0.160)	(-)	(0.350)	(0.055*)	(-)	(0.078*)

H. Informed trading and transparency regime

In Table H.1, I analyze the impact of an insider on market quality under both transparent and opaque regimes. As in the main analysis, each cohort is an independent data point and I average the data over different market replications in the same cohort under the same informational setting. I conduct a two-sample Wilcoxon-Mann-Whitney rank-sum test to analyze differences between cohorts.

Regardless of the transparency regime, a monopolistic insider introduces an adverse selection cost, which is visible through its significant impact on both volatility and the bid-ask spread (e.g., Foucault, 1999).[20] The major difference between the two transparency regimes is in the first trading cycle and right after public news release. While spreads increase significantly in the first part of trading in opaque markets, there is no difference in transparent markets. The opposite happens right after news release. In line with the evidence in Table 8, this finding suggests that insiders are capable of using undisclosed orders strategically and do not hasten to cash in their informational rent under an opaque regime. This strategic behavior of informed traders makes opaque markets more resilient to news events.

[20] The positive relation between adverse selection and bid–ask spread has been recently challenged in the context of multiple insiders (Collin-Dufresne and Fos, 2015).

Table H.1

Informed trading and transparency regime

This table reports median values for various market quality measures under transparent and opaque regimes. I compare markets under symmetric and asymmetric information using a two-sample test (11 cohorts) and report one-sided Wilcoxon-Mann-Whitney rank-sum rank p-values. I compute message traffic as the sum of limit, marketable, and undisclosed orders (in the case of opaque markets) submitted to the LOB, the total transacted volume in shares, and the number of shares per trade. I report quoted bid-ask spread for the entire trading period, for each trading cycle, and each minute. Cycles 1, 2, and 3 refer to the trading period between 1-120 secs, 121-240 secs, and 241-360 secs, respectively. The effective (realized) spread is the distance between the transaction price and the midquote (prevailing after five trades). The permanent price impact is the difference between the midquote and the midquote prevailing after five trades. (Visible) BBO depth refers to (visible) shares at best bid offer (BBO), while (visible) book depth are the (visible) shares at all levels of the LOB. Price (midquote) volatility is the standard deviation of transaction prices (midquotes). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

	Transparent			**Opaque**		
Panel A. Liquidity	No insider	Insider	p-value	No insider	Insider	p-value
Message traffic	281	294	0.409	287	318	0.448
Transacted volume	204	261	0.300	216	190	0.371
Shares per trade	1.78	2.01	0.256	1.77	1.78	0.396
Bid-ask spread	1.85	2.59	0.044**	1.60	2.88	0.004***
Cycle 1	1.97	2.16	0.235	1.73	2.48	0.004***
1-min	2.48	3.21	0.256	2.04	3.48	0.084*
2-min	1.66	1.86	0.300	1.18	2.27	0.000***
Cycle 2	1.36	2.04	0.019**	1.36	1.48	0.347
3-min	1.26	1.93	0.047**	1.27	1.43	0.041**
4-min	1.23	2.15	0.011**	1.90	1.44	0.500
Cycle 3	1.47	2.64	0.013**	1.37	2.07	0.033**
5-min	1.48	2.73	0.003***	1.32	2.45	0.057*
6-min	1.33	1.68	0.079*	1.20	1.70	0.028**
Effective spread	0.57	0.87	0.197	0.48	0.88	0.095*
Realized spread	0.34	0.60	0.300	0.27	0.70	0.106
Permanent price impact	0.12	0.44	0.235	0.19	0.31	0.256
Panel B. Depth	No insider	Insider	p-value	No insider	Insider	p-value
BBO depth	20.90	16.22	0.084*	18.87	18.71	0.235
Visible BBO depth	20.90	16.22	0.084*	17.41	12.41	0.179
Book depth	123.73	120.52	0.500	125.94	152.43	0.371
Visible Book depth	123.73	120.52	0.500	98.63	107.51	0.197
Panel C. Volatility	No insider	Insider	p-value	No insider	Insider	p-value
Midquote volatility	4.87	6.78	0.002***	4.64	7.07	0.004***
Price volatility	3.12	5.41	0.002***	2.40	4.07	0.033**