Pre-Trade Transparency and Informed Trading
An Experimental Approach to Hidden Liquidity

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Abstract

This paper proposes an experimental study to analyze trading in opaque limit order books under different informational settings with a particular focus on the sources of hidden liquidity. Previous literature attributes hidden liquidity either to large liquidity traders or informed trading. We design an asset market experiment in light of recent theory treating private information in isolation. Hence we analyze the implications of reducing pre-trade transparency under symmetric and asymmetric information. We find that both private information and liquidity concerns play an important role in hidden liquidity provision. However, we do not find major differences between transparent and opaque markets across various market quality indicators, especially when informed traders are present. Differences in traders' characteristics partly explain the heterogeneity in hidden liquidity supply. Our results suggest that even though some informed traders opt for undisclosed orders, the current trend towards darker trading venues cannot be explained only on informational grounds.

(J.E.L Classification: C91, C92, G28)

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

1 Introduction

Electronic limit order books (LOB) are becoming the norm rather than the exception in today's highly technological venues for trading financial securities. Pure LOB's are order-driven markets without designated market makers. Computerized systems coordinate liquidity demand and supply by matching orders applying precedence rules (Parlour and Seppi, 2008). In most of the modern trading venues, orders posted to LOB also include instructions specifying the degree of disclosure; the so-called *hidden* or *Iceberg* orders allow traders to limit quantity exposure by concealing a portion of the order (Cheuvreux, 2012)[1]. This feature reduces pre-trade transparency of the market, since traders face uncertainty regarding the total depth supplied to LOB.

Recent literature on hidden liquidity documents the importance of such orders; they account for a large proportion of trading activity, e.g. more than 44% of Euronext volume (Bessembinder et al., 2009), about 28% of the Australian Stock Exchange volume (Aitken et al., 2001), and 16% of executed shares on Xetra (Frey and Sandas, 2008). Yet, the sources of hidden liquidity is still controversial. Two separate views emerge regarding the types of traders and their motivation for submitting Iceberg orders. According to the first view, large liquidity traders enter markets for exogenous reasons and prefer hidden liquidity to avoid competition with other liquidity suppliers and/or to protect their orders from fast traders. If only large liquidity traders (Harris, 1996, 1997) opt for opacity, then Iceberg orders improve market quality via enhanced liquidity without any negative consequences. The second view on the other hand posits that informed traders prefer hidden liquidity to conceal private information and thus minimize the price impact of large orders. If this is the underlying reason, then opacity introduced through Iceberg orders increases informed trading and worsens information asymmetries. Thus this view highlights the potential role of hidden liquidity as a tool to obscure insider trading and price manipulation. Therefore, the source of hidden liquidity and its implications on market quality is relevant for all parties involved in

[1] By submitting Iceberg orders traders can hide only a portion of their order quantity (e.g. Euronext) whereas hidden orders can be defined as completely undisclosed (e.g. NASDAQ). But these two terms have been used interchangeably in the literature on hidden liquidity.

trading.

One way to gather information on hidden liquidity is to conduct a questionnaire with professional traders. This is our first attempt. We conduct a questionnaire with traders who have experience with Iceberg/hidden orders[2]. We ask traders to state their motivation to submit hidden liquidity to LOB. Among possible explanations, we list superior information, competition for liquidity provision, protection from fast traders against mispricing, protection from informed traders and trading around informational events (see appendix). The results are informative; there is no consensus on a single primary motive among professional traders. But, competition for liquidity provision and protection of superior information stand out as evident sources of hidden liquidity. However, one major drawback of this methodology is that it lacks a truth-revealing mechanism. Indeed, as one notices, few respondents say that they opt for hidden liquidity around informational events, a practice which raises concerns about informed trading.

Given the controversy in previous literature and problems associated with survey-type studies, we design experimental asset markets introducing incentives to trade and study market opacity through Iceberg orders both in the absence and presence of private information. Laboratory experiments are particularly appealing in this context, since private information is hard to observe and hence difficult to measure in reality. To this end, we first start with a baseline setting where we exclude adverse selection to test implications of hidden liquidity under a symmetric information environment. We contrast the opaque regime with a transparent alternative which excludes undisclosed orders. In a second treatment, we introduce private information in the experimental markets maintaining all the other features. We compare trading mechanisms under both symmetric and asymmetric information settings.

Our findings contribute to the recent debate on dark trading and have important implications for market design. In the absence of private information, opacity improves liquidity by reducing

[2] Our sample consists of traders who have on average more than 5 years trading experience in either equity and/or fixed income markets). Respondents state that they submit on average (median) 20% of their order volume as hidden, consistent with empirical evidence previously found in the literature.

quoted spreads and price impact of market orders; and hence increase market resiliency. However, in the presence of private information opacity does not have major effects on market quality[3]. On the other hand, the major impact of private information is both on quoted spreads and price volatility. Both in transparent and opaque markets, the presence of informed traders significantly increases spreads and volatility, confirming previous literature on adverse selection component of bid-ask spreads (e.g. de Jong and Rindi, 2009) and information driven volatility (e.g. Foucault, 1999).

Experimental asset markets suggest that both private information and liquidity concerns play an important role in hidden liquidity provision. This result is consistent with the questionnaire responses by professional traders. In experimental asset markets, differences in trading strategies arise in terms of price aggressiveness and submitted Iceberg order volume. Both large liquidity and informed traders submit on average more Iceberg orders compared to noise and small liquidity traders, yet there is substantial heterogeneity in Iceberg order use by informed traders; they either submit no Iceberg orders at all (56%) or provide hidden liquidity in large quantities relative to other trader types and at price levels further away from the mid-quote. This evidence sheds light on potential ways to detect informed trading via Iceberg orders, in particular by exploiting the informational content of LOB in higher price levels (Degryse, 1999; Cao et al., 2009).

Heterogeneity in trading strategies may arise for different reasons. One potential source can be differences in risk attitudes, since hidden liquidity is inherently linked to various risks such as price, exposure and execution risks. To control for differences in risk aversion across traders, we first measure individual risk aversion using Holt and Laury (2002) procedure (see appendix). Risk turns out to be an important factor in hidden liquidity provision. To check the robustness of this result, we also extract a risk measure as a principal component from the responses to various domain specific risk attitude questions (Weber et al. (2002) and control separately for trader impatience (Reuben et al., 2010). Results remain to be robust to these additional controls.

[3] A similar result has beeen documented in a recent study by Bloomfield et al. (2011).

We extend our analysis along two other dimensions for robustness check; first, to complement the trading data, we design a treatment with an auction for private information. Auction bids help us identify the relative price for private information under opaque and transparent regimes. Opaque markets do not lead to higher bids for private information, suggesting that trader do not believe that private information is easier to exploit in opaque markets. Second, we introduce a treatment with more informed traders, but main results are not sensitive to this design change.

There are few theoretical papers on hidden liquidity[4]. In a recent paper, Buti and Rindi (2009) study the optimal order strategies in a dynamic LOB allowing Iceberg orders; in their model risk neutral traders take simultaneous strategic decisions on price, quantity and exposure conditional on the state of the LOB and their private valuation of the asset. Buti and Rindi model extends both Parlour (1998) and Foucault (1999) models, where the authors abstract from private information. In equilibrium large traders submit hidden liquidity to electronic LOB for two different motivations, namely to avoid competition for liquidity provision and/or being *picked off* by fast traders in case of a public information shock. The former refers to a situation where a competitor would undercut a large limit buy (sell) order via sending a limit buy (sell) order at a slightly higher (lower) price (typically by the minimum tick size) and thus gain price priority[5]. Iceberg orders help to prevent undercutting by hiding order quantity. In the latter case, supplying hidden liquidity would complicate detection of mispriced orders (e.g. due to new information arrivals) that are likely to be exploited by scalpers. In one of the earliest studies, Aitken et al. (2001) analyze 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)[6] and hence to protect themselves from parasitic traders. Recent papers (Bessembinder et al., 2009; Pardo Tornero and

[4] We present here two discrete time models that provide justification for the use of Iceberg orders as a trading strategy in equilibrium. Alternatively, there are continuous time models (e.g. Esser and Mönch, 2007) that focus on the trade-off between optimal limit and peak size of an Iceberg order. In these models, Iceberg orders are seen as a substitute for order split and used to eliminate potential adverse price impacts of large orders.

[5] This strategy is also termed as front-running or quote-matching (Harris, 1996).

[6] Copeland and Galai (1983) interpret buy (sell) limit orders as put (call) options provided to other market participants.

Pascual, 2011) confirm previous evidence that traders use Iceberg orders to manage exposure and picking-off risk. Other empirical studies (De Winne and D'Hondt, 2007; Frey and Sandas, 2008) also do not find any impact of private information on hidden liquidity provision.

Moinas (2008) proposes the first theoretical model with private information to analyze the effect of Iceberg orders on market performance and traders' welfare[7]. She builds a sequential and discrete model of trading with incomplete information and concludes that hidden liquidity is part of the informed (insider) agent's equilibrium camouflage strategy. Her analysis supports the idea that Iceberg orders are driven by informational concerns, i.e. not revealing private information to market through large orders which are likely to have price impact. Anand and Weaver (2004) show evidence from Toronto Stock Exchange that informed traders use hidden liquidity to minimize price impact if the trading activity is high. Recent studies (Belter, 2007, Kumar et al., 2009) also document evidence supporting the hypothesis that the use of Iceberg orders may be information-driven.

Overall, previous literature on Iceberg orders is far from being conclusive. Given the controversy, experimental asset markets are intrumental in testing the main theoretical predictions on hidden liquidity and compare the results obtained from empirical studies (Sunder, 2008)[8]. In this respect, this study contributes to the recent experimental market microstructure literature (Bloomfield and O'Hara, 1999, Bloomfield et al., 2005, 2009, 2011, BOS, henceforth; Biais et al., 2005; Perotti and Rindi, 2006) and complements previous theoretical and empirical findings.

The paper proceeds as follows. Section II introduces experimental design. Section III describes statistical analysis and reports the findings. Section IV provides robustness analysis. Last section concludes.

[7] A recent version of the paper (Moinas, 2010) extends the model allowing the large uninformed traders to submit Iceberg orders.

[8] There is also an extensive experimental economics literature on financial markets with a different focus, e.g. double auction mechanism, investor rationality, information aggregation, price bubbles, etc. (Smith, 1962; Smith et al.,1988, Haruvy et al., 2007, see the review by Sunder, 1995).

