The Impact of Reduced Pre-Trade Transparency Regimes on Market Quality

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Abstract

This paper studies the effects of pre-trade quote transparency on spread, price discovery and liquidity in an artificial limit order market with heterogeneous trading rules. Our agent-based numerical experiments suggest that full quote transparency incurs substantial transaction costs to traders and dampens trading activity in an order-driven market. Our finding reveal that exogenous restriction of displayed depth, up to several best quotes, does not benefit market performance. On the contrary, endogenous restriction of displayed quote depth, by means of iceberg orders, improves market quality in multiple dimensions: it reduces average transaction costs, maintains higher liquidity and moderate volatility, balances the limit order book, and enhances price discovery.

JEL classification: D4, D8, G1

Keywords: agent based models, market transparency, iceberg orders, liquidity, bid-ask spread

1. Introduction

As a branch of financial market regulation debates, there is a growing literature on the benefits and pitfalls of reduced market transparency with a special alacrity regarding electronic limit order markets where the mere speed of trading exacerbates any malfunctioning of the system and can potentially undermine the principles of fair trading. This paper investigates the problem of limited market transparency using an artificial double auction setup.

Within the spectrum of markets with reduced transparency, some exchanges display only the depth at a few best quotes in the limit order book, whereas other exchanges endogenize the regulation of transparency by permitting traders to submit iceberg orders that conceal partly or entirely the limit order size, such as the Toronto Stock Exchange, Euronext, the Swiss Stock Exchange, the Madrid Stock Exchange, and the Australian Stock Exchange. Many new trading venues display only partial information about incoming orders and market depth striving to gain a competitive advantage over older existing exchanges, by circumventing the positive order flow externality that those older exchanges exercise. This is particularly the case of dark pools: according to Fidessa datasource (Fidessa, 2012), the cumulative volume transacted on the European dark venues has increased more than tenfold in the past years[1] and continues a stable positive trend. The proliferation of dark and semi-transparent venues gives rise to a variety of interesting questions: what are the aggregate gains from reduced pre-trade transparency rules, what type of agents take advantage of opacity, and how frequently traders are misled by excessive uncertainty in these markets? Narrowing exogenously the number of displayed quotes potentially mitigates price manipulations. However, in case of less liquid assets the visible part of the limit order book may prove insufficient to form accurate expectations and become misleading in this respect. On the other hand, iceberg orders are designed primarily for large institutions that employ block trading and thereby require delicate cost and exposure management.

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[1]Figures have grown from around €250 million in November 2008 to almost €3.5 billion in November 2012.

In order to understand the regulators' dilemma in prescribing or banning the use of iceberg orders, consider a following example. Up until the formal introduction of iceberg orders in public limit order markets, brokers established their own automated order processing systems that divided particularly large orders received from the customers into several smaller tranches and then routed these tranches to the market in succession. This strategy permitted to sell the whole amount of stocks preserving the price. However, this strategy, without being explicitly communicated to the exchange, would not eliminate the risk of being traded through. Indeed, suppose that the market is trading at £23 – 25 and a seller has an order with a broker for 10,000 shares at £25. If an aggressive buyer arrived to purchase 2,500 stocks at the market, he would fill 1,000 at £25 and buy the rest from the next seller, for example, at £26. As a result both parties would have missed the opportunity of better trade terms: the large seller would have suffered from longer total execution time or only partial execution, and the buyer would have bought at a higher price being unaware of a better price offer. In response to the inefficiency of this large order transmission routine iceberg orders appeared as an innovation that enabled brokers to hold a full customer order in the public order book whilst displaying only a small fraction of it. In the above scenario with an aggressive buyer all 2,500 shares would be purchased at £25, benefiting the buyer by achieving a better price, and the seller by faster execution, and thus increase overall market liquidity.

Beneficial as iceberg orders seem, they entail a certain trade-off: hidden liquidity affects the ability of traders to evaluate the true market conditions, deeming the collective benefits of opacity obscure. As from the individuals perspective, there are three types of risks incumbent for iceberg orders: execution risk, pick-off risk and front running risk. Execution risk, that is the risk an order of a given size and price not to get filled in a specified time period, is amplified for iceberg orders, since each renewal of the peak loses time priority. To compete for liquidity traders should increase the visible part of an iceberg order, thereby attracting impatient traders that monitor the market and facilitating quicker execution. At the same time, with new information arriving to the market, such as change in the fundamental asset value, passive orders recorded in the book may become mispriced and can be quickly "picked off" by incoming market orders. Minimizing the visible part of the iceberg, therefore, protects traders from winner's curse trap. Lastly, displaying an order in the book gives a signal about trader's private information and can result in undercutting. Traders can reduce their exposure impact and discourage such front-running by hiding the full order size and minimizing the visible part. In designing their strategy, traders must balance these risks and find the optimal trade-off.

Our paper contributes to the research on pre-trade market transparency by exploring how it affects the bid-ask spread, price efficiency and market liquidity. In an artificial double auction market, where agents use the information about volumes in the limit order book to formulate their trading strategies, we compare four market types: a quasi-transparent market structure, whereby the exchange explicitly regulates the number of publicly displayed quotes, an opaque market structure, where the amount of displayed volume is determined by the proportion of iceberg orders, and two extreme cases of a dark and price, quantity a perfectly transparent markets.

Empirical studies, for instance, Aitken et al. (2001); Anand and Weaver (2004); Boehmer et al. (2005); Henderhott and Jones (2005); Bloomfield and O'Hara (1999), as well as theoretical works of Baruch (2005) and Moinas (2010) explore the subject of market opacity and its influence on market quality, while a number of papers investigate empirically the determinants of the decision to hide order size (Anand and Weaver, 2004; DeWinne and D'Hondt, 2007; Frey and Sandås, 2009; Bessembinder et al., 2009) and evaluate analytically the effects of hidden orders on traders' welfare (Buti and Rindi, 2013). Despite availability of data, there is no consensus in the literature on the role of imperfect transparency: in certain markets reduced transparency widens the spread and deteriorates efficiency (Flood et al., 1999; Henderhott and Jones, 2005), other research reports partially or exactly opposite outcomes (Bloomfield and O'Hara, 1999; Madhavan et al., 2005) or no significant impact (Anand and Weaver, 2004). Pardo and Pascual (2012) examine stocks traded on the Madrid Stock Exchange, documenting that spreads do not widen and depth does not shrink after hidden order executions. A recent comparative study of an introduction, ban (in 1996) and subsequent reinstallment (in 2002) of hidden orders on the Toronto Stock Exchange conducted by Anand and Weaver (2004) does not detect any discernible changes in the spread width. Bloomfield and O'Hara (1999) use laboratory experiment to determine the effects of trade and quote disclosure on market efficiency, bid-ask spreads, and trader welfare, and find that trades disclosure significantly improves the informational efficiency of the markets but causes opening spreads to widen dramatically. In contrast, quote disclosure appears to have no effect on opening spreads. Madhavan et al. (2005) examine the April 1990 decision by the Toronto Stock Exchange to provide the top five prices on either side rather than just the top of the book and find a wider spreads post-event. In contrast Boehmer et al. (2005) study the 2002 introduction of OpenBook, a real-time NYSE limit order book data feed, and find a lower trading costs and more aggressive limit order submission as a result of the increase in quote transparency. Similarly Henderhott and Jones (2005) showed that when Island went dark in 2002, the exchange-traded funds market worsens in terms of price discovery and trading costs, as a consequence of an altered competition for order flows from other trading venues with the provision of liquidity becoming less competitive on Island. Finally Flood et al. (1999) compares the effects of price disclosure on market performance in an experimental multiple-dealer market with professional market makers who trade either via fully public price queues (pre-trade transparent market) or bilateral quoting (pre-trade opaque). In the transparent market, with all quotes disclosed, opening spreads are smaller, and volume is higher, but in the over the counter intra dealer opaque market pricing errors decline more rapidly as a result of dealers' optimal speculative response to reduced search costs in the transparent market. On the theoretical side, Moinas (2010) rationalizes, in a sequential trade model with high transparency level, that limit order traders are reluctant to offer free options to other traders, thus market liquidity shrinks. The reaction to the increased risk of being picked off was discussed in earlier literature by Seppi (1997); Foucault (1999); Copeland and Galai (1983) among others.

While empirical studies seem to diverge in their conclusions partly due to discrepancies in the structures of actual analyzed markets, theoretical models suffer from the rigidity of assumptions. For example, Buti and Rindi (2013) use a discrete time trading game to study the optimal submission strategy, in a limit order book, of traders who choose simultaneously the order price, size, type, and the degree of exposure (that is the amount of the order to hide). The optimization problem can be solved by backward induction, but stringent assumptions on the shape of the limit order book are necessary, such as that the order book consists of a grid of six prices, symmetrically placed respect the common value of the asset, and agents can only provide liquidity on the first two levels of the book. These assumptions restrict dramatically the possible types of orders that can be submitted and make it possible to compute which one maximizes the traders' utility. Furthermore, the 3 period setting, implicitly assumes that traders have a very short time horizon when trading, which affects their trade-off between execution costs and exposure costs. In our paper we adopt a complementary agent-based modeling approach that surpasses the mentioned limitations of empirical and other theoretical frameworks and facilitates the comparison of emergent market properties produced by various transparency regimes. While we do not attempt to model the optimal decision of individual traders, which is driven by plausible but exogenously determined rules, we have a proper dynamical setting, with a realistic limit order book, whose evolution affects and is affected by traders strategies. Few attempts have been made to date to apply agent-based models to the problem of market transparency. In a recent paper Yamamoto (2011) argues that the level of quote transparency has little influence on long memory properties of financial data. However, the author concentrates solely on restricting quote visibility in the limit order book to the five best prices, leaving opaque microstructures with hidden and iceberg orders outside his scope.