2 The Experiment

We design the experiment in light of recent theories on hidden liquidity. In particular, we test the consequences of additional opacity introduced via Iceberg orders on market quality both under symmetric and asymmetric information settings. Thus, our design allows us to separate the implications of adverse selection from the lack of pre-trade transparency. There are two main treatments; a) Symmetric information, b) Asymmetric information and two additional treatments with auctions for private information and more informed traders.

In the *symmetric information* treatment; trading is abstracted from motives related to private information. Information structure is common knowledge, hence there are no informational advantages across traders. According to the Buti and Rindi model, in this treatment we should observe hidden liquidity due to competition for liquidity provision and/or protection from fast traders after public information releases. The *asymmetric information* treatment introduces adverse selection in the market via a single insider with superior information. This treatment is closer to the environment envisaged by Moinas' theory which suggests informational concerns behind hidden liquidity[9]. To test the sensitivity of our results to a single monopolistic insider, we also conduct a treatment with two informed traders in each market.

Finally as a direct test on the relative importance of Iceberg orders in the presence of private information, we introduce a treatment with a market for private information, where markets under asymmetric information are preceded by second price sealed bid (Vickrey) auctions. We use submitted auction bids to measure the relative price of private information under both transparent and opaque regimes. Thus, we can extract information on the perceived importance of Iceberg orders to exploit private information without relying on trading data.

[9] We refer to Moinas' model to convey the intuition in an environment with an informed trader. Yet, it is not a counterpart for Buti and Rindi's model, since she does not directly incorporate the dynamic interaction with LOB. Other models in the literature (e.g. Rosu, 2008, Goettler et. al., 2009) capture this feature, but do not allow for Iceberg orders.

2.1 Experimental Asset Markets

In this section we describe the experimental design in detail[10] and introduce the main features of experimental markets. An experimental asset *market* is defined as a six-minute trading period. Traders (in *cohorts* of 6-7-8 traders) attend a sess*ion* under a particular treatment which consists of a series of experimental markets (*replications*). We introduce a within cohort transparency manipulation; in all sessions under different treatments, traders attend both markets under *transparent regime (3-4 replications)* with no Iceberg order option, and under *opaque regime (3-4 replications)* with Iceberg order option. Iceberg 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 only a single security ($E[v^S_{0-180}] = 45$, see Table 1) is traded. Trading starts with an empty book. Traders are endowed with different amount of cash and a number of securities depending on the trader type (see the section below), but total initial endowment of each trader is the same in expectation. Cash and securities are given as a grant, i.e. not subtracted at the end from final cash balances, so that no-trade can also be considered as a strategy[11].

2.1.1 Information Structure

Trading starts with three initial states[12]; a single security has either $\{L, M, H\}$ level of liquidation value with equal probability and satisfying $M - L \neq H - M$. The distribution of the liquidation value is common knowledge to all traders and known before trading starts. In the middle of the trading period (t=180 sec), we release public information regarding the fundamental value of the security; the mean value of liquidating dividends either moves up ($E[v^S_{181-360}] = 55$) or

[10] Instructions are available at http://www2.warwick.ac.uk/fac/soc/wbs/subjects/finance/faculty1/arie_gozluklu/research/

[11] Even though traders start with endowments, this does not reflect a inter-dealer market, since they are not required to submit two-sided quotes. Traders can simply provide or demand liquidity taking one side of the trades. This feature is different than dealership mechanism.

[12] Alternatively, one can also introduce a security with continuous distribution, e.g. a uniform distribution similar in BOS (2005). We opt for a three-state design (Plott and Sunder, 1988) in order to simplify already complicated trading mechanism.

down ($E[\mu^S_{181-360}] = 35$) by \$10. This can be interpreted as an *earnings announcement* about the security traded (Chakrabarty and Shaw, 2008). The equal time span before and after the public information release allows us to compare the evolution of hidden liquidity before and after the shock.

Insert here Table 1

2.1.2 Trader Types

Before each market opens, we randomly assign trader types to each participant. There are three different trader types in symmetric information sessions; traders with no trading targets, we label them as *noise traders* [13], traders with small trading targets and traders with larger targets (BOS, 2005, 2009). Trading targets are defined per two-minutes cycles to keep types stable over relatively long trading periods, but the direction of trading targets (i.e. buy or sell) remains the same during the whole period. Thus, there are three trading cycles in each market; two or three noise traders with no trading targets, two liquidity traders with small targets (i.e. one buy or one sell target of 8 shares per cycle) and two with large trading targets (i.e. one buy or one sell target of 20 shares per cycle), i.e. most impatient liquidity traders. This symmetric design implies zero aggregate net liquidity demand in experimental markets. Traders who have trading targets are subject to a large punishment (\$1000) which is subtracted from their end-of-period payoffs for not fulfilling their trading obligations[14]. Hence we introduce heterogeneity among uninformed traders using trading obligations, a standard technique in experimental literature (Bloomfield and O'Hara, 1999; BOS, 2005) to capture the idea that liquidity traders are transacting for exogenous reasons related to the need to invest or to liquidate positions. Moreover, having liquidity traders with differing trading obligations help us capture the private valuation parameter (β_t) in theoretical models.

[13] Noise traders start with \$4000 and 75 shares. Since these traders are given a large amount of cash and shares as grant, they do not have exogenous reasons to trade and yet can make substantial profits.

[14] We do not allow partial fullfilment of trading targets; the same punishment applies even if the trader fails her (his) target by one share.

In asymmetric information sessions, we replace a noise trader with an informed trader who does not have any trading obligation, but knows ex-ante the true state of the world before the trading period starts. This gives informational advantage to the informed trader until public information release and (s)he knows the true value of the liquidating dividend after the informational event, i.e. informed trader becomes an insider after the public information release. Presumably this substitution affects both the supply and demand of liquidity in both treatments. To see the marginal impact of adverse selection, in each market under asymmetric information treatment, there is only one privately informed trader which keeps the concentration of informed traders at a minimum. In a further treatment as a robustness check, we also report results for markets with more than one informed trader.

2.1.3 Trading Mechanism and LOB

The trading mechanism is exactly the same under all treatments. Traders attend markets under both transparent and opaque regime in a random order. In transparent markets, traders can post limit orders specifying the price, $p \in \{1, .., 90\}$ and the quantity $q \in \{1, 2, ...9, 10\}$[15] and submit market orders[16] stating only the quantity to hit outstanding limit orders. Limit orders reduce the price risk at the expense of execution probability, while market orders guarantee execution introducing price risk. In these markets, first price and then time priority rules apply; orders that improve trading price, i.e. 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 Iceberg orders, i.e. they can choose to hide their orders, but a predefined portion of the order (peak size=1) remains visible

[15] Traders can submit block trades at once up to 10 shares. This gives us the flexibility to study larger trade sizes (Easly and O'Hara, 1987). Moreover, submission of different order sizes is crucial to study competition for liquidity provision (Buti and Rindi, 2009).

[16] These are market orders that cannot walk up the book, i.e. if the market bid (ask) order quantity is greater than the quantity at best limit ask (bid), the remaining quantity after execution remains on the same side of the book.

in the LOB. In this case, first price, then visibility and finally time priority rules apply; orders that improve trading price, i.e. 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 which are visible are executed first, while the hidden part of Iceberg orders looses time priority against visible limit orders that arrive later in the book. The visible part of the Iceberg orders, which is equal to peak size, does not loose time priority against other limit orders posted at the same price. Every time the visible part is executed, another unit equal to peak size becomes visible until the entire order is executed (see the example in Appendix A).

In both markets, orders can be cancelled any time during the trading period. All price levels are shown on the screen (see Appendix B for trading interface). All bids and ask prices are integers, hence the tick size d is one experimental currency unit (BOS, 2005). We impose short sale restrictions and bankruptcy conditions[17], but traders are allowed to trade on margin, i.e. a trader cannot sell shares s(he) does not own, but as long as (s)he has enough shares on her/his account, cash account can go negative until bankruptcy condition becomes binding.

2.1.4 Participants and Incentives

We test the experimental design with several subject pools and different incentive schemes; we first run four paid pilot sessions (i.e. four cohorts, n=24) with Tilburg University students at CentER lab. Tilburg University students are recruited through CentER subject pool which is a mixed pool including undergraduate, graduate and PhD students. Pilot sessions last 2,5 hours and participants are paid 25 Euros on average. All Participants start with some cash and security endowment and the interest rate is zero. The initial endowment is the same (among the same trader types) at the beginning of each trading period, i.e. trading gains from one period are not transferred to other periods, but recorded to calculate cumulative payoffs. Traders' earnings in each market is the liquidation value of the asset they hold at the end of the trading period, plus the

[17] However, since traders are endowed with enough cash and securities, this condition is rarely binding.

capital gains (losses) obtained through trading of assets minus the fixed penalty for not fulfilling each trading target. Participants are paid according to their end-of session wealth (cumulative across trading periods except training + real payoffs from binary lottery choices). All price and values are denominated in laboratory currency and converted in Euro at the end of experiment using an exchange rate that guarantees on average 10 Euros per hour. Participants are told the explicit formula used to compute their payoffs to ensure that they unambiguously understand the incentives and how they relate to trading.

Questionnaires after the first pilot sessions reveal that participants have difficulties in understanding the trading mechanism with Iceberg orders. Moreover participants lack the time and extensive training to develop trading strategies. To overcome this problem, we design a longitudinal study with students who have basic knowledge on the functioning of security exchanges. We run a two- month pilot study with PhD students (n=6) who follow Market microstructure course as PhD course requirement. The performance in the trading experiment determines 15% of their course grade. We use these sessions to test the sensitivity of parameter values and to link between traders' performance and their course grade. The actual sessions are conducted at Bocconi University with undergraduate students (n=72) who attend a series of market experiments as a part of the market microstructure course requirement in 2009 (n=31) and 2011(n=41). We choose this subject pool since it resembles most the professional trader pool. The whole population of the study consists of undergraduate students who are following market microstructure course. In 2009, we present the experiment as an opportunity to increase the course grade (up to 20%)[18]. Thirty one students apply for the experiment and commit themselves to attend a series of sessions for a month during the exam period[19]. In 2011, we replicate the same experiment, but this time introducing an av-

[18] Participants obtained 0-3 points (Students are graded in scale of 30 points at Bocconi University, a student needs 18 points to pass the course) based on their cumulative performance in all actual trading sessions. The results, highlighting the best trader of the week were also posted on the experiment website after each session to exploit *reputation effects*.

[19] The use of course grade as an incentive scheme is controversial in experimental economics. Yet, given the longitudinal nature of our experiment, grades provide a better scheme to guarantee commitment for an extended period. Moreover, this incentive mechanism has the advantage of introducing the possibility of *loss*, i.e. obtaining no points after attending one month of trading sessions (Kroll and Levy, 1992).

erage payment of 12.5 Euros/hour on top of the bonus course grade[20]. In our analysis we report the aggregate results for both experiment controlling for potential differences between two subject groups, e.g. different exposure to course material.

The subjects first attend a lab session for the introduction of instructions and trading rules, it lasts 90 minutes and participants have extensive training with the trading interface. They attend a second online training session to improve familiarity with trading rules and develop trading strategies. In the last three online sessions, participants trade under three different treatments, i.e. symmetric markets, asymmetric markets, auction for private information (2009) or asymmetric information with multiple insiders (2011). Each time participants have to trade in a different cohort, but against traders with the same experience level. Traders' grade and monetary payoff depends on the cumulative performance in all actual trading sessions.

2.1.5 Trader Characteristics

An interesting inquiry is whether traders' behavior in general and submission of Iceberg orders in particular depends on individual differences among traders. Even though all the participants (N=72, male=47, female=25) have a similar background in terms of education and knowledge about finance, there may be other differences that affect trader behavior. In particular, heterogeneity with respect to risk attitudes may play an important role in hidden liquidity provision, since price, exposure and execution risks are crucial determinants of quantity disclosure. To account for individual differences in risk attitudes, we measure individual risk aversion of the participants using the Holt and Laury (2002) procedure. Holt and Laury test is designed as a menu of binary lotteries (see appendix) where participants choose between two gambles for each binary lottery; one *safe* gamble with small payoff difference ($6750 vs. $8000) and one *riskier* with higher payoff difference ($1250 vs. $15000). For example, for *Decision 1* a participant should choose between the *Option A* and *Option B* which deliver $6875 and $2625 in expectation, respectively, while for Decision 10

[20]With a maximum (minimum) payment of 60 (15) Euros.

Option B delivers \$15000 with certainty compared to \$8000 from Option A.

Most participants start with Option A and switch to Option B depending on their risk aversion as they move down the choice list. Hence degree of risk aversion is measured on a scale of $\{1, ..10\}$, where 1 refers to extreme risk loving behavior and 10 to extreme risk aversion. Traders receive payoffs based on one randomly selected draw from their ten decisions which are added to the final trader payoff. We use the same instructions as in the original study except that the payoffs are expressed in the same experimental currency used in actual trading[21].

Clearly, subjects' behavior towards risk is a fairly complex process and a simple lottery may not capture the entire picture. There is psychological evidence that risk attitudes may differ in content domains such as financial decisions (Weber et al., 2002). We take this into account by asking domain specific survey questions (see appendix) to our participants following Weber et al. (2002). Another important parameter in the theoretical models (Buti and Rindi, 2009) which describe opaque LOB, is the private valuation (β) is of the traded securities. In our experiments, exogenously determined trader types capture differences in private valuation. However, private valuation of the security is hard disentangle from traders' impatience. In our recent experiment, we elicit subjects' time discounting and measure traders' impatience towards monetary payoffs using a procedure suggested by Reuben et al. (2010) as explained in appendix E.

3 Results

In this section, we analyze the aggregate results from the experiments conducted with undergraduate students. We conduct statistical analysis both at market and individual subject level. First, we follow a non-parametric approach (Hollander and Wolfe, 1973; Kvam and Vidakovic, 2007) to avoid distributional assumptions. We treat each cohort as a single independent data point averaged over different replications. At market level, we compare within and between cohort differences with respect to market quality and report Wilcoxon signed rank p-values for paired samples and

[21] We thank Rosemarie Nagel for this suggestion.

Wilcoxon-Mann-Whitney rank-sum p-values for two sample analysis, respectively. At individual level, we aggregate dependent variables for each trader under relevant treatment and run a pooled panel regression analysis.

In order to calculate market quality measures, we follow an algorithm that merges orders from LOB with transaction data from transaction book. We collect all submitted limit, market and Iceberg orders submitted on a tick-by tick basis. We reconstruct the LOB for outstanding orders using the following algorithm; first we record all the entries entering within a time interval (to the nearest second), we clean the first interval for transactions and cancellations and then restart the loop from the second interval, copy outstanding limit (and Iceberg) orders from the previous interval and check whether any transactions or cancellations occurred in the new interval that entered the book in previous intervals and update it. We repeat the procedure for all intervals. Thus, we obtain snapshots of the LOB for each second which allows us to calculate all depth related measures in all price levels of LOB.

We calculate a list of market quality indicators to compare experimental markets under different transparency and information regimes. We focus on various trading dimensions; market activity, price impact, volatility and market liquidity. We measure *trading activity* by the total number of limit and market orders (and Iceberg orders under opaque regime) submitted to the LOB, *average trade size* by the number of shares traded in a transaction and *trade duration* by the time elapsed between two consecutive transactions. As volume related measures we compute *liquidity supply*, i.e. submitted limit order shares and limit plus Iceberg order shares under opaque regime, *submission rate*, i.e. liquidity supply over total submitted shares, *liquidity demand*, i.e. submitted market order shares and *taking rate* as liquidity demand over total submitted shares. Market liquidity is further measured by total *transacted volume* (shares), quoted *depth at BBO* (Best Bid Offer), total quoted depth (in all price levels of LOB, labeled as *book depth*) and by implicit transaction cost measures such as quoted *Bid-Ask spread*, i.e. the spread between the best quotes, $A_1 - B_1$, total price impact of market orders (BOS, 2009), i.e. for a buy (sell) order is defined by $P_t - M_t(M_t - P_t)$

, where P_t, M_t are the transaction price and the mid-quote, respectively. Finally, we measure price volatility (sample estimate of standard deviation of prices) using both transaction *price volatility* and *mid-quote volatility*.

3.1 Overview: Order Submission

In order to better understand the dynamics of LOB in opaque markets, we plot the time evolution of submitted shares of different order types. Figure 1 shows how liquidity supply and demand evolve over time in symmetric and asymmetric markets. We aggregate data from different markets and across cohorts over 24 fifteen-second intervals and compute the average values.

Insert here Figure 1

Both figures reveal some important facts regarding the functioning of opaque markets. First of all, since traders start with an empty book, we observe high accumulation of liquidity supply at the beginning of the period when the book builds. Submitted limit order shares are uniformly higher relative to Iceberg order shares over the whole trading period. The series shows a downward trend in the whole period exhibiting cyclical spikes coinciding with trading targets and there is a sharp decrease in liquidity supply around the public information release. Liquidity demand via market orders is more stable during the trading period. Market order volume is in general below the supplied liquidity, except right after the public information release and at the end of the period where traders close their positions. The sudden spike after the information release suggests that some traders respond very rapidly to the information shock, virtually acting as scalpers in these markets[22]. Hidden liquidity shows a stable pattern at lower levels and decreases over time which is consistent with the fact that Iceberg orders lose time priority in execution.

In asymmetric markets, one major difference we notice is larger swings in order submission across time, especially in Iceberg order submission. Next, we plot separately each order type in both symmetric and asymmetric markets. First panel of Figure 2 shows that on average more limit shares

[22] Cancelled volume also increases after the information release consistent with fast trading behavior.

are posted in asymmetric markets, a pattern stable over time. Higher liquidity provision can be either due to informed trading or increased competition between informed and liquidity traders, or both. Liquidity demand, on the other hand, is highly volatile around the public information release. In the second panel of Figure 2, we notice the sharp decline in market order submission just before the information shock, which is more pronounced in symmetric markets. But the reaction after the shock is even a steeper spike in asymmetric information markets suggesting aggressive informed trading. Iceberg shares both in symmetric and asymmetric markets show a similar pattern before the information release; they start at a high level followed by gradual decline until the information shock. After the shock, as last panel reveals, traders submit more Iceberg shares in asymmetric markets with eventual convergence at the end of the trading period. All in all, these figures indicate a change in the trading behavior related to information, especially in the second half of trading. In the following sections, we conduct formal statistical analysis to see whether information plays a significant role.

Insert here Figure 2

Finally, we also compare liquidity supply and demand in transparent and opaque markets. In particular, we plot the time evolution of submitted limit and market shares under different transparency regimes. Data aggregated over both symmetric and asymmetric markets reveal that on average more limit shares are sent to LOB in transparent markets, while market shares closely track each other both in transparent and opaque markets. Presumably, the availability of Iceberg option explains the reduction in limit order supply in opaque markets, rather than a reduction in liquidity supply. Next, we move to formal tests of differences in various market quality measures across different transparency regimes and information treatments.

Insert here Figure 3

3.2 Market Quality

It is an important regulatory concern whether reducing pre-trade transparency affects market quality[23]. Hence, we now turn to the analysis of changes in market quality due to lack of pre-trade transparency introduced via Iceberg orders. We compare the implications of opacity under both symmetric and asymmetric information settings. We measure market quality using different metrics mentioned in the previous section. In this section, we treat each cohort as an independent data point and average the data over different market replications in the same cohort under the same manipulation (opaque versus transparent), and conduct a non-parametric Wilcoxon signed-rank test to analyze within cohort differences in paired samples under different transparency regimes. Both the order of securities and direction of the shift in fundamental value are randomized across replications and over different manipulations. Table 2 reports the median values of different market quality measures under transparent and opaque regimes both for symmetric and asymmetric information treatments. We report Wilcoxon p-values (the null hypothesis is that there are no differences in median values). Asterisks *, ** and *** indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Insert here Table 2

In symmetric information markets, the lack of transparency due to Iceberg orders mainly affects the price impact of the market orders; the use of Iceberg orders significantly reduces total price impact (p-value=0.016) and hence increases market resiliency. Positive effects on liquidity are also visible on implicit transaction costs, i.e. average bid-ask spread decreases significantly (p-value=0.021). In asymmetric information markets, however, opacity does not have significant effects on market quality. The latter result is consistent with the experimental findings of BOS (2011) in a different setting. Our findings suggest that it is important to control for information asymmetries to assess the usefulness of Iceberg orders. In markets where private information is

[23] There is also an extensive academic literature on the topic (see, for example, the survey by Foucault et al., 2010).

not a major concern, e.g. markets with less institutional traders, reducing pre-trade transparency improves market quality and benefit liquidity traders. On the other hand, in the presence of informed traders, it is not clear whether enhanced opacity has any positive effects on market quality.