Our framework supports the evidence that absolute quote transparency widens the bis-ask spread and disturbs liquidity, which translates into lower cumulative trading volumes. Furthermore, our simulation analysis reveals that a quasi-transparent rule exacerbates a winner's curse problem and intensifies market volatility but otherwise has no profound effect on market quality. Order placements move farther away from the quotes whereas the best quotes remain representative of the entire book. Finally, we demonstrate that an opaque transparency rule, contrary to Buti and Rindi (2013), alleviates the transaction costs: the spread becomes tighter and trading activity revives. Our results suggest that the latter transparency policy promotes sustainable liquidity which is vital for non-intermediated microstructures.

The remainder of this paper proceeds as follows. Section 2 outlines traders' order placement routine and order choice determinants. Section 3 defines specifications and describes market design and clearing principle. Section 4 scrutinizes the evolution of market quality characteristics: the size of bid-ask spread, order book shape, volatility, price regularities, and market liquidity, assessed by various indicators. Section 5 concludes and points out directions for future research.

2. Order Submission Mechanism

Our model extends the framework of Chiarella et al. (2009) to internalize the influence of quote transparency. We assume a double auction market, for a single non-dividend paying stock, where N_A heterogeneous agents trade during a repeated number of rounds. In each time step t a random agent i submits an order to the trading book. Trader i's expectation of the future price is driven by two principal components – the proximity of the current asset price to the fundamental value and the visible order book depth, plus a noise factor. Traders are fundamentalists and expect in the long run (i.e. over a period τ^f) the market to revert to trading at the fundamental price of the asset p^f. In the short run traders take into account the order imbalance to evaluate in which direction the market is likely to move.

The order imbalance D_t here is defined as the signed difference between the demand and supply in the market at time t. According to this definition, given positive order imbalance $D_t > 0$, that is the combined volume of buy orders recorded in the book exceeds the combined volume of sell orders, the trader expects a price increase, and vice-versa. Finally, the trader faces an aggregate uncertainty factor ξ_t that we assume to be normally distributed with zero mean and variance σ_ξ^2, $\xi \sim N(0, \sigma_\xi^2)$. Overall, trader i builds his expectation of the return on the asset that can be achieved within his time horizon τ^i according to the following rule:

$$\hat{r}^i_{t,t+\tau^i} = \frac{1}{\nu_1^i + \nu_2^i + \eta^i}\left[\nu_1^i \frac{\ln(p^f/p_t)}{\tau^f} + \nu_2^i \bar{D}_t + \eta^i \xi_t\right], \tag{1}$$

where

$$\tau^i = \left[\tau \frac{1+\nu_1^i}{1+\nu_2^i}\right], \tag{2}$$

$\bar{D}_t$ is the average order imbalance over the past τ^i periods, and the coefficients ν_1^i , ν_2^i and η^i guide fundamentalist, imbalance and noise components of trader's i strategy respectively. The forecast rate of return $\hat{r}^i_{t,t+\tau^i}$ yields the maximum expected price over a τ^i periods

$$\hat{p}^i_{t+\tau^i} = p_t \exp(\hat{r}^i_{t,t+\tau^i} \tau^i). \tag{3}$$

We assume that every trader in the market is risk-averse and holds a portfolio of stocks and cash. The optimal composition of the portfolio is determined via the maximization of a utility function with a constant absolute risk aversion (CARA).[2] At each trading round the invoked trader computes his range of admissible prices, subject to short selling and borrowing restrictions. The maximum, p_M, and minimum, p_m, prices at which a trader can place his order are determined by short-selling and his budget constraints. In addition, there exists a satisfaction price p^*, that makes the current portfolio composition optimal: if the current market price of the stock is above this level then the trader is willing to sell, otherwise, the trader intends to buy more stocks. The trader is boundedly rational: he picks randomly a price p from the range of admissible prices in period t. The propositions below describe the mechanism that guides traders' strategies.

Proposition 1. *Assume that the region of admissible buy and sell prices for a trader with CARA preferences is given by $[p_m, p^*]$ and $[p^*, p_M]$ respectively, then both the satisfaction price p^* and the minimum price p_m are monotonic increasing in the maximum expected price p_M, but the sensitivity of p^* to p_M is higher than the sensitivity of p_m to p_M.*

[2]See Appendix A.

Proof. See Appendix A. □

Proposition 1 implies that if the trader is optimistic ($\hat{r}^i_{t,t+\tau^i} > 0$) but wishes to sell stocks, he is likely to place a limit order farther away in the book and wait till the market reaches this price level. However, if the seller expects a price depreciation ($\hat{r}^i_{t,t+\tau^i} < 0$) then he is more likely to trade at the market price via a market order. Likewise, buyers that believe in a price decline are more likely to submit limit orders, while optimistic buyers are more likely to demand immediacy and submit market orders.

Proposition 2. *The trader's propensity to sell (buy) the stock is higher*

(1) the higher the order imbalance towards buy (sell) side and the higher (lower) the weight of imbalance component in his strategy, and

(2) the higher (lower) the volatility of returns.

Proof. See Appendix B. □

Proposition 3. *The higher (lower) the imbalance towards buy (sell) side in the limit order book*

- *the higher (lower) the propensity of a seller (buyer) to trade via a limit order, and*
- *the higher (lower) the propensity of a buyer (seller) to trade via a market order.*

Proof. See Appendix C. □

The relationship between order imbalance and traders' propensity to buy or sell the asset suggests that quote transparency intensifies contrarian behavior among market population. Indeed, if order imbalance is skewed to one side, then the new agent that arrives to trade is inclined to join the opposite side of the market or deplete the currently prevalent one. Given that positive order imbalance translates into higher price expectations, its effect is to push buyers to submit more aggressive orders and sellers – more passive. Similarly, when sell limit orders prevail in the book and order imbalance is negative, new incoming sellers are more prone to consume liquidity and buyers are more likely to provide liquidity to the market. Drawing from the result in Proposition 3, impatient traders are bound to reinforce the trend in imbalance, and patient agents to reverse it.

The resulting mixture of trend-following and contrarian behavior that stems from Propositions 1, 2 and 3 are rooted to recurring empirical evidence. Ranaldo (2004) discovers that patient traders seek liquidity when the same side of the book is dense and the opposite side is slim. Lo and Sapp (2005) document a complementary effect: traders switch to more passive orders if many aggressive traders precede on the same side of the market. In addition, Chiarella et al. (2009) demonstrate that the behavior induced on noise traders by CARA preferences implies that if the noise traders are optimistic, they submit all types of orders symmetrically around the quotes, whereas pessimistic expectations makes them more likely to buy with limit orders and sell with market orders. As we reveal in the numerical simulation analysis, once traders take market depth into consideration, the book becomes more symmetric and bears closer resemblance to the average book shape observed in real markets.

3. Simulations Design

In this section we outline main simulation features and provide numerical parameters. We juxtapose four transparency regimes, described in Table 1, to trace the emergent market properties inflicted by the availability or scarcity of market depth information.

We determine the order imbalance D_t here as the signed ratio between the total amount of stocks demanded Q_t^b and offered Q_t^a in the market as visible to traders at time t

$$D_t = \operatorname{sgn}\left(Q_t^a - Q_t^b\right) \cdot \ln\left(1 - \frac{\left|Q_t^a - Q_t^b\right|}{Q_t^a + Q_t^b}\right). \tag{4}$$

First, we consider a transparent market, where agents observe the depth of the entire limit order book before trading to collect information about the volumes Q_t^a and Q_t^b. While in certain markets such an assumption is perfectly viable (e.g. NYSE OpenBook), many other exchanges (e.g. Tokyo Stock Exchange, Euronext Paris) restrict the available information to only several best quotes on each side of the limit order book at any time. We define a quasi-transparent market that accommodates this exogenous transparency restriction. As typical to most exchanges, in our quasi-transparent market traders estimate the visible order imbalance D_t using only five top orders on the buy and sell sides respectively and formulate their strategies according to the same principle as in a transparent market.

Table 1: The definitions of the five market transparency regimes.

Transparency regime		Description
1	Transparent	Fundamentalist, noise and order imbalance impact with all quotes visible.
2	Quasi-transparent	Fundamentalist, noise and order imbalance impact with only five best quotes visible.
3	Opaque (n)	Fundamentalist, noise and order imbalance impact with naive splitting via iceberg orders.
4	Opaque (s)	Fundamentalist, noise and order imbalance impact with smart splitting via iceberg orders.
5	Dark	Fundamentalist and noise impact.

An alternative mode of regulating quote transparency, adopted by a wide range of trading venues is exogenous via iceberg orders, which allow traders to fix the limit price and leave a fraction of the order size temporarily hidden. We refer to this microstructure as an opaque market. Any trader in this opaque market can take advantage of an iceberg order to manage his exposure subject to an imposed minimum size. The algorithm for order submission is similar to our basic model with additional steps to determine the appropriateness of splitting via an iceberg order. We design the routine for the latter part based on some common observations from empirical research (DeWinne and D'Hondt, 2007; Frey and Sandås, 2009; Bessembinder et al., 2009; Buti and Rindi, 2013), which is thoroughly explained further on in this section.

Finally, we include another benchmark – a dark market, where market depth is unknown to traders and does not affect their order placements directly.[3]

3.1. Iceberg Order Submissions

Three types of risks are generally distinguished for iceberg orders: execution risk, pick-off risk, and exposure risk. Our framework embeds exposure risk into order submission strategy by virtue of its key variable – the visible part of the order book imbalance D_t. On the one hand, results in Proposition 2 and 3 imply, for instance, that if a certain buyer chooses to display a large order, then subsequent traders are likely to sell via limit orders, so our trader risks not filling his order in time. On the other hand, if a subsequent trader that arrives at the market also decides to purchase the asset, then the latter is likely to use a more

[3]It is not feasible to draw a rigorous comparison between the degree of transparency in quasi-transparent and opaque specifications: while a potentially larger fraction of market volumes is displayed in the opaque market, however, the information about the orders that cluster around the best quotes is usually of higher importance since most of the trading happens there. On the other hand, in dark pools, which is related to our dark regime, the distribution of orders can be more flat across the book, given that orders are confidential and carry no market impact.

aggressive buy order at a higher price and undercut the former one.[4] This property captures exposure risk. While exposure considerations leads traders to minimize the visible size of their orders, the execution risk aspect plays antagonistic role by increasing it. In the opaque regime we devise additional rules, whereby execution risk governs the propensity of an agent to split his trade via an iceberg order.

First, the trader chooses his price p^i and total order size q^i as usual. If his order turns out to be a limit order and the total order size q^i is greater than the threshold $\hat{q}$ imposed by the exchange,[5] then he is eligible to use an iceberg order. Next the trader will determine the optimal peak size to be revealed in the limit order book.

First we consider a simplistic rule, that does not accommodate the trade-off between the risks involved with iceberg orders per se, but rather the addresses empirical finding (DeWinne and D'Hondt (2007); Bessembinder et al. (2009)) showing that traders are more likely to hide a portion of their orders when they have selected a large order size. Upon passing the minimum threshold $\hat{q}$, a trader with a *naive* mimetic strategy simply matches the visible peak size of his order to the average limit order size on the respective side of the book, plus a small perturbation

$$q_V := q_t^i = (1 + 0.1\varepsilon)\bar{Q}^L_{t,t-\tau^i}, \tag{5}$$

where $\varepsilon \sim U(0, 1)$ and $\bar{Q}^L_{t,t-\tau^d}$ is the average (visible) size of incoming limit orders to the relevant side of the book over a period of time chosen equal to the trader's time horizon τ^i. This is a reasonable assumption since without observing directly from the limit order book the sizes of individual limit orders, the traders can use market statistics published by the exchange on the previous day to estimate the average limit order size. In addition, traders can monitor order flow to infer the sizes of incoming market and limit orders. This rule is in agreement with results from Frey and Sandås (2009) who find that traders try to mimic ordinary limit orders and with Buti and Rindi (2013) who demonstrate that in equilibrium the peak size chosen by large traders is equal to the order size of small traders.

Further, in order to incorporate additional empirical evidence, we consider a more sophisticate rule where pick size is chosen as follows:

$$q_V := q_t^i = \begin{cases} \max\left(\hat{q},\ q^i \frac{Q^M_{t,t-\tau^i}}{Q^L_{t,t-\tau^i}}\right), & \text{if} \quad Q^M_{t,t-\tau^i} < Q^L_{t,t-\tau^i} \\ q^i, & \text{otherwise} \end{cases} \tag{6}$$

where $Q^M_{t,t-\tau^i}$ is the cumulative volume of all market orders that arrived from the opposite side of the market in the past τ^i periods, and $Q^L_{t,t-\tau^i}$ is the cumulative volume of all limit orders that were submitted at the same distance from the best quote or closer than the order of current agent i, on the same side of the book, in the past τ^i. Although traders are unable to infer the sizes of individual orders by observing the state of the limit order book, it is plausible to assume that they monitor the order flow and can observe the size of incoming orders. The $Q^M_{t,t-\tau^i}/Q^L_{t,t-\tau^i}$ ratio in equation (6) provides an estimate of the likelihood to get a fill within the next τ^i trading rounds. The lower this probability the higher the proportion of the order that is hidden. This rule is consistent with results achieved in earlier studies, and in particular with Bessembinder et al. (2009) and DeWinne and D'Hondt (2007) who show that increased price aggressiveness is associated with shares exposed: impatient traders who seek quick execution use aggressively priced orders that are exposed while more patient traders, submitting non-marketable limit orders, tend to hide order size. This effect is captured by our rule as $Q^L_{t,t-\tau^i}$ increases, and q_V decreases, as the price distance of the order from the best quote increases. Empirical fundings also show that traders are more likely to hide part of their limit orders when when they submit orders on the weak side of the book (DeWinne and D'Hondt, 2007). Market imbalance in our model does not affect the decision to hide directly, but it does so indirectly. Proposition 2 shows that if

[4]This will be the case because $\partial p_m/\partial \bar{D}_t > 0$ and $\partial p_M/\partial \bar{D}_t > 0$.

[5]This assumption is compatible with requirements of many exchanges, for instance, the minimum peak size of an iceberg order on Euronext is 10 times the unit of trading.

the visible depth on the buy (sell) side is larger than on the sell (buy) side, then aggressive sells (buys) are less likely. Given that less aggressive orders are more likely to be hidden as a consequence of equation (6), our model incorporates the feature suggested by DeWinne and D'Hondt (2007).

In our model we ignore the possibility that agents use sophisticate trading strategies to discover undisclosed liquidity and react to it. In real market, traders have an incentive to estimate the hidden depth when they form trading strategies because hidden depth reduces the price impact of market orders. DeWinne and D'Hondt (2007) empirically find that hidden depth detection is possible and frequent, and the presence of hidden depth affects traders' behavior. DeWinne and D'Hondt (2007) and Frey and Sandås (2009) both show that the presence of hidden liquidity influences traders strategies: traders bid aggressively when they guess hidden liquidity at the best quote on the opposite side of the order book, suggesting that they do not associate hidden orders with informed trading. While we do not model the effect of hidden orders, if traders could correctly guess hidden depth on the opposite side of the market, their reaction would depend on how the detected depth impacts on order imbalance: if it reduces the imbalance then, by Proposition 2, they would trade more aggressively, if it increases the imbalance then they would trade less aggressively. We could assume that a random proportion of hidden orders may be guessed, with different precisions, by different traders but, in our setting, this would simply represent an intermediate step between the transparent and the opaque markets. This is because our agents are not concerned with the price impact of their market orders but are concerned with the information content of limit orders. We thus disregard this intermediate setting and perform the comparison directly to the limit case of a fully transparent market.

3.2. Simulation Parameters

The parameter values adopted in the numerical simulations of the five market specifications are summarized in Table 2. There is a fixed population of N_A agents in the market, who are initially allocated a random amount of stocks uniformly distributed on the interval $[0, N_S]$ and an amount of cash $[0, N_S p_0]$ with a maximum number of shares N_S per trader and the common risk aversion factor φ. The price grid is determined by the minimum tick size Δ. The noise term ξ_t is normally distributed with dispersion σ_ξ^2. Agents trade sequentially and in a random order. Agents with shorter time horizons are selected with higher probabilities to revise their orders.[6] When called to trade, an agent determines his price interval $[p_m, p_M]$ and draws any price p from that interval with an equal probability. If the trader already has an outstanding order in the book, it is replaced by a new one. Agents do not revise or cancel their orders prior to expiry otherwise. The trading horizons of agents are determined by a factor τ, so that the average horizon is approximately two trading days τ_d of 200 trading sessions. We assume that the fundamental asset value follows a mean reverting process with the long-run price level p^f and the expected reversion time of τ^f periods. The fundamental price, order imbalance and noise impact coefficients are drawn from three independent exponential distributions for the entire population of traders: $\nu_1^i \sim \exp(1/\sigma_{\nu_1})$, $\nu_2^i \sim \exp(1/\sigma_{\nu_2})$, $\eta^i \sim \exp(1/\sigma_\eta)$, $\forall i = \overline{1, N_A}$, and are fixed during the course of trading. While we report results only for a specific set of parameters, we did run the simulations for a wide range of values of σ_{ν_1} and σ_{ν_2} in order to study the influence of different ratios between fundamentalist, imbalance and noise components on prices, order flows and the book, and establish robustness of results.[7]

Each simulation run consists of 150,000 rounds. Since every market simulation commences with an empty limit order book, we discard the first 50,000 rounds and analyze the data from the remaining 50,000 rounds, which comprises 500 trading days. In order to gauge how transparency regimes affect the collective behavior of heterogeneous traders and what emergent market properties they generate, we replicate each simulation 100 times and compute average estimates of the key market statistics. In the subsequent sections

[6] The trading horizon of agent i, who is called to trade at time t satisfies: $\tau^i = \lceil \tau_t^\varepsilon \rceil$, where $\tau_t^\varepsilon \sim U(\tau_m, \tau_m + \varepsilon_t)$, with ε_t drawn from exponential distribution $\varepsilon_t \sim \exp(\sigma_\varepsilon^\tau)$ for $\tau_m = \min\limits_{i \in N_A} \tau^i$, $\tau_M = \max\limits_{i \in N_A} \tau^i$, and $\sigma_\varepsilon^\tau = \frac{1}{\tau_M - \tau_m}$. In effect, at each time step t a trading horizon (with the corresponding agent) is selected from a randomly chosen subset of total range $[\tau_m, \tau_M]$

[7] Appendix D highlights other important robustness evidence that reinforces our main findings.

Table 2: Key input parameters of the numerical simulations.