Another important question is whether adverse selection has different effects under different transparency regimes. In Table 3 we analyze the impact of private information on market quality under both transparent and opaque treatments. We measure market quality using the same metrics mentioned above. We treat each cohort as an independent data point as before and average the data over different market replications in the same cohort under same treatment (symmetric versus asymmetric information) and conduct a non-parametric (two-sample) Wilcoxon-Mann-Whitney rank-sum test to analyze between cohort differences in two samples. We report the median values of different market microstructure measures comparing symmetric and asymmetric information treatments under both opaque and transparent regimes.

Insert here Table 3

One of the major impacts of private information is on price volatility and bid-ask spreads both in transparent and opaque markets. In transparent markets, the presence of an informed trader significantly increases both transaction price volatility (p-value=0.001), midquote volatility (p-value=0.002) and bid-ask spread (p-value=0.044). Similarly, in opaque markets price volatility (p-value=0.033), midquote volatility (p-value=0.003) and bid-ask spread increase significantly (p-value=0.004). The presence of an insider also increases total price impact both in transparent and opaque markets (p-value=0.054 and p-value=0.018, respectively) as one would expect. These result confirms previous literature findings on information driven volatility (e.g. Foucault, 1999) and adverse selection component of bid-ask spreads (de Jong and Rindi, 2009). Therefore, we conclude that irrespective of the transparency regimes, information asymmetries exhibit detrimental effects on liquidity.

3.3 Trader Behavior

We rely on subject-level analysis to analyze differences among trader types in terms of trading strategies. First, we shall verify that exogenously manipulated trader types lead to differences in trading behavior arising from different trading motivations. We aggregate each dependent variable over participants and test whether same participants behave differently under randomly assigned trading roles. We label traders without trading obligations as *noise traders*; given their high level of initial endowment these traders have no exogenous reason to trade. We introduce *liquidity traders* by assigning trading targets (small and large) and *informed traders* by providing superior information to a subset of traders before markets open. To the extent that we are able to induce different trading roles, we should observe differences in trading behavior, in particular with respect to liquidity demand and supply over the trading period.

Insert here Table 4

In Table 4 we report the average number of shares (standard deviations in parentheses) of different order types, i.e. limit, market and (marketable) Iceberg orders[24], submitted by each trader type. We also introduce three measures of *aggressiveness* for liquidity supply, i) number of orders submitted to the first level of the book, i.e. at BBO, ii) the number of orders that improve prices (undercutting), i.e. orders submitted inside the Bid-Ask spread and iii) Iceberg order aggressiveness measured by the average distance of Iceberg orders to the prevailing midquote (Bessembinder et al., 2009). We aggregate the data by each individual trader in opaque markets and average by trader type. We report significance based on paired sample t-tests (Wilcoxon signed ranked p-values for $n<30$) comparing the trading behavior across different types.

In our experiments, we impose liquidity traders' behavior using trading targets and control private valuation of the trader by the target size. We expect large liquidity traders to be the most impatient traders, either demanding liquidity through market orders and/or competing aggressively

[24] Marketable Iceberg orders are immediately executed upon arrival to the market.

for liquidity supply. Table 2 is consistent with this prediction. Large liquidity traders submit significantly more orders relative to small and noise traders both in symmetric and asymmetric markets. They also send more shares to the top levels of the LOB, i.e. BBO, and improve prices more often suggesting aggressive trading. Large liquidity traders send Iceberg orders on average to higher levels of the book, but the differences are not significant.

Another interesting question is regarding the behavior of informed and liquidity traders in terms of liquidity demand and competition for liquidity supply. Traditionally, informed traders are associated with short-lived information and hence perceived as impatient traders who would like to exploit informational advantages as fast as possible. But, recent literature (BOS,2005; Kaniel and Liu, 2006; Rindi, 2008) suggests that informed traders can also contribute substantially to liquidity supply in particular when the information is sufficiently persistent. One important aspect of hidden liquidity is that it increases the life of private information by decreasing pre-trade transparency. Therefore, in opaque markets we expect some evidence supporting theories that suggest informed liquidity supply.

In terms of submitted shares, we do not observe significant differences between large liquidity and informed traders. In other words, informed traders are as active as large liquidity traders in both liquidity demand and supply (Menkhoff et al., 2010), including hidden liquidity. This evidence suggests fierce competition (race to trade, Holden and Subrahmanyam, 1992) between two trader types for liquidity provision. However, as far as aggressiveness is concerned, informed traders submit significantly less limit orders to both BBO and inside spread. Moreover, they submit Iceberg orders to significantly lower levels compared to large liquidity traders. Even though this evidence provides some hope to detect informed trading by chasing Iceberg orders at lower levels (Degryse, 1999), one challenge is that we observe substantial heterogeneity among informed traders which makes it more difficult to detect informed traders among noise and other liquidity traders.

3.4 Make or Take

Liquidity demand and supply decision, *make or take* decision (BOS, 2005) by traders is an important concern both for market participants, in particular sell-side institutions who provide exchange services. Modern trading platforms offer incentive mechanisms, such as rebates and fees, to attract more liquidity to their venues. Ultimately, the decision to provide or consume liquidity determines the overall market quality. In this section, we run pooled (across traders and markets) panel regressions to test the main determinants of such decisions in our experimental markets. In particular, we consider submission rate (SR), taking rate (TR) and hidden rate (HR), submitted Iceberg shares over total shares as dependent variables.

We report results separately for both aggregated data and 2011 experiment where we tested additional control variables. As independent variables, we include *asymmetric,* a dummy variable that takes 1 if market is under asymmetric information treatment and 0 otherwise, *trader type*, which different values for noise, small liquidity large liquidity and informed traders, an additional *informed* dummy, which takes 1 if the trader is informed and 0 otherwise, *HL risk,* Holt and Laury (2002) risk aversion measurement, gender dummy, that takes 1 for make and 0 otherwise. Moreover, we control for the *cohortsize,* since number of traders in a cohort varies between 6 and 8, and for the *year,* whether the experiment is conducted in 2009 or 2011. In our recent experiment, we also extract a *risk pc*, first principal component extracted from responses to seven questions in different financial risk domains (Weber et al., 2002). The latter variable is coded in a way such that higher values indicate more risk loving behavior. Finally, we also control for trader *impatience* based on time discounting elicitation mechanism proposed by Reuben et al. (2010).

Below, we report the pooled panel regression coefficients. The reported p-values are based on Driscoll-Kraay (1998) standard errors robust to general forms of cross-sectional (spatial) and temporal dependence The first three columns relate to aggregate results. We first note that trading under an asymmetric information environment affects both liquidity supply (SR) and demand (TR). However, this result is not confirmed by the new data. On the other hand, decision to hide seems to be only weekly related to asymmetric asymmetries[25]. Trader types strongly affect make or take decision. Submitted limit shares are higher for more impatient traders, however, the portion of limit shares over total submitted shares is lower for traders with higher private valuation, i.e. impatient traders such as liquidity traders. The opposite is true for liquidity demand. Higher portion of market shares are submitted by more impatient traders. While submitted Iceberg shares are higher for more impatient traders, the result is not significant for HR. Merely being informed does not change the trading decision, once we control for trader type[26].

Insert here Table 5

An interesting result is related to risk aversion. Individual risk aversion measured by Holt and Laury test[27] is positively (negatively) related to liquidity supply (demand). This result suggests that more risk averse traders prefer to limit price risk once we control for both private valuation and impatience. On the other hand, risk aversion is negatively related to hidden liquidity provision. Presumably, risk averse traders are more concerned about execution risk, since Iceberg orders lose time priority against other limit orders at the same price. The results are consistent once we add risk pc as an additional control[28]. Both variable appear significant in all regressions with opposite sign, suggesting that they capture different risk dimensions. The results are also robust once we include the impatience control. The latter variable is not significant in SR regression, but positively related to liquidity demand and negatively related to hidden liquidity as one would expect. Finally, gender does also seem to be significant in all regressions (except in HR_{2011}), suggesting that male traders are more likely to demand liquidity by sending aggressive market orders, while female traders offer liquidity by submitting limit orders.

[25] A separate regression of Iceberg shares, rather than HR reveal no significant coefficient. This suggest that significance at 10% level is mainly driven by increased total number of shares (denominator in HR) under asymmetric information.

[26] Once we exclude trader type, informed becomes significant.

[27] HL test is incentive-compatible, since the payoffs are actual added to the trader account and determines the final payoffs.

[28] HL risk and risk pc have a very low correlation ($\rho = -0.02$).

3.5 Trader Welfare

Welfare analysis is often very difficult, especially in an empirical study. One major advantage of our experiment is that we observe the individual trader payoffs in each market. Hence, we are able to study how trader welfare is determined by individual trader behavior and characteristics under several controls. In this section, we run panel regressions (both for pooled and recent 2011 experiments) of trader payoff on explanatory and control variables considered in section 3.4. Additionally, we test how the make/take and disclosure decisions affect trader welfare in opaque experimental markets. The only additional control is *punish*, a dummy variable which takes 1 if a trader cannot fulfill the trading obligation in a particular market and 0 otherwise. As one would expect, this variable is highly significant and negative, suggesting that those liquidity traders who cannot meet trading targets left the market with substantially less money. Another expected result is that informed traders on average earn more than the other trader types. In our experimental markets, informed traders have a clear advange since they know the true fundamental value and it seems that they are able to exploit asymmetric information despite the short sale contraints[29].

Insert here Table 6

Interestingly, providing liquidity by submitting limit order shares results in reduced trader welfare. This result is in line with the *sitting duck* argument (Copeland and Galai, 1983) that limit orders provide free options to other liquidity consumers and justifies the use of liquidity rebates offered by several trading venues (Foucault et al., 2012). Importantly, opting for Iceberg orders does not increase trader welfare. On the contrary, in the pooled sample, submitted Iceberg shares significantly reduce trader payoff. A similar coefficient is obtained in the recent experiment, but it is not statistically significant.

[29] Given the initial endowments, these contraints were binding only in few cases.