Parameter	Value	Parameter	Value
number of agents	$N_A = 5000$	time horizon	$\tau = 200$
number of stocks	$N_S = 50$	day length	$\tau_d = 200$
initial fundamental price	$p^f = £200$	fundamentalist impact	$\sigma_{\nu_1} = 0.1$
reversion horizon	$\tau^f = 10\tau_d$	imbalance impact	$\sigma_{\nu_2} = 0.011$
noise volatility	$\sigma_\xi = 0.001$	noise impact	$\sigma_\eta = 0.01$
tick size	$\Delta = £0.01$	risk aversion	$\varphi = 0.05$

we discuss the results of our numerical experiments in relation to empirical facts from double auction markets and to the principal research questions.

4. Markets Quality Analysis

In this section we explore the consequences of reduced pre-trade transparency regimes on observable market characteristics. The main findings of our simulation analysis indicate strong preference towards opaque regime and the results are not contingent upon naive or smart iceberg order submission principles.

4.1. Price Discovery and Transaction Costs

The comparison of transaction price patterns generated independently in the five markets indicates that the availability of market depth information on average exacerbates the excursions from fundamental asset price. As was discovered in our earlier order flow analysis (Kovaleva and Iori, 2014), full quote transparency mitigates traders' aggressiveness, limit orders tend to be smaller and more scattered in the book. The estimates in Table 3 reveal that the average transaction price deviates more from the fundamental value, as indicated by the increased price volatility, in the transparent and quasi-transparent markets because agents that demand immediacy in this market trade through several limit orders straightaway, skipping gaps in the book. The restriction of displayed depth to the five best quotes in a quasi-transparent market slightly reduces volatility at the expense of mild more underpricing. This rise in the volatility of prices and returns afflicts risk-averse investors and leads to a decline in the market activity, measured by the total number of executed trades and the cumulative trading volume over the whole 500-days period. In contrast, the opaque environment assists price discovery and the average transaction price remains close to the fundamental stock value, whether traders choose the visible order size with a smart or naive rule. According to the mechanism of traders' expectations formulated in Proposition 2, sellers are motivated to hide their order size to alleviate the selling pressure and thus draw more buyers to the market, and vice versa for the buyers. This mechanism translates into higher volume of trading and increased efficiency in the opaque market relative to both transparent and quasi-transparent markets. While the trading volume and the total number of trades is increasing in opaque regimes, this is achieved with fewer market orders of larger size. For instance, under transparent and opaque (s) specifications the total number of market orders is 30,070.2 and 30,170.5 respectively. However, the average sizes of market orders are 24.38 and 26.16, which explains larger total trading volume in opaque case, even though the proportion of market orders is smaller according to Table 6.

Yet, a more dramatic consequence of enhanced quote transparency is the widening of the bid-ask spread by 48% under full and quasi-transparency compared to the dark market. The contrast in evidence inflicted by the transparent and quasi-transparent policies is coherent with the explanation Madhavan et al. (2005), who advocate that too much transparency leads to higher volatility and execution costs. On the contrary, in the two opaque environments transaction costs (given by the spread) are significantly lower with a notable revival in trading activity (indicated by cumulative volumes transacted), almost matching the levels of a dark market.

We implement the first order stochastic dominance test to better quantify the effect of transparency on the bid-ask spread over the entire distribution, with values of the spread sampled at the end of each trading day,

Table 3: Statistics of the bid-ask spread, trading volumes and prices under five transparency regimes. The results represent averages over 100 simulation runs.

Indicator	Transparency regime				
	transparent	quasi-transp.	opaque (n)	opaque (s)	dark
Spread	1.0599	1.0422	0.7892	0.8732	0.7163
	(0.0036)	(0.0054)	(0.0051)	(0.0038)	(0.0031)
Transactions					
trading volume	739,273.8	742,623.3	831,586.1	863,742.9	860,529.4
	(2,710.5)	(3,512.1)	(3,855.7)	(4,064.5)	(5,434.2)
no. trades	59,136.8	59,742.5	71,770.1	70,752.9	65,216.4
	(297.9)	(350.1)	(314.0)	(303.0)	(396.7)
trade size	12.52	12.44	11.61	12.22	13.20
	(0.04)	(0.04)	(0.07)	(0.06)	(0.03)
trade price	199.76	199.30	200.44	200.62	199.69
	(0.08)	(0.06)	(0.06)	(0.07)	(0.03)
Volatility					
trade price	11.43	10.81	8.73	9.22	2.08
	(0.09)	(0.10)	(0.12)	(0.11)	(0.01)
return	0.0033	0.0032	0.0021	0.0024	0.0024
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

and pulled together over all simulation runs. Using the methodology of Barrett and Donald (2003), we verify the null hypothesis:

$$H_0 : F \geq G \iff F(z) \geq G(z), \quad \forall z \in [0, \bar{z}], \tag{7}$$

where F and G are the cumulative distribution functions associated with the independent samples of the bid-ask spread, drawn from two distinct transparency regimes.[8] The outcomes of pairwise comparisons across the various transparency regimes, with p-values reported in Table 4, generally coincide with the conclusion made on the basis of average spread estimates: for any given probability, the dark market provides the tightest spread, followed by opaque markets and then transparent and quasi-transparent cases. The test confirms that dark market dominates stochastically the other four market specifications almost surely (with probability 99.94-100%). The null hypothesis that the spread is tighter in opaque (n) market, where agents chose naively to trade via iceberg orders, rather than in opaque (s) market, with smart strategic splitting, is not rejected with probability 99.59%. We also observe that transparent is preferred to quasi-transparent market with probability 92.51%, as opposed to the conclusion from the average bid-ask spread relations in Table 3.

Overall, our results on the implications of transparency for the bid-ask spread align with the experimental findings of Bloomfield and O'Hara (1999) and the empirical study of Madhavan et al. (2005).[9] The results of Bloomfield and O'Hara (1999) are justified by the information asymmetry aspect (not modeled in our framework), whereby informed traders gain an option to hide partially their order sizes, by splitting via iceberg orders. Madhavan et al. (2005) associate higher execution costs in transparent regime on Toronto Stock Exchange with the unwillingness of traders to provide free options when their order sizes are fully

[8]Note that we implicitly assume that tighter spread is preferred to a wide spread. Hence, the sign in inequality (7) differs from the situation discussed in Barrett and Donald (2003) and related studies, where the test was applied to welfare.

[9]Our experiments do not control for the direction in transparency regime changes, which proves essential in the empirical implementation of transparency rules. Anand and Weaver (2004), for instance, show that a ban and a subsequent reintroduction of iceberg orders cause different market reactions. With this caveat in mind, we only compare the correlations between the direction of the transparency regime change and the ensuing movements in market indicators.

Table 4: Test for first order stochastic dominance: p-values for the null hypothesis in equation (7) that the distribution of spread (F) under specification in row i dominates the distribution of spread (G) under specification in column j.

Transparency regimes	transparent	quasi-transp.	opaque (n)	opaque (s)	dark
transparent	–	92.51	0.00	0.03	0.00
quasi-transp.	8.48	–	0.00	0.00	0.00
opaque (n)	99.53	99.73	–	99.57	3.71
opaque (s)	98.62	99.90	0.81	–	0.00
dark	100.00	100.00	100.00	99.95	–

disclosed. Regading the studies that discover the opposite effect of transparency on the spread, Flood et al. (1999) reason the narrowing of the bid-ask spread by the reduction in the search costs for the counterparty in their inter-dealer framework. Henderhott and Jones (2005) provide evidence that the quoted spreads widened after the electronic trading platform Island went completely dark in September 2002, mostly because traders migrated to other markets.

4.2. Liquidity Indicators

In the comparative examination of transparency regimes, we apply several methodologies to evaluate the key aspects of market liquidity, such as depth, breadth and resilience of the limit order book, and immediacy.

4.2.1. Market Depth

In terms of visible market depth, any increase of book transparency has an advantageous impact, as Table 5 depicts. We observe that full disclosure of market depth as well as endogenous disclosure regulation in the opaque market have a positive effect on the balance between total buy and sell volumes in the book. This reaction of traders to order book depth is in line with our analytical predictions stated in Proposition 2 and 3. Moreover, the effects of reduced pre-trade transparency on the book depth and trading volumes coincide with the effects documented by Aitken et al. (2001) and Anand and Weaver (2004) in their recent empirical research of the Australian and Toronto Stock Exchanges respectively. The visible order book imbalance in a quasi-transparent market is marginal on average and amounts to mere 2.3% of the actual imbalance, whereas the overall imbalance is more inclined towards buyers and partially reverts to the level of the dark market. Thereby, restricting the visibility of the book exogenously generates more uncertainty and more buyers queue in the book.

Most of the trading in the markets occurs near the best quotes, however, even full pre-trade transparency does not remove the imbalance between the buy and the sell depth. With only few quotes displayed, the risk of non-execution is mitigated by the agents' over-reaction to the observed imbalance and drastic price swings become less rare, confirmed by the volatility of the trade price (Table 3). The visible volume in the opaque books exhibits the best balance between buy and sell sides as in a quasi-transparent setting. The displayed volume accounts for approximately 56-59% symmetrically for buyers and sellers in the former case, even though hidden volume is more likely to be created on the buy side of the limit order book than on the sell side or inside the spread. The balance between aggregate demand and supply improves: an average gap between buy and sell volumes shrinks to 15.4% and 17.5% of the total market depth in the opaque (n) and opaque (s) markets respectively, while in a quasi-transparent market the cleavage accounts for 34.1%, which exceeds the percentage imbalance of fully transparent regime.

4.2.2. Order Flow and Conditional Aggressiveness

Order flow is an undoubtedly rich source of information regarding liquidity motives of market participants. We distinguish between three order categories for buyers and sellers alike: market orders, aggressive

Table 5: Statistics of market depth and imbalance under five transparency regimes. The results represent averages over 100 simulation runs.

Indicator	Transparency regime				
	transparent	quasi-transp.	opaque (n)	opaque (s)	dark
Buy depth	518.7	544.3	468.2	541.4	564.5
	(3.5)	(5.9)	(3.7)	(3.3)	(3.6)
visible, %	100.0	9.2	56.2	58.1	0.0
	(0.0)	(0.1)	(0.1)	(0.2)	(0.0)
Sell depth	322.4	267.1	343.2	379.9	234.8
	(1.3)	(1.0)	(2.4)	(2.3)	(1.2)
visible, %	100.0	16.2	56.9	59.6	0.0
	(0.0)	(0.1)	(0.1)	(0.1)	(0.0)
Total depth	841.1	811.4	811.4	921.3	799.3
	(4.5)	(6.1)	(5.9)	(5.4)	(4.3)
visible, %	100.0	11.5	56.5	58.7	0.0
	(0.0)	(0.1)	(0.1)	(0.1)	(0.0)
Order imbalance	196.3	277.2	125.0	161.6	329.7
	(2.8)	(5.9)	(1.8)	(1.9)	(3.3)
visible, %	100.0	2.3	54.3	54.5	0.0
	(0.0)	(0.0)	(0.3)	(0.5)	(0.0)

limit orders inside the spread, and passive limit orders further away in the book outside the spread.

The distribution of orders that are submitted to the market reported in Table 6 confirms that in transparent environments agents are reluctant to provide free option to trade, as evidenced by Moinas (2010) and Madhavan et al. (2005), and rely on market orders instead. This results in reduced liquidity of the limit order book and pushes the market price of the asset down (Table 3). We observe that in the opaque regimes about a quarter of all limit orders, both submitted within the bid-ask spread and outside it, have a hidden part. Even though iceberg order detection is not directly incorporated in trader's submission strategies, we replicate the findings of DeWinne and D'Hondt (2007) and Frey and Sandås (2009), which suggest that agents bid aggressively when there are hidden orders on the opposite side of the order book, because the price impact from the aggressive order tends to be small: the total hidden depth in opaque (n) market is larger than in opaque (s) market, resulting in the higher probability of limit order placement inside the spread is the former.

In order to dissect these liquidity patterns we assign order sequences into the following categories:

- undercutting (UC),
- resilient liquidity (RS),
- transient liquidity (TR), and
- depletion of liquidity (DP).

The grouping of 36 possible order placement events into these four categories is visually represented in Table 7. Property UC is the aggregate probability of those order sequences when aggressive limit orders undercut passive limit orders by price, which represents tight competition for liquidity provision. The second property, RS, unites the events whereupon a passive order succeeds an aggressive order: when the latter sweeps liquidity at the best quote or quotes, then a new order arrives to replenish consumed liquidity. Transient liquidity TR is a mirror situation to resilient liquidity: if a limit order improves market depth, the

Table 6: Order submissions by type (as a percentage of all submitted orders) and cancellations (as a percentage of submitted orders of a given type) under five transparency regimes. The results represent averages over 100 simulation runs.

Indicator	Transparency regime				
	transparent	quasi-transp.	opaque (n)	opaque (s)	dark
Submissions					
market orders	32.04	32.71	27.08	27.32	34.09
	(0.07)	(0.08)	(0.08)	(0.08)	(0.04)
limit in spread	21.54	21.46	21.31	16.93	24.99
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
iceberg/standard, %	–	–	23.02	17.67	–
			(0.07)	(0.12)	
limit out spread	46.42	45.83	51.60	55.76	40.92
	(0.15)	(0.24)	(0.23)	(0.20)	(0.07)
iceberg/standard, %	–	–	23.91	25.85	–
			(0.10)	(0.08)	
Cancellations					
standard limit	40.13	38.98	29.40	29.51	27.44
	(0.42)	(0.47)	(0.28)	(0.27)	(0.11)
iceberg	–	–	12.75	16.21	–
			(0.69)	(0.56)	

ensuing trader fills orders on the same side of the market. Lastly, property DP indicates a chain of aggressive trades.

Table 7: The diagram of liquidity provision patterns based on conditional order distributions. Each value in this table would be the probability an order type in row i arrives after order type in column j given the probability of i.

<table>
<tr><th rowspan="2"></th><th rowspan="2">market buy</th><th colspan="2">limit buy</th><th rowspan="2">market sell</th><th colspan="2">limit sell</th></tr>
<tr><th>in spread</th><th>out spread</th><th>in spread</th><th>out spread</th></tr>
<tr><td>market buy</td><td>DP</td><td colspan="2">–</td><td>DP</td><td colspan="2">TR</td></tr>
<tr><td>limit buy in spread</td><td rowspan="2">–</td><td colspan="2">UC</td><td rowspan="2">RS</td><td colspan="2" rowspan="3">–</td></tr>
<tr><td>limit buy out spread</td><td colspan="2">–</td></tr>
<tr><td>market sell</td><td>DP</td><td colspan="2">TR</td><td>DP</td></tr>
<tr><td>limit sell in spread</td><td rowspan="2">RS</td><td colspan="3" rowspan="2">–</td><td colspan="2">UC</td></tr>
<tr><td>limit sell out spread</td><td colspan="2">–</td></tr>
</table>

For the quantitative assessment of the defined patterns we sum unconditional probabilities of those events that fall within the corresponding group as highlighted in Table 7. As follows from Table 8, there is a significant difference in the distribution of the four liquidity patterns across transparency regimes. Property UC is the highest in the dark market: indeed, the rotation among the agents that place orders inside the book indicates increased competition among traders to provide liquidity, as registered in cumulative trading volumes (Table 3), because when order sizes are fully observed, large aggressive orders are more likely to occur. However, when the degree of order book transparency is endogenously determined by the agents, as it is in the opaque markets, undercutting becomes less frequent. Our justification of this effect is similar to the argument of Buti and Rindi (2013): since iceberg orders enable traders to control their exposure, they lower incentives for the incoming traders to undercut. Property TR is a little stronger in a transparent and especially a quasi-transparent market with partial information about the volumes, suggesting that liquidity is sporadic. I both opaque cases liquidity is more persistent, driven by the same feature the averts undercutting.

Table 8: The estimates of liquidity provision patterns based on conditional order distributions under five transparency regimes. The results represent averages over 100 simulation runs.

Property	Transparency regime				
	transparent	quasi-transp.	opaque (n)	opaque (s)	dark
UC	6.51	6.50	4.47	4.66	7.48
	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)
RS	13.32	13.84	11.11	11.33	13.16
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)
TR	12.61	13.15	10.34	10.53	12.10
	(0.05)	(0.04)	(0.04)	(0.05)	(0.01)
DP	9.91	10.34	9.32	9.28	11.05
	(0.10)	(0.10)	(0.09)	(0.10)	(0.04)

Accordingly, the resilience property of the book mildly subsides as agents gain full information about quote depth and improves in opaque markets. There is a high demand for immediacy on both sides of the book and arriving agents trade with existing orders and widen the bid-ask spread, as indicated by property DP in a quasi-transparent regime. Implementation of iceberg orders, especially when the choice of the visible size is based on the ratio between market and limit order arrivals – smart splitting, – helps to avoid systematic depletion of the book.

4.2.3. Liquidity Ratios

Unlike quote-driven markets where a market maker is responsible for supplying liquidity, in pure order-driven markets traders themselves generate liquidity. In this contest the prevalence of passive orders that fill the book or, on the contrary, aggressive orders that consume market depth provides an insight into the market liquidity level. We define another liquidity indicator that captures the structure of the order flow in terms of market versus limit orders. More precisely, we measure the relation

$$\text{Liquidity Provision} = \sum_{t=\tau_d}^{N_d} \left(\frac{Q^{M(b)}_{t,t-\tau_d}}{Q^{L(a)}_{t,t-\tau_d}} + \frac{Q^{M(a)}_{t,t-\tau_d}}{Q^{L(b)}_{t,t-\tau_d}} \right) / 2N_d, \tag{8}$$

where $Q^{M(b)}_{t,t-\tau_d}$ and $Q^{M(a)}_{t,t-\tau_d}$ are the cumulative volumes of buy and sell market orders, respectively, that arrived that were submitted in the past day τ_d up to time t, $Q^{L(b)}_{t,t-\tau_d}$ and $Q^{L(a)}_{t,t-\tau_d}$ are the corresponding quantities for buy and sell limit orders, and N_d is the total number of days in the sample. The value of this indicator is bounded between zero and one. The lower the liquidity provision ratio is, th thicker is the limit order book at any point in time. Abundant passive liquidity in the market with a weaker stream of incoming market orders is associated with near-zero values of the ratio, indicating divergence in the sellers' and buyers' valuation of the asset. A liquidity provision ratio close to unity implies that there is a high demand for immediacy and insufficient liquidity in the market. A well balanced market, therefore, is characterized by a low liquidity provision in the region of 0.5, when there is an active trading with a fair market depth at any point in time.