4 Robustness

We conduct robustness check along two dimensions; i) in the third treatment of 2009 experiment, we create bidding markets for private information before entering each trading period, ii) in the third treatment of 2011 experiment, we introduce markets with two informed traders replacing another noise trader. Markets for private information are designed as a second price sealed-bid auction (Vickrey auction). Before markets open, each participant sends a sealed bid to the experimenter, i.e. an amount in experimental currency to be the informed trader. The trader who submits the highest bid becomes the informed trader in the next market, i.e. knows ex-ante 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[30]; for the sake of illustration, let's assume that there are two traders, $t_1(she)$ and $t_2(he)$. Suppose that t_1 bids below her valuation $v_{t1} > b_{t1}$, if t_2 bids higher than her valuation $b_{t2} > v_{t1}$, then she will not be the insider so bidding up to her valuation v_{t1} will not harm her. If her bid is higher $b_{t2} < b_{t1}$, then she will be the insider and again bidding up to her valuation will not change anything since she pays b_{t2}. However, if $b_{t1} < b_{t2} < v_{t1}$, then by bidding lower than her valuation, she cannot be the insider whereas by bidding the true valuation $b_{t1} = v_{t1}$, she becomes the insider by paying b_{t2}. On the other hand, bidding more than the private valuation, $b_{t1} > v_{t1}$ is never a good strategy, especially if $b_{t1} > b_{t2} > v_{t1}$ where trader 1 ends up paying higher than her valuation.

Our aim is to measure relative valuation of private information under opaque and transparent markets. If Iceberg orders are primarily used for hiding private information, we would expect higher valuation for private information in opaque markets, because it can be better exploited via Iceberg orders. This can be seen as a direct test on the role of hidden liquidity in the context of private information without relying on trading data. We average bids over replications at individual level (n=31) and obtain two average bids per trader both for opaque and transparent markets. We

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

conduct paired sample Wilxocon signed rank test to see differences in personal valuation under both regimes. Even though the mean value paid for private information in opaque markets is slightly higher than the one in transparent markets $\mu^{PIbid}_{opaque} = \$1182 > \mu^{PIbid}_{transparent} = \$1056$, this difference is not statistically significant (n=31,Wilcoxon p-value=0.231)[31]. All in all, indirect evidence from the private information auctions does not support information-based arguments behind Iceberg orders.

Our second robustness check relates to the number of informed traders under asymmetric information treatment. The results reported so far rely on monopolistic informed traders in our experimental markets. One can argue that competition between informed traders may lead to different market outcomes which would not arise in a market with a single informed trader. To alleviate this concern, we repeat the same analysis in section 3.2, analyzing the implication of both pre-trade transparency and asymmetric information, separately. Table 7 confirms the results from Table 2 that under asymmetric information, we do not observe major differences (except the increase in book depth in opaque markets) in market quality by reducing pre-trade transparency. Similarly, results in Table 8 are similar to the ones in Table 3 except that we observe higher liquidity supply and faster trading in opaque markets under asymmetric information, due to increased competition across informed and liquidity traders. Finally, a comparison between asymmetric markets with a single and dual informed traders confirm that the major results are not sensitive to the number of informed traders.

Insert here Table 7/8/9

5 Concluding Remarks

The complex nature of financial markets and sophisticated trading strategies of market participants conceal the real motivation of traders submitting hidden orders and thus its implications

[31] As a robustnes check we also conduct two sample Wilxocon sum rank tests with first bids in both opaque and transparent markets, results remain similar ($\mu^{PIbid}_{opaque} = \$714 > \mu^{PIbid}_{transparent} = \$645$, p-value=0.165).

on market quality. We conduct a series of asset market experiments with undergraduate students to analyze (the lack of) pre-trade transparency under different informational settings. We note that conclusions regarding the effects of Iceberg orders on market quality largely depend on the informational structure of the market. We find that limiting pre-trade transparency can be beneficial for securities, e.g. large firms and bonds, that are less subject to private information, while in markets with a potential for asymmetric information, e.g. higher institutional participation, small firms, Iceberg orders do not necessarily improve market quality.

In line with the previous literature we also observe that traders' use of hidden liquidity varies substantially across markets and trader types. Traders use Iceberg orders with different motivations; some to protect private information others for liquidity reasons. We report differences in trading strategies in terms of Iceberg order use in the presence of private information. Detection of informed trading is a challenging task, but markets provide some hints by closer inspection; unusually large hidden volumes on lower levels of the book and around informational events can signal trading related to insider information. We observe that informed traders participate substantially in liquidity supply confirming the previous experimental study by BOS (2005). Active participation of informed traders to liquidity provision suggests that we can extract more information from electronic LOB's to detect informed trading. Yet, the challenge remains given substantial noise and liquidity trading in financial markets. A related aspect is traders' risk aversion which partly explains individual heterogeneity for hidden liquidity preference. Implications of risk aversion on hidden liquidity are certainly important and require further theoretical analysis.

One potential caveat of our study is that experimental markets are limited to human traders. The lack of robots reduces the external validity of our design and falls short of reflecting the actual trading environment with increasing use of algorithmic trading (Hendershott et al., 2011). However, while an extention including both human and algorithmic traders is a step forward towards more realistic markets, conceptually it is not clear how the algos adjust to opaque trading environment.

APPENDIX

Appendix A. Description of Electronic Limit Order Books (LOB)

This section explains peculiar features of electronic limit order books (*LOB*). LOB's are commonly used in many exchanges around the world. An electronic limit order book (LOB) is a centralized automated market where agents submit buy and sell orders to a computerized system. In this paper, we focus on *order-driven* markets which is 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 *market orders*. A limit order specifies both the quantity and the price (maximum price for limit buy or minimum price for limit sell) for execution. A market orders only specify the quantity and are executed *at best price (highest bid/lowest ask)* available. A market 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, i.e. 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*
$\mathbf{A}_1$	**51.00**	**10**	**10**
$\mathbf{B}_1$	**49.00**	**20**	**20**
B_2	47.00	30	*30*
B_3	46.00	15	*15*

In this illustration, we 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 Iceberg 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 the exposure, by stating the portion of the quantity to they are willing to hide. In some markets there is a minimum quantity (peak size) for hidden orders that cannot be hidden (*Iceberg orders*), while in other markets the hidden order can be completely *dark (i.e. peak size=0).* In these markets visible depth might be equal or smaller than actual depth.

To give an example, assume that an Iceberg Order HLO_{10}^{A} 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*
$\mathbf{A}_1$	**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 $\mathbf{A}_1$ 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.

We 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*
$\mathbf{A}_1$	**50.00**	**11**	**20**
B_1	49.00	20	20
B_2	47.00	30	*30*
B_3	46.00	15	*15*

LOB's are governed by *order precedence rules* for matching orders. In most of the exchanges, first *price priority*, i.e. orders at best prices are executed first, then *visibility priority;* the visible quantity has precedence over hidden quantity and finally *time priority* is applied, i.e. 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 MO_{10}^{B} of 10 shares arrives *at time t*. Since the visible part of HLO_{10}^{A} has time priority over the LO_{10}^{A}, but the hidden part looses visibility priority against LO_{10}^{A}, only the visible unit from HLO_{10}^{A} and 9 units from LO_{10}^{A} are executed, decreasing the actual depth from 20 to 10 shares. Since the minimum visible unit from the Iceberg order must be 1, another unit from HLO_{10}^{A} becomes visible and thus the visible depth becomes 2 shares, one visible unit from HLO_{10}^{A} and the unexecuted part of LO_{10}^{A}.

Ask / Bid	**Price**	**Visible Depth**	Actual Depth
A_3	52.00	40	*40*
A_2	51.00	10	*10*
$\mathbf{A}_1$	**50.00**	**2**	**10**
B_1	49.00	20	20
B_2	47.00	30	*30*
B_3	46.00	15	*15*

Appendix B. Trading Interface

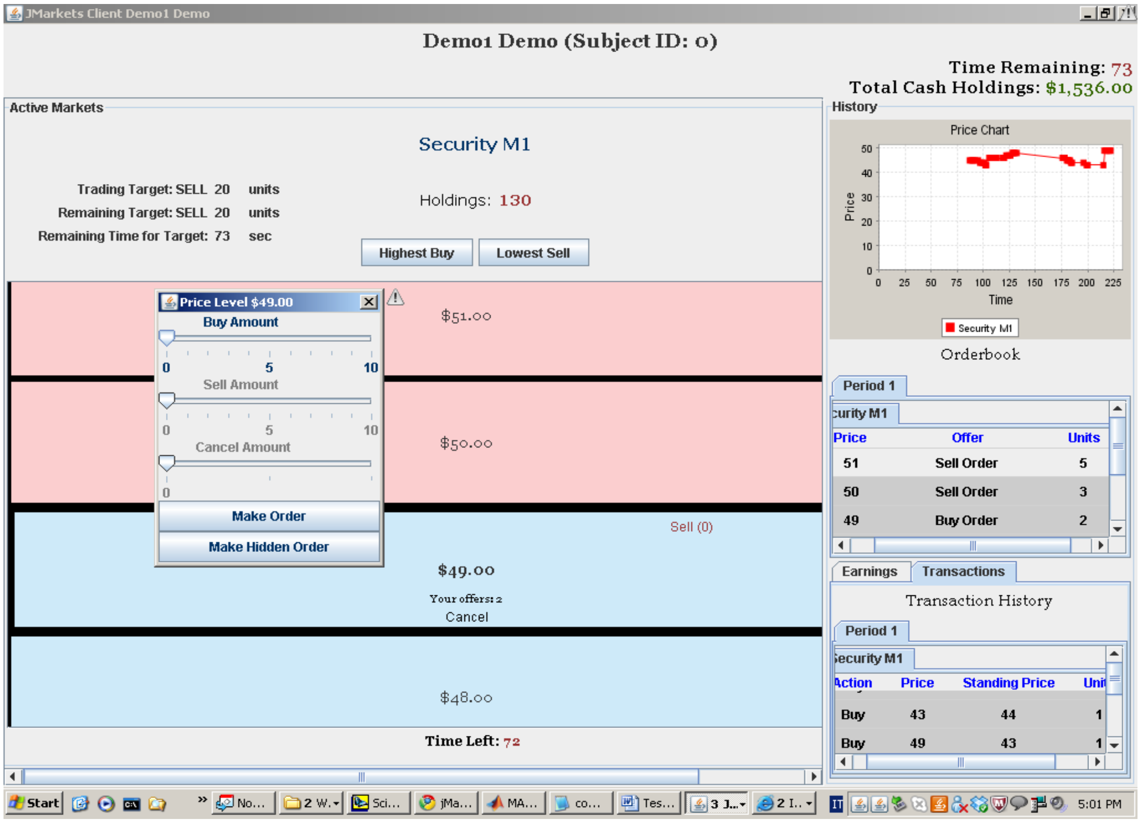
We use jMarkets[32], an open-source, java-based web application developed by Caltech Social Sciences Experimental Lab. It supports continuous double-sided electronic markets. It has been tested and used in various asset market experiments (in a series of paper by Peter Bossaerts and his coauthors). We modify the program to include our design features, in particular we allow submission of Iceberg orders in jMarkets, hence change the priority rules of the system to include visibility priority and add one more panel on the interface to inform liquidity traders regarding their trading target and remaining time for each target during trading period.