Simulation outcomes in Table 9 reveal that the dark market yields the highest liquidity provision coefficient, whereas the quasi-transparent regime reconciles the demand and supply of liquidity. This observation reflects that availability of market depth information increases the heterogeneity between agents and thickens the limit order book, which, in turn, impedes the price discovery process despite the common observable fundamental stock price. Conversely, limited market depth disclosure accelerates price discovery by balancing passive agents and those who seek immediacy. In this respect the opaque market furnishes the most efficient rules.

We also estimate the composite measure of liquidity proposed by Chordia et al. (2001) in their empirical

Table 9: The summary of liquidity indicators under five transparency regimes. The results represent averages over 100 simulation runs with the standard deviations provided in parentheses.

Indicator	Transparency regime				
	transparent	quasi-transp.	opaque (n)	opaque (s)	dark
Liquidity provision	0.4039	0.4380	0.2732	0.3189	0.7447
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Composite liquidity	2.2909	2.2752	1.9426	2.0002	1.5710
	(0.0465)	(0.0445)	(0.0321)	(0.0546)	(0.0279)
Kyle's lambda	0.0164	0.0160	0.0027	0.0039	0.0135
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)

analysis to evaluate the average slope of the liquidity function. This measure is calculated as

$$\text{Composite Liquidity} = \frac{\%\text{QuotedSpread}}{\$\text{Depth}}, \tag{9}$$

where %QuotedSpread is the quoted bid-ask spread divided by the mid-point of the quote (in percent), and $Depth is the average of the ask depth times ask price and bid depth times bid price. Consistent with the story of Chordia et al. (2001) and our earlier observations on average bid-ask spread and order book depth in Table 3, we find that Composite Liquidity is highest in the transparent market, where the slowed trading activity appears to cause a small increase in market depth as well as an increase in quoted spreads, as evidenced by the estimates of averages of these variables.

4.2.4. Price Impact

Finally, we obtain the estimates of the liquidity indicator proposed in the paper by Kyle (1985), usually referred to in the literature as Kyle's lambda. This indicator essentially embraces several aspects of liquidity including market resilience and depth, and is associated with the price impact of aggressive trades. For each executed trade we record the signed order flow q_t that is assumed positive for the buyer-initiated trades and negative for seller-initiated trades, the change in the price Δp_t inflicted by the trade and the average asset return $\bar{r}_t$. Using the data from 100,000 trading rounds we estimate the following equation:

$$\Delta p_t = \lambda^K q_t + \mu \bar{r}_t + \zeta_t. \tag{10}$$

The coefficient $\hat{\lambda}^K$ is reciprocal to liquidity: the higher is $\hat{\lambda}^K$, the more drastic effect an aggressive order makes on the limit order book depth and the wider is the resulting spread.

The lowest estimate of Kyle's lambda is for the opaque market which is entirely consistent with the idea of exposure control via iceberg orders. Consider, for example, a large market sell that exhausts all visible volume at the best bid and then new peaks are released at this price providing additional fills to the impatient seller. The same mechanism is activated for the neighboring buy quotes, and thereby slows down the seller walking down the book and alleviates the total price decrease created by his aggressive trade. Receded price impact in opaque regimes also relates to the study of stocks traded on the Madrid Stock Exchange by Pardo and Pascual (2012), who document that spreads do not widen and depth does not shrink after hidden order executions. The crucial driver in generating this result is the capability of traders to regulate the displayed order sizes and to find an optimal trade-off between exposure risk, that pushes them to minimize the peak size, and execution risk, that requires larger peak size.

The next best market in terms of price impact appears to be the dark market, according to results in Table 9. However, recall that unlike real order books a simulated dark market generates intensive order clustering around the best quotes with sparse submissions farther away. This is the reason why under this market specification the impact of trades is moderate – there are simply too few counterparties far from the current asset price. Hence, the value of $\hat{\lambda}^K$ in this case is not very indicative. Regarding the empirical findings on this topic, Anand and Weaver (2004) apply this comprehensive liquidity measure and find that neither a ban, nor a reintroduction of hidden orders provokes liquidity adjustments. Exogenously reduced transparency pertains a marginally smaller price impact than perfect transparency in our simulations. We conclude that intermediate levels of transparency in displayed quote depth, and particularly the opaque microstructure, stimulate liquidity measured by the Kyle's lambda.

5. Concluding Remarks

This paper provided an extensive analysis of the impact that distinct pre-trade quote transparency rules pertain for market performance. We include in our scope two extreme policies – transparent and dark, as well as two intermediate cases: a market with only top five orders visible on each side of the book – a quasi-transparent market, and a market with a permission to use iceberg orders for large trades – an opaque market with two different decision rules for iceberg orders. The evidence on benefits and adverse effects caused by limited market transparency is gained in the artificial double auction market simulations.

The core implication of our numerical simulations is that perfect transparency is harmful. At the same time, partial disclosure of order book depth entails reverse effects, depending on the concrete policy chosen. Both the quasi-transparent and opaque regimes intensify the speed of trading relative to the transparent market: the cumulative transacted volume increases while the non-execution risk of limit orders moderates. In the quasi-transparent market traders are more prone to seek immediacy and hesitate to fill the book, which, in turn, becomes on average thinner than under full depth disclosure rule. Not surprisingly, the control over disclosed depth information impedes the price discovery process, with buyers dragging the price down and a persistent gap between the buy and sell sides of the book.

In contrast, the opaque microstructure preserves market stability better than any other regime: the limit order book is more symmetric, the departures of transaction price from fundamental asset value are weaker and the volatility of returns is the lowest. In addition, this reduced transparency regime protects patient limit order traders from being picked-off to a certain degree, and, as a consequence, relieves the average transaction costs in the market measured by the bid-ask spread.

It follows from the experiments reported in this paper that markets with hidden layers ensure more solid liquidity and smaller price impact of aggressive trades. Also, such markets are more active and carry out substantial trading volumes in line with Aitken et al. (2001); Anand and Weaver (2004); Madhavan et al. (2005). Restricting quote transparency to several best quotes has negligible influence on market profile. Based on the numerical market simulations, Yamamoto (2011) also concludes that the level of pre-trade transparency is not crucial in terms of market performance and long memory. It is coherent with the real market observations that suggest that most of the asset pricing information is encapsulated in the best bid and ask, and any information beyond the best quotes has marginal influence on the direction of trading. Moreover, the distribution of the recorded limit orders under restricted quote information remains rather sparse as in the case of perfect transparency and abundant aggregate market depth does not result in liquidity improvement since many of the orders are placed too far away from the quotes and expire unfilled. At the same time, the gaps in the book result in more dramatic price swings and higher volatility in returns as compared to an absolutely transparent market environment. Issuing the traders a permission to choose themselves the revealed order size allows to circumvent these problems. The empirical outcome closest to our opaque market simulations was achieved by Madhavan et al. (2005) who propose a theoretical framework in their earlier research and reconcile it with the Toronto Stock Exchange (TSE) data. In fact, the TSE served as a prototype for most of automated trading systems in existence, including our artificial market, which justifies extrapolation of their results to similar microstructures and amplifies the significance of our findings.

In summary, full quote transparency incurs substantial transaction costs for investors and dampens trading activity in an order-driven market, and exogenous restriction of displayed quote depth does not alter substantially the dynamics. On the other hand, the endogenous restriction of displayed quote depth via iceberg orders appears to improve market quality in multiple dimensions.

Insofar, this study has revealed some important distinctions between two types of moderate transparency regimes and emphasized the benefits of iceberg orders. In practice, 'undisplayed' orders, their implementation and priority protocols, are quite diverse. It is valuable, therefore, to comprehend what patterns emerge when sophisticated traders apply strategically these exposure management tools. In order to address this problem, we aim to examine, in a subsequent paper, market profiles resulting from a variety of iceberg schemes and discretionary orders via agent-based simulations with learning.

Another direction for our future research would be to consider the implications of multiple trading venues for a given asset – the co-existence of a main transparent exchange and alternative less transparent markets. For instance, the EU financial markets regulation, articulated in MiFID II (Markets in Financial Instruments Directive), prescribes a double cap mechanism on the total trading volumes that can be executed in opaque markets, striving to secure the predominance of transparent exchanges. In relation to this problem one can question whether opaque segments can stipulate systemic risk and whether the restrictions imposed on the volumes executed in opaque markets can deplete overall liquidity.

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Appendix A. Proof of Proposition 1

Assume that a trader with a risk aversion φ^i and a portfolio of S_t^i stocks and C_t^i cash maximizes the expected CARA utility of his future wealth $W^i_{t+\tau^i}$. Suppose that the current stock price, i.e. the price of a last transaction or a mid-point price if no transaction has occurred in period t, is p_t. Let the trader form his expectation of the stock price $\hat{p}^i_{t+\tau^i}$ in τ^i periods according to rules (1) and (3). As Chiarella et al. (2009) demonstrate, the trader's demand for a risky asset or the optimal number of stocks required to hold in his portfolio at time t is given by:

$$\pi_t^i(p) = \frac{\ln(\hat{p}^i_{t+\tau^i}/p_t)}{\varphi^i V_t^i p_t}, \tag{A.1}$$

where V_t^i is the variance of the spot returns $V_t^i = \frac{1}{\tau^i}\sum_{j=1}^{\tau^i}(r_{t-j}-\bar{r}_t^i)^2$ with the mean spot return $\bar{r}_t^i = \frac{1}{\tau^i}\sum_{j=1}^{\tau^i} r_{t-j} = \frac{1}{\tau^i}\sum_{j=1}^{\tau^i}\ln\left(\frac{p_{t-j}}{p_{t-j-1}}\right)$. Suppose that the trader's private valuation of the stock is p. At this price p trader i wishes to buy more stocks if his demand exceeds present stock holdings $\pi_t^i(p) > S_t^i$, while if his portfolio contains more stocks than required $\pi_t^i(p) < S_t^i$, then he wishes to reduce his exposure and sell stocks. There *satisfaction level* price p^* makes the current portfolio composition optimal. As a result, if the realized price is lower $p < p^*$ then the trader wishes to buy the security; conversely, he will be willing to sell when $p > p^*$. The range of admissible prices that a particular trader can choose is $p \in [p_m, p_M]$: the upper bound p_M is determined by a no short selling restriction and the lower bound p_m is subject to a no borrowing condition. Departing from the expected return in (1) and the associated expected price in (3), trader i that is called to the market at time t solves the following three equations:

$$\forall p \le p_M : \ \pi_t^i(p) \ge 0 \quad \Leftrightarrow \quad p_M = \hat{p}^i_{t+\tau^i}, \tag{A.2}$$

$$\pi_t^i(p^*) = S_t^i \quad \Leftrightarrow \quad \frac{\ln(\hat{p}_{t+\tau^i}^i / p^*)}{\varphi^i V_t^i p^*} = S_t^i, \tag{A.3}$$

$$p_m \left(\pi_t^i(p_m) - S_t^i\right) = C_t^i \quad \Leftrightarrow \quad \frac{\ln(\hat{p}_{t+\tau^i}^i / p_m)}{\varphi^i V_t^i} - p_m S_t^i = C_t^i. \tag{A.4}$$

Since neither of the equations (A.3) or (A.4) admits an explicit solution, we apply the implicit function theorem to obtain the derivatives of p^* and p_m with respect to p_M. We use substitution $\ln(p_M/p^*) = p^*\varphi^i V_t^i S_t^i$ implied by (A.3) and arrive at the following two expressions

$$\frac{\partial p^*}{\partial p_M} = \frac{p^*}{p_M(1 + p^*\varphi^i V_t^i S_t^i)}, \tag{A.5}$$

$$\text{and} \quad \frac{\partial p_m}{\partial p_M} = \frac{p_m}{p_M(1 + p_m\varphi^i V_t^i S_t^i)}. \tag{A.6}$$

Notice, that derivatives (A.5) and (A.6) are both positive since all the parameters are positive and have the same functional form $f(x) = x/(1 + x\varphi^i V_t^i S_t^i)$. Given that function $f(x)$ is strictly monotonic increasing ($f'(x) > 0 \ \forall x \in \mathbb{R}$), it follows

$$\frac{\partial p^*}{\partial p_M} > \frac{\partial p_m}{\partial p_M} > 0. \tag{A.7}$$

∎

Appendix B. Proof of Proposition 2

The trader picks any price $p \in [p_m, p_M]$ with an equal probability, therefore, in order to evaluate the impact of a certain factor z on the propensity of trader i who arrived to the market at time t to buy or sell shares, it suffices to compute the derivative of the ratio of the appropriate subinterval (buy or sell) to the interval of admissible prices with respect to z. Consider the sell subinterval $[p^*, p_M]$ and denote trader's propensity to sell by

$$A = \frac{p_M - p^*}{p_M - p_m}, \tag{B.1}$$

then

$$\frac{\partial A}{\partial z} = \frac{(p_M - p_m)\left(\frac{\partial p_M}{\partial z} - \frac{\partial p^*}{\partial z}\right) - (p_M - p^*)\left(\frac{\partial p_M}{\partial z} - \frac{\partial p_m}{\partial z}\right)}{(p_M - p_m)^2}. \tag{B.2}$$

If $\partial A/\partial z > 0$, then the trader becomes more likely to be a seller once z increases; if $\partial A/\partial z < 0$, then the trader becomes more likely to be a buyer once z increases. We first establish the necessary results for statement (1), and then prove the effect of volatility in statement (2).

Statement (1)

Since p^* and p_m depend on the order imbalance $\bar{D}_t$ and v_2^i only through p_M, we write the differentials of prices with respect to a change in factor z as follows:

$$\frac{\partial p^*}{\partial z} = \frac{\partial p^*}{\partial p_M} \cdot \frac{\partial p_M}{\partial z}, \quad \text{and} \quad \frac{\partial p_m}{\partial z} = \frac{\partial p_m}{\partial p_M} \cdot \frac{\partial p_M}{\partial z},$$

therefore, in this case expression (B.2) simplifies to

$$\frac{\partial A}{\partial z} = \frac{\partial p_M/\partial z}{(p_M - p_m)^2}\left[(p_M - p_m)\left(1 - \frac{\partial p^*}{\partial p_M}\right) - (p_M - p^*)\left(1 - \frac{\partial p_m}{\partial p_M}\right)\right]. \tag{B.3}$$

By substituting the expressions (A.5) and (A.6) from Appendix A, we rewrite the derivative of term A as follows:

$$\frac{\partial A}{\partial z} = \frac{\partial p_M/\partial z}{p_M(p_M-p_m)^2}\underbrace{\left[(p_M-p_m)\left(p_M-\frac{p^*}{1+p^*\varphi^i V_t^i S_t^i}\right)-(p_M-p^*)\left(p_M-\frac{p_m}{1+p_m\varphi^i V_t^i S_t^i}\right)\right]}_{B_1}.$$

Given that by definition $p_m < p^* < p_M$, substitute $p^* = a \cdot p_m$ and $p_M = b \cdot p_m$, where $b > a > 1$. Then term B_1 is expressed by

$$\begin{aligned} B_1 &= p_m(b-1)\left(bp_m-\frac{ap_m}{1+ap_m\varphi^i V_t^i S_t^i}\right)-p_m(b-a)\left(bp_m-\frac{p_m}{1+p_m\varphi^i V_t^i S_t^i}\right) \\ &= p_m^2(ab+abp_m\varphi^i V_t^i S_t^i+b-a)\left[\frac{1}{1+p_m\varphi^i V_t^i S_t^i}-\frac{1}{1+ap_m\varphi^i V_t^i S_t^i}\right]. \end{aligned}$$

Notice that function $f(x) = 1/(1+x\varphi^i V_t^i S_t^i)$ is monotonic increasing $\forall x \in \mathbb{R}$, hence $B_1 > 0$ and the sign of $\partial p_M/\partial z$ determines the change in the propensity to sell. Denote the weight of order imbalance in the expected return by $\tilde{v}_2^i = v_2^i/(v_1^i + v_2^i + \eta^i)$. Recall that from equation (3) the maximum price is $p_M = p_t \exp(\hat{r}^i_{t,t+\tau^i}\tau^i)$, so the derivatives with respect to the visible imbalance $\bar{D}_t$ and imbalance weight $\tilde{v}_2^i$ determine the sign of $\partial A/\partial \bar{D}_t$ and $\partial A/\partial \tilde{v}_2^i$ as follows

$$\frac{\partial p_M}{\partial \bar{D}_t} = p_M\tau^i\tilde{v}_2^i, \quad \Rightarrow \quad \frac{\partial A}{\partial \bar{D}_t} > 0, \tag{B.4}$$

$$\text{and} \quad \frac{\partial p_M}{\partial \tilde{v}_2^i} = p_M\tau^i\bar{D}_t, \quad \Rightarrow \quad \operatorname{sgn}\left\{\frac{\partial A}{\partial \tilde{v}_2^i}\right\} = \operatorname{sgn}\{\bar{D}_t\}. \tag{B.5}$$

Therefore, we conclude that the propensity to sell increases when the order imbalance in the limit order book increases towards buyers. Similarly, higher sensitivity to imbalance prompts the trader to join the opposite side of the market relative to the visible imbalance trend.

Statement (2)

Notice, that the maximum expected price p_M is not related to asset return volatility in this model, therefore, $\partial p_M/\partial V_t^i = 0$. The minimum and satisfaction prices depend on the spot volatility, so we simplify the expression of the derivate of A with respect to V_t^i as follows

$$\frac{\partial A}{\partial V_t^i} = \frac{(p_M-p^*)\frac{\partial p_m}{\partial V_t^i}-(p_M-p_m)\frac{\partial p^*}{\partial V_t^i}}{(p_M-p_m)^2}. \tag{B.6}$$

Again, applying the corollary of the implicit function theorem, we compute partial derivatives with respect to the spot volatility V_t^i:

$$\frac{\partial p^*}{\partial V_t^i} = -\frac{p^*\ln(p_M/p^*)}{V_t^i(1+p^*\varphi^i V_t^i S_t^i)}, \tag{B.7}$$

$$\text{and} \quad \frac{\partial p_m}{\partial V_t^i} = -\frac{\ln(p_M/p_m)}{V_t^i(1+p_m\varphi^i V_t^i S_t^i)}. \tag{B.8}$$

Next, we substitute the derivatives (B.7) and (B.8) into the expression (B.2) and obtain

$$\frac{\partial A}{\partial V_t^i} = \frac{1}{V_t^i(p_M-p_m)^2}\underbrace{\left[(p_M-p_m)\frac{p^*\ln(p_M/p^*)}{(1+p^*\varphi^i V_t^i S_t^i)}-(p_M-p^*)\frac{\ln(p_M/p_m)}{(1+p_m\varphi^i V_t^i S_t^i)}\right]}_{B_2}.$$