Insert here Figure B1

In the standard jMarket interface (see Figure B1) there is a scroll-down column which corresponds to a market for the security. The security name is indicated on top. The column consists of a number of price levels at which traders enter offers to trade. When the trader moves the cursor to a particular price level box, she gets specifics about the available offers. On top, at the left hand side, she sees the number of units requested for purchase. Each time she click on it, she sends an order to buy one unit herself. On top, at the right hand side, the number of units offered for sale is given. She sends an order to sell one unit each time she herself clicks on it. At the bottom, she sees how many units she offered. (Her offers are also listed under Current Orders to the right of the Active Markets panel) Rows in red (blue) indicate price levels with sell (buy) offers. Traders have direct access to *Order Book* which lists all the orders made during the trading period that are not transacted, *History Panel* that shows a chart of past transaction prices for the security, *Transaction History Table* which shows price and quantity information on past transactions (each traders sees her own transactions) and *Earning History Table* which shows for each period the final holdings for the security shares and cash (net of penalty), as well as the resulting market earnings.

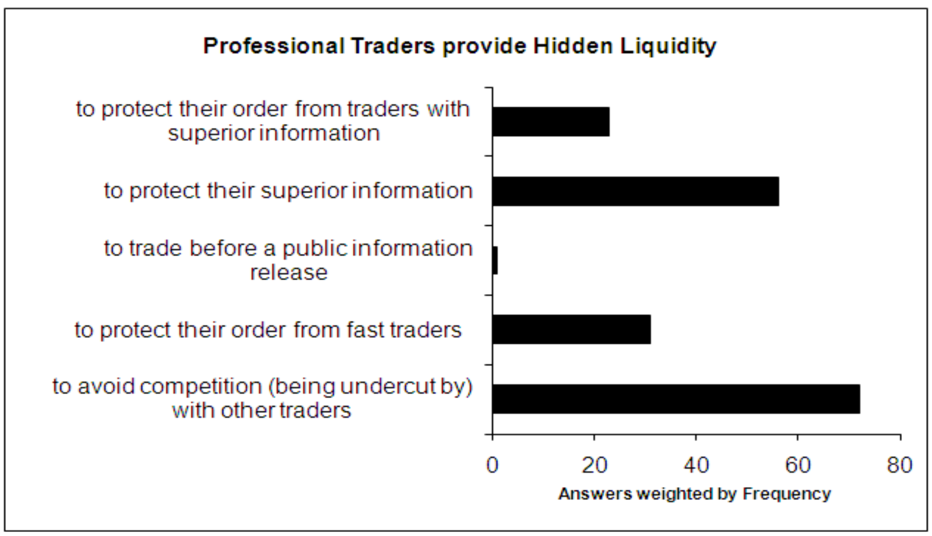
[32] http://jmarkets.ssel.caltech.edu/wiki/WikiStart

Figure B1 Trading Interface (modified jMarkets)



Appendix C. Questionnaire Responses by Professional Traders

We conduct a questionnaire with professional traders who have experience with Iceberg/hidden orders. We ask traders to state their motivation to submit hidden liquidity to LOB. Among possible explanations, we list superior information, competition for liquidity provision, protection from fast traders against mispricing, protection from informed traders and trading around informational events. The questionnaire was available online in five European languages; English, Italian, Spanish, French and German. We thank Laura Garcia Lorés, Annaïg Morin and Felix Suntheim for their help in translating the text. We send out the link of the questionnaire to contacts in all cash members of Euronext and ASSIOM (Italian Association of Capital Markets Operators). Each answer included four alternative frequency specification, namely most frequently (MF), frequently (F), seldom (S) and never (N). The answers are weighted by frequency alternatives; $w^{MF} = 5$, $w^F = 3, w^S = 1$ *and* $w^N = -1$. Below we report the answers (number of responses weighted by their frequency) on possible motivations behind hidden liquidity. Sample size is 30.



Appendix D. Holt and Laury (2002) Risk Aversion Measurement

The Table below reports ten binary choices of Holt and Laury (2002) procedure to measure individual risk aversion. The option A represents safer lotteries, while option B choices are riskier. The expected values of the lotteries increase as one moves down the list, i.e. from decision 1 to decision 10. For decision 10 the rational choice is to pick option B, since it offers a higher payoff with certainty. All payoffs are denoted in experimental currency.

Binary	Holt&Laury Risk Aversion Test		Your Choice
Decisions	Option A	Option B	A or B
Decision 1	1/10 of $8000 9/10 of $6750	1/10 of $15000 9/10 of $1250	
Decision 2	2/10 of $8000 8/10 of $6750	2/10 of $15000 8/10 of $1250	
Decision 3	3/10 of $8000 7/10 of $6750	3/10 of $15000 7/10 of $1250	
Decision 4	4/10 of $8000 6/10 of $6750	4/10 of $15000 6/10 of $1250	
Decision 5	5/10 of $8000 5/10 of $6750	5/10 of $15000 5/10 of $1250	
Decision 6	6/10 of $8000 4/10 of $6750	6/10 of $15000 4/10 of $1250	
Decision 7	7/10 of $8000 3/10 of $6750	7/10 of $15000 3/10 of $1250	
Decision 8	8/10 of $8000 2/10 of $6750	8/10 of $15000 2/10 of $1250	
Decision 9	9/10 of $8000 1/10 of $6750	9/10 of $15000 1/10 of $1250	
Decision 10	10/10 of $8000 0/10 of $6750	10/10 of $15000 0/10 of $1250	

Appendix E. Survey-based Questions

Questions below are taken from Weber et al. (2002) who propose a domain-specific risk-attitude scale to measure risk behavior.

For each of the following statements (D1-D7), please indicate the likelihood of engaging in each activity. Provide a rating from 1 (extremely unlikely) to 5 (extremely likely).
D1. Investing 10% of your annual income in government bonds (treasury bills).
D2. Betting a day's income at the horse races.
D3. Investing in a business that has a good chance of failing.
D4. Lending a friend an amount of money equivalent to one month's income.
D5. Investing 10% of your annual income in a very speculative stock.
D6. Taking a day's income to play the slot-machines at casino.
D7. Taking a job where you get paid exclusively on a commision basis.

To elicit time discounting and measure participants' impatience towards monetary payoffs, we use following questions taken from Reuben et al. (2010):

For each row below, indicate whether you would prefer to be paid €50 today or a higher amount in one week. In other words, you have to make 9 binary choices. For example choice 1 is betwen €50.00 now or €50.00 next week and choice 9 is between 50.00E now and 60.00E next week.

1. Receive €50.00 now or receive €50.00 in one week.
2. Receive €50.00 now or receive €50.50 in one week.
3. Receive €50.00 now or receive €51.50 in one week.
4. Receive €50.00 now or receive €52.50 in one week.
5. Receive €50.00 now or receive €53.00 in one week.
6. Receive €50.00 now or receive €54.50 in one week.
7. Receive €50.00 now or receive €55.00 in one week.
8. Receive €50.00 now or receive €57.50 in one week.
9. Receive €50.00 now or receive €60.00 in one week.

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FIGURES
Figure 1

Figure 1 compares the dynamic evolution of limit, market and Iceberg order volume (shares). Data are aggregated (average) over markets under symmetric and asymmetric information treatments and reported over 24 fifteen-seconds intervals. The vertical line indicates time of the public information release about the final dividend distribution.

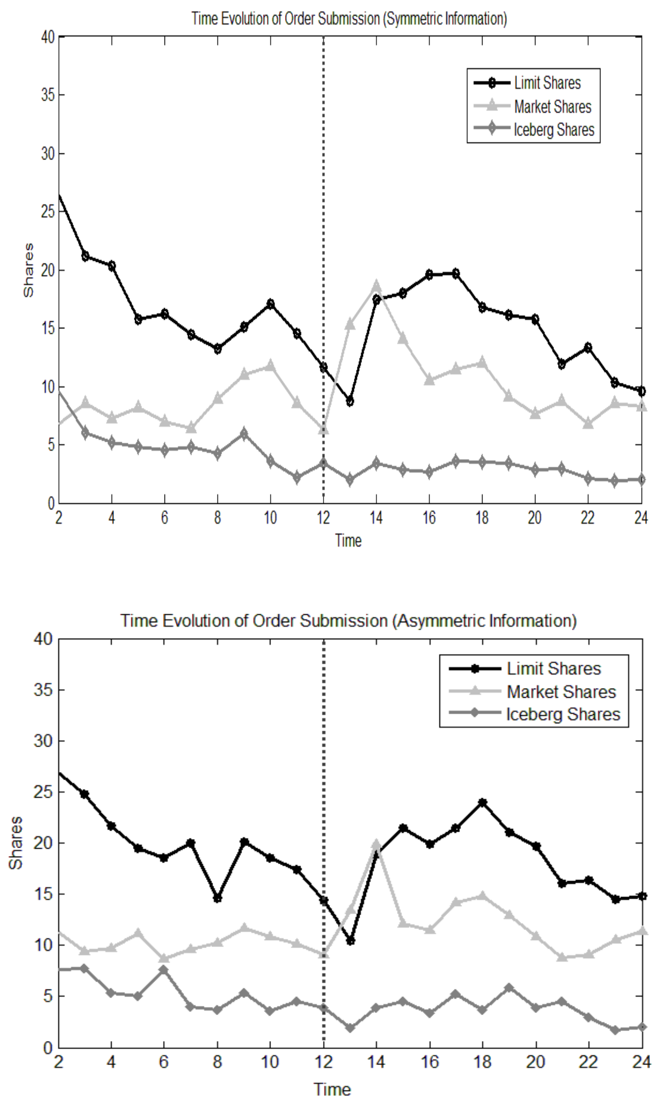


Figure 2

Figure 2 compares the dynamic evolution of limit, market and Iceberg order volume (shares) across markets under symmetric and asymmetric information settings. Data are aggregated (average) over markets and reported over 24 fifteen-seconds intervals. The vertical line indicates time of the public information release about the final dividend distribution.

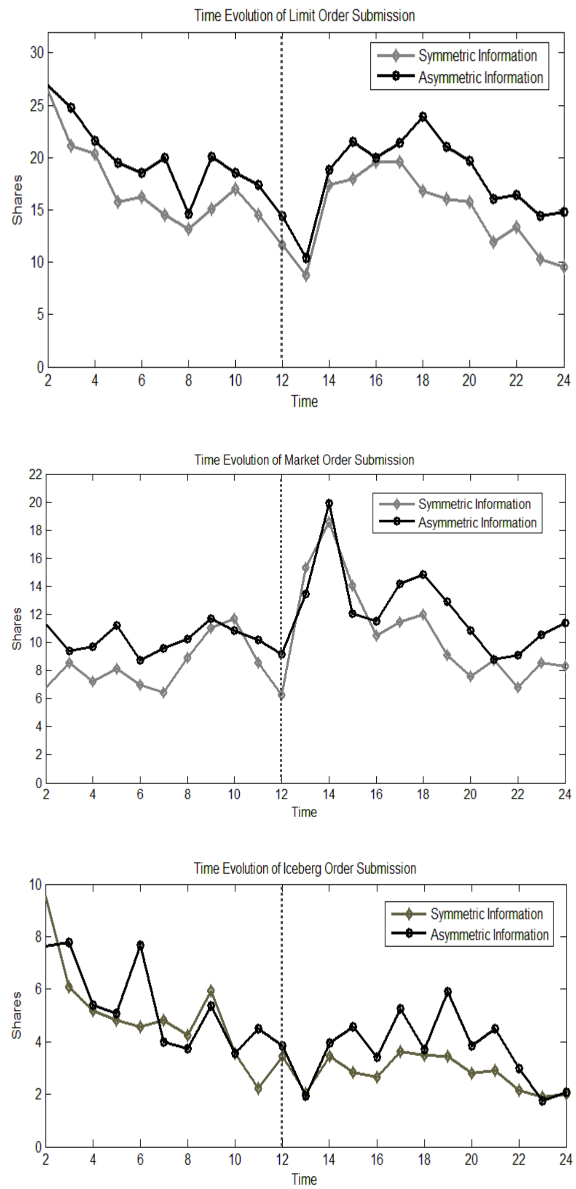
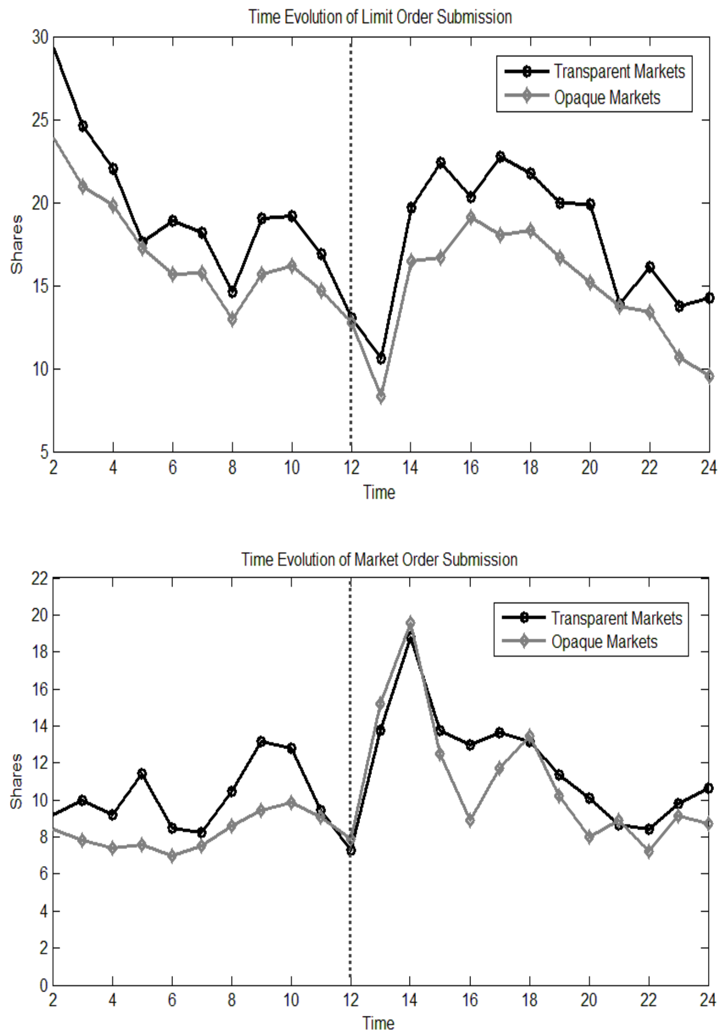


Figure 3

Figure 6 compares the dynamic evolution of limit and order volume (shares) across transparent and opaque markets. Data are aggregated (average) over markets and reported over 24 fifteen-seconds intervals. The vertical line indicates time of the public information release about the final dividend distribution.



TABLES

Table 1

This table reports the liquidating dividend values of the securities traded in experimental asset markets. For each market, a security from this pool is randomly selected. The first block corresponds to initial values of the dividends (until the public information arrival) which either uniformly increase (second block) or decrease (third block) after the public information release.

	Initial States			Up			Down		
Security	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

Table 2 reports the median values for various market quality measures under symmetric and asymmetric information treatments. We compare transparent and opaque markets using a paired sample analysis and report Wilcoxon signed rank p-values. In particular, we compute liquidity supply as the number of limit order shares submitted, liquidity demand as the number of market order shares, trading activity as the number of limit, market and Iceberg (in case of opaque markets) submitted to LOB, average trade size as the number of shares executed in a transaction, trade duration as the time elapsed between to consecutive trade executions, total transacted volume (shares), volume per trade, quoted depth at BBO (Best Bid Offer), total quoted depth (in all price levels of LOB, labeled as book depth), quoted Bid-Ask spread, price and midquote volatility and total price impact measures as the distance between the transaction price and the midquote.

Pre-trade Transparency	**Symmetric Information**			**Asymmetric Information**		
Market Quality	Transparent	Opaque	p-value	Transparent	Opaque	p-value
Liquidity supply	423	375	0.416	517	469	0.382
Liquidity demand	222	228	0.350	276	207	0.207
Market activity	281	287	0.449	294	318	0.551
Transacted volume	204	216	0.588	261	190	0.207
BBO depth	20.9	18.87	0.711	16.22	18.71	0.287
Book depth	123.73	125.94	0.287	120.52	152.43	0.382
Bid-Ask spread	1.85**	1.6	0.021	2.59	2.88	0.551
Price volatility	3.12	2.4	0.449	5.41	4.07	0.517
Midquote volatility	4.83	4.16	0.120	6.78	7.07	0.350
Volume per trade	1.78	1.77	0.817	2.01*	1.78	0.084
Trade duration	3.62	3.73	0.175	3.51	3.00	0.581
Total price impact	0.45**	0.41	0.016	0.65	0.84	0.817

Table 3

Table 3 reports the median values for various market quality measures under opaque and transparent markets. We compare markets under symmetric and asymmetric information settings using a two sample test and report Wilcoxon-Mann-Whitney rank-sum p-values. In particular, we compute liquidity supply as the number of limit order shares submitted, liquidity demand as the number of market order shares, trading activity as the number of limit, market and Iceberg (in case of opaque markets) submitted to LOB, average trade size as the number of shares executed in a transaction, trade duration as the time elapsed between to consecutive trade executions, total transacted volume (shares), volume per trade, quoted depth at BBO (Best Bid Offer), total quoted depth (in all price levels of LOB, labeled as book depth), quoted Bid-Ask spread, price and midquote volatility and total price impact measures as the distance between the transaction price and the midquote.

Private Information	**Transparent Markets**			**Opaque Markets**		
Market Quality	Symmetric	Asymmetric	p-value	Symmetric	Asymmetric	p-value
Liquidity supply	423	517**	0.020	375	469	0.121
Liquidity demand	222	276	0.219	228	207	0.424
Market activity	281	294	0.409	287	318	0.449
Transacted volume	204	261	0.303	216	190	0.374
BBO depth	20.9*	16.22	0.086	18.87	18.71	0.239
Book depth	123.73	120.52	0.500	125.94	152.43	0.374
Bid-Ask spread	1.85	2.59**	0.044	1.60	2.88***	0.004
Price volatility	3.12	5.41***	0.001	2.04	4.07**	0.033
Midquote volatility	4.83	6.78***	0.002	4.16	7.07***	0.003
Volume per Trade	1.78	2.01	0.256	1.77	1.78	0.422
Trade duration	3.62	3.51	0.604	3.73	3.00	0.281
Total price impact	0.45	0.65*	0.054	0.41	0.84**	0.018

Table 4

This table reports orders submitted by different trader types, namely noise traders without a target, small and large liquidity traders and informed traders in the asymmetric information markets. The first and second panels show the results for symmetric and asymmetric markets, respectively. First four columns exhibit the average shares submitted in limit, market, Iceberg and marketable Iceberg orders. The last three columns report measures of trader aggresiveness and competition. In particular, number of limit shares submitted at Best Bid Offer (BBO), within spread, i.e. price undercutting and iceberg order aggressiveness, i.e. the average distance of Iceberg orders to prevailing midquote. Parentheses report the standard deviations. The table also reports the paired sample t-test results of two consecutive rows in the same column. Asterisks *, ** and *** indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively. For sample size less than 30 the significance is based on Wilcoxon signed ranked p-values.

Trader Type	Limit Shares	Market Shares	Iceberg Shares	Marketable Iceberg Shares	Limit Orders at BBO	Limit Orders within Spread	Iceberg Order Aggressiveness
Symmetric Markets	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)
Noise trader	53.85 (54.88)	21.70 (22.23)	11.69 (21.06)	2.37 (8.31)	11.09 (11.25)	1.80 (1.71)	2.58 (2.56)
Small liquidity	59.11** (56.17)	31.49*** (22.03)	9.64* (17.69)	4.45** (13.39)	14.89*** (11.52)	2.65*** (1.84)	2.84 (1.86)
Large liquidity	65.99** (43.84)	51.97*** (30.48)	15.41*** (29.40)	5.91 (16.07)	17.42*** (11.67)	3.56*** (1.92)	1.58 (1.36)
Asymmetric Markets	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)	$\widehat{\mu}$ (std)
Noise trader	66.10 (58.01)	26.34 (31.54)	9.70 (18.99)	1.52 (5.18)	9.68 (8.57)	2.19 (2.00)	3.74 (3.74)
Small liquidity	67.64 (51.52)	37.17*** (38.78)	9.11 (17.69)	2.41 (7.38)	14.56*** (10.01)	3.34*** (1.94)	4.04 (3.67)
Large liquidity	76.62** (46.12)	47.62*** (34.75)	16.53* (34.79)	3.53 (7.20)	18.11*** (13.99)	4.07*** (2.78)	2.80 (2.34)
Informed trader	69.26 (62.20)	50.52 (54.23)	24.82 (53.86)	4.92* (10.80)	15.15** (11.96)	3.37** (3.43)	3.60** (3.03)

Table 5

Table 5 reports the pooled (across traders and markets) regression coefficients. As independent variables, we include asymmetric, a dummy variable that takes 1 if market is under asymmetric information treatment and 0 otherwise, trader type, which different values for noise, small liquidity large liquidity and informed traders, an additional informed dummy, which takes 1 if the trader is informed and 0 otherwise, HL risk, Holt and Laury (2002) risk aversion measurement, gender dummy, that takes 1 for male and 0 otherwise. Moreover, we control for the cohortsize, since number of traders in a cohort varies between 6 and 8, and for the year, whether the experiment is conducted in 2009 or 2011. In our recent experiment, we also extract a risk pc, first principal component extracted from responses to seven questions in different financial risk domains (Weber et al., 2002).The reported p-values are based on Driscoll-Kraay (1998) standard errors robust to general forms of cross-sectional (spatial) and temporal dependence. Asterisks *, ** and *** indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively. Last column reports within group R2.

Table 5. Pooled Panel Regressions, n=70(37), T= 481(270)

dependent variable	SR	TR	HR	SR_{2011}	TR_{2011}	HR_{2011}
intercept	0.486*** (0.004)	0.132 (0.454)	0.381*** (0.000)	0.408 (0.156)	0.454** (0.033)	0.138 (0.506)
asymmetric	0.041*** (0.000)	−0.028*** (0.007)	−0.013* (0.051)	0.016 (0.364)	0.010 (0.516)	−0.026* (0.058)
trader type	−0.043*** (0.000)	0.052*** (0.000)	−0.009 (0.326)	−0.041** (0.027)	0.045** (0.023)	−0.004 (0.694)
informed	0.022 (0.629)	−0.066 (0.220)	0.045 (0.143)	−0.013 (0.821)	−0.015 (0.727)	0.028 (0.304)
HL risk	0.039*** (0.000)	−0.027*** (0.000)	−0.012*** (0.005)	0.049*** (0.000)	−0.033*** (0.000)	−0.016*** (0.000)
gender	−0.079*** (0.001)	0.112*** (0.000)	−0.033*** (0.003)	−0.154*** (0.000)	0.168*** (0.000)	−0.014 (0.504)
cohortsize	−0.017 (0.424)	0.005 (0.864)	0.013 (0.269)	0.011 (0.787)	0.020 (0.487)	0.009 (0.755)
year	0.057*** (0.000)	0.089*** (0.000)	−0.146*** (0.000)			
risk pc				−0.026** (0.012)	0.011* (0.094)	0.015* (0.051)
impatience				−0.003 (0.459)	0.006** (0.045)	−0.003** (0.010)
R^2	0.08	0.11	0.10	0.14	0.15	0.03

Table 6

Table 6 reports the pooled (across traders and markets) regression coefficients. The dependent variable is the scaled individual trader payoff in each market. As independent variables, we include punish, a dummy variable which takes 1 if the trader cannot fulfill the trading obligation and 0 otherwise, asymmetric, a dummy variable that takes 1 if market is under asymmetric information treatment and 0 otherwise, limit volume (lv), number of shares submitted as limit orders, market volume (mv), number of shares submitted as market orders, hidden volume (hv), number of shares submitted as Iceberg orders, trader type, which different values for noise, small liquidity large liquidity and informed traders, an additional informed dummy, which takes 1 if the trader is informed and 0 otherwise, HL risk, Holt and Laury (2002) risk aversion measurement, gender dummy, that takes 1 for male and 0 otherwise. Moreover, we control for the cohortsize, since number of traders in a cohort varies between 6 and 8, and for the year, whether the experiment is conducted in 2009 or 2011. The reported p-values are based on Driscoll-Kraay (1998) standard errors robust to general forms of cross-sectional (spatial) and temporal dependence. An intercept term is included in both specifications, but are not reported to save space. Asterisks *, ** and *** indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively. Withing group R2 are reported in squared brackets.

Table 6. Trader Welfare

Payoff	punish	asymmetric	lv	mv	hv	trader type	informed	HL risk	gender	cohortsize	year
Pooled $[R^2=0.08]$	-1.103^{***} (0.001)	-0.105 (0.821)	-0.004^{***} (0.000)	0.005 (0.172)	-0.002^{**} (0.038)	-0.037 (0.454)	1.224^{***} (0.000)	$-.007$ (0.707)	0.171^{**} (0.017)	-0.224 (0.315)	0.176 (0.717)
2011 $[R^2=0.10]$	-1.002^{**} (0.030)	-0.352 (0.566)	-0.004^{***} (0.008)	0.007 (0.246)	-0.002 (0.464)	-0.053 (0.581)	1.143^{**} (0.031)	0.031 (0.336)	0.081 (0.190)	-0.305 (0.501)	

Table 7

This table the median values for various market qualitymeasures under symmetric and asymmetric information (with two informed traders) treatments. We compare transparent and opaque markets using a paired sample analysis and report Wilcoxon signed rank p-values. In particular, we compute liquidity supply as the number of limit order shares submitted, liquidity demand as the number of market order shares, trading activity as the number of limit, market and Iceberg (in case of opaque markets) submitted to LOB, average trade size as the number of shares executed in a transaction, trade duration as the time elapsed between to consecutive trade executions, total transacted volume (shares), volume per trade, quoted depth at BBO (Best Bid Offer), total quoted depth (in all price levels of LOB, labeled as book depth), quoted Bid-Ask spread, price and midquote volatility and total price impact measures as the distance between the transaction price and the midquote.

Pre-trade Transparency	**Asymmetric Information II**		
(Market Quality)	Transparent	Opaque	Wilcoxon p-value
Liquidity supply	562	517	0.219
Liquidity demand	273	233	0.422
Market activity	352	415	0.219
Transacted volume	231	203	0.423
BBO depth	16.16	19.46	0.219
Book depth	123.53	154.16**	0.016
Bid-Ask spread	2.54	2.04	0.500
Price volatility	8.09	7.77	0.500
Midquote volatility	6.78	7.07	0.500
Volume per trade	1.77	1.38	0.156
Trade duration	2.47	2.25	0.422
Total price impact	0.61	0.64	0.422

Table 8

Table 8 reports the median values for various market quality measures under transparent and opaque markets. We compare markets under symmetric and asymmetric information (with two informed traders) settings using a two sample test and report Wilcoxon-Mann-Whitney rank-sum p-values. In particular, we compute liquidity supply as the number of limit order shares submitted, liquidity demand as the number of market order shares, trading activity as the number of limit, market and Iceberg (in case of opaque markets) submitted to LOB, average trade size as the number of shares executed in a transaction, trade duration as the time elapsed between to consecutive trade executions, total transacted volume (shares), volume per trade, quoted depth at BBO (Best Bid Offer), total quoted depth (in all price levels of LOB, labeled as book depth), quoted Bid-Ask spread, price and midquote volatility and total price impact measures as the distance between the transaction price and the midquote.

Private Information	**Transparent Markets**			**Opaque Markets**		
Market Quality	Symmetric	Asymmetric II	p-value	Symmetric	Asymmetric II	p-value
Liquidity supply	423	462	0.108	375	517**	0.039
Liquidity demand	222	273	0.262	228	233	0.442
Market activity	281	352	0.366	287	415	0.128
Transacted volume	204	232	0.262	216	203	0.634
BBO depth	20.9	16.16	0.202	18.87	19.46	0.596
Book depth	123.73	123.53	0.634	125.94	154.16	0.175
Bid-Ask spread	1.85	2.54**	0.024	1.60	2.04***	0.001
Price volatility	3.12	5.65***	0.001	2.40	7.02***	0.004
Midquote volatility	4.83	8.09***	0.002	4.16	7.77***	0.002
Volume per Trade	1.78	1.77	0.440	1.77	1.38	0.108
Trade duration	3.62	2.47	0.439	3.73	2.25**	0.049
Total price impact	0.45	0.61	0.196	0.41	0.64***	0.004

Table 9

Table 9 reports the median values for various market quality measures under transparent and opaque markets. We compare markets asymmetric information (one versus two informed traders) settings using a two sample test and report Wilcoxon-Mann-Whitney rank-sum p-values. In particular, we compute liquidity supply as the number of limit order shares submitted, liquidity demand as the number of market order shares, trading activity as the number of limit, market and Iceberg (in case of opaque markets) submitted to LOB, average trade size as the number of shares executed in a transaction, trade duration as the time elapsed between to consecutive trade executions, total transacted volume (shares), volume per trade, quoted depth at BBO (Best Bid Offer), total quoted depth (in all price levels of LOB, labeled as book depth), quoted Bid-Ask spread, price and midquote volatility and total price impact measures as the distance between the transaction price and the midquote.

Private Information	**Transparent Markets**			**Opaque Markets**		
Market Quality	Asymmetric	Asymmetric II	p-value	Asymmetric	Asymmetric II	p-value
Liquidity supply	517	462	0.442	469	517	0.330
Liquidity demand	276	273	0.404	207	233	0.211
Market activity	294	352	0.295	318	415	0.108
Transacted volume	261	232	0.442	190	203	0.308
BBO depth	16.22	16.16	0.596	18.71	19.46	0.404
Book depth	120.52	123.53	0.442	152.43	154.16	0.202
Bid-Ask spread	2.59	2.54	0.656	2.88	2.04	0.520
Price volatility	5.41	5.65	0.151	4.07	7.02**	0.039
Midquote volatility	6.78	8.09*	0.060	7.07	7.77	0.128
Volume per Trade	2.01	1.77	0.123	1.78	1.38	0.151
Trade duration	3.51	2.47	0.295	3.00	2.25	0.211
Total price impact	0.65	0.61	0.330	0.84	0.64	0.520