Further, we apply the same substitution $p^* = a \cdot p_m$ and $p_M = b \cdot p_m$ with $b > a > 1$, and rearrange term B_2 as follows

$$\begin{aligned} B_2 &= p_m(b-1)\frac{ap_m \ln(b/a)}{(1+ap_m\varphi^i V_t^i S_t^i)} - p_m(b-a)\frac{\ln(b)}{(1+p_m\varphi^i V_t^i S_t^i)} \\ &= (b-1)\ln(b/a)\left[p_m \frac{ap_m}{(1+ap_m\varphi^i V_t^i S_t^i)} - \frac{\ln(b)}{b-1}\cdot\frac{b-a}{\ln(b/a)}\cdot\frac{p_m}{(1+p_m\varphi^i V_t^i S_t^i)}\right]. \end{aligned}$$

Notice that function $f(x) = 1/(1 + x\varphi^i V_t^i S_t^i)$ is monotonic increasing in x, therefore,

$$\frac{ap_m}{(1+ap_m\varphi^i V_t^i S_t^i)} > \frac{p_m}{(1+p_m\varphi^i V_t^i S_t^i)}. \tag{B.9}$$

On the other hand, function $g(x) = \ln(b/x)/(b-x)$ is monotonic decreasing in x, so $\frac{\ln(b)}{b-1}\cdot\frac{b-a}{\ln(b/a)} > 1$. Taking into account $\lim_{a\to b^-}\left[\frac{\ln(b)}{b-1}\cdot\frac{b-a}{\ln(b/a)}\right] = \frac{\ln(b)}{b-1}\cdot\lim_{a\to b^-}\left[\frac{\partial(b-a)/\partial a}{\partial \ln(b/a)/\partial a}\right] = \frac{b\cdot\ln(b)}{b-1}$, it follows that[10]

$$p_m > \frac{\ln(b)}{b-1}\cdot\frac{b-a}{\ln(b/a)}. \tag{B.10}$$

The product of the two inequalities (B.9) and (B.10) thus yields $B_2 > 0$ and

$$\frac{\partial A}{\partial V_t^i} > 0, \tag{B.11}$$

which proves statement (3) of Proposition 2. Therefore, we establish that the trader's propensity to sell increases with the volatility of returns in this model. ■

Appendix C. Proof of Proposition 3

Consider trader i who chooses to sell the asset. Suppose that the current asset price p_t is in the interval $[p^*, p_M]$, so that the trader may use either a market or a limit order to execute his trade. The propensity to sell via a limit order is given by

$$L_s = \frac{p_M - p_t}{p_M - p^*}, \tag{C.1}$$

and $1 - L_s$ is the propensity to sell at the market. The change in the propensity to sell with a limit order in response to the change in visible oder imbalance $\bar{D}_t$ is

$$\frac{\partial L_s}{\partial \bar{D}_t} = \frac{(p_M - p^*)\left(\frac{\partial p_M}{\partial \bar{D}_t} - \frac{\partial p_t}{\partial \bar{D}_t}\right) - (p_M - p_t)\left(\frac{\partial p_M}{\partial \bar{D}_t} - \frac{\partial p^*}{\partial \bar{D}_t}\right)}{(p_M - p^*)^2}.$$

After simple algebraic manipulations this expression reduces to

$$\frac{\partial L_s}{\partial \bar{D}_t} = \frac{\partial p_M/\partial \bar{D}_t}{(p_M - p^*)^2}\left[p_t - p^*\frac{e^{-\hat{r}^i_{t,t+\tau^i}\tau^i} + \ln(p_M/p^*)}{1 + \ln(p_M/p^*)}\right]$$

[10]This inequality holds for almost all price levels, unless both p^* and p_m are near zero while p_M is substantially high. The range of market parameters that we use in our simulations, in particular, common risk aversion φ and the maximum initial number of stocks per trader N_A, prevent such situations.

By assumption $p_M > p_t$, which implies that $\hat{r}^i_{t,t+\tau^i} > 0$ and follows immediately that

$$p_t > p^* > p^* \frac{e^{-\tau^i \hat{r}^i_{t,t+\tau^i}} + \ln(p_M/p^*)}{1 + \ln(p_M/p^*)} > 0 \quad \Longleftrightarrow \quad \frac{\partial L_s}{\partial \bar{D}_t} > 0. \tag{C.2}$$

And the propensity to use a sell limit order increases with an increase in the visible order imbalance towards buyers.

In a similar manner, for the buyer's propensity to use a limit order $L_b = \frac{p_t - p_m}{p^* - p_m}$ it is easy to show that

$$\frac{\partial L_b}{\partial \bar{D}_t} < 0. \tag{C.3}$$

Therefore, the higher the visible order imbalance towards buyers, the more likely the traders to sell with limit orders and buy with market orders. ■

Appendix D. Robustness Checks

In this section we provide some additional results that align with the general conclusions from our analysis and provide further support to the main cases considered above.

First, we adjust the number of traders in the transparent market such that the total number of viable limit orders in the book matches that of an opaque environment. In particular, we estimated total visible depth of 543.5 and the average bid-ask spread 1.0164 when $N_A = 200$ in transparent market, while in opaque market with sophisticated rule (6) and $N_A = 5000$ total visible depth comprises 540.8, as reported in Table 5, with the bid-ask spread of 0.8732. This outcome validates the result that full transparency of the limit order book widens the spread, as we conclude in the main analysis. Moreover, we monitored the changes inflicted by the size of traders' population in opaque (s) regime, and notice (Table D.10) that the spread is not affected significantly by the size of the economy, which implies scalability of the model.

As a further robustness check, we examine a range of intermediate cases between fully transparent limit order book and opaque, where traders are given partial information about hidden depth in the limit order book. We do ,so by introducing a fixed proportion of market depth $\delta = \delta_i \ \forall i = \overline{1, N_A}$ that each trader is able to detect correctly at any point in time to calculate buy and sell volumes Q_t^b, Q_t^a and book imbalance from equation (4):

$$Q_t^\omega = Q_t^{\text{vis},\omega} + \delta Q_t^{\text{hid},\omega}, \qquad \text{where } \omega = \{a, b\}. \tag{D.1}$$

As Table D.11 indicates, the poorer is traders' prediction of hidden liquidity available in the limit order book, the wider the bid-ask spread. Even 20% probability of being undetected (i.e. the case of $\delta = 80\%$) has a significant value for large traders and reduces the spread by almost 15%: from 1.2753 in transparent market to 1.0277 in opaque (d) with 80 hidden order detection percent.

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Table D.10: The summary of key market indicators under opaque (s) regime with varying number of agents N_A and fully transparent regime with baseline case parameters. The results represent averages over 100 simulation runs with the standard deviations provided in parentheses.

Indicator	Transparency regime						
	opaque (s)						transparent
	$N_A = 1000$	$N_A = 2000$	$N_A = 2500$	$N_A = 3500$	$N_A = 4000$	$N_A = 5000$	$N_A = 5000$
Total depth	837.8	870.5	884.1	910.7	913.6	921.3	841.1
	(7.2)	(6.1)	(16.3)	(14.1)	(13.9)	(5.4)	(4.5)
visible, %	61.0	57.9	58.4	58.5	58.7	58.7	100
	(0.6)	(0.7)	(0.5)	(0.4)	(0.4)	(0.1)	(0.0)
Spread	0.84	0.82	0.83	0.86	0.85	0.87	1.06
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.0036)
Transactions							
trading volume	774,191.9	845,489.1	825,170.7	853,267.1	861,200.2	863,742.9	739,273.8
	(37,054.1)	(8,354.9)	(12,989.6)	(9,409.1)	(11,968.1)	(4064.5)	(2,710.5)
no. trades	65,004.5	70,576.5	68,265.8	69,901.1	70,408.8	70,752.9	59,136.8
	(864.5)	(385.5)	(1,333.2)	(1,029.9)	(1,232.4)	(303.0)	(297.9)
trade size	11.90	11.98	12.11	12.22	12.25	12.22	12.52
	(0.41)	(0.05)	(0.19)	(0.11)	(0.22)	(0.06)	(0.04)
trade price	201.55	201.09	201.51	201.29	200.84	200.62	199.76
	(0.69)	(0.40)	(0.44)	(0.17)	(0.33)	(0.07)	(0.08)

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Table D.11: The summary of key market indicators under opaque (d) regime with varying proportion of detectable depth δ and fully transparent regime with baseline case parameters. The results represent averages over 20 simulation runs 5,000 time steps each with the standard deviations provided in parentheses.

Indicator	Transparency regime						
	transparent	opaque (d)					
		$\delta = 100\%$	$\delta = 80\%$	$\delta = 60\%$	$\delta = 40\%$	$\delta = 20\%$	$\delta = 0\%$
Spread	1.2753	1.2753	1.0277	1.0854	1.0257	1.1108	0.9980
	(0.0584)	(0.0584)	(0.0471)	(0.0654)	(0.0577)	(0.0646)	(0.0362)
Transactions							
trading volume	38,812.9	38,812.9	38,175.3	37,898.9	37,968.3	37,943.8	38,151.7
	(990.1)	(990.1)	(756.1)	(776.4)	(807.8)	(725.3)	(757.8)
no. trades	3,059.0	3,059.0	3,501.2	3,505.2	3,486.9	3,529.0	3,518.3
	(64.1)	(64.1)	(53.2)	(48.3)	(58.9)	(45.2)	(64.8)
trade size	12.68	12.68	10.90	10.81	10.89	10.75	10.85
	(0.12)	(0.12)	(0.13)	(0.14)	(0.11)	(0.14)	(0.13)
Total depth	828.3	828.3	927.5	919.2	922.6	892.8	884.6
	(23.7)	(23.7)	(31.3)	(24.7)	(19.5)	(30.9)	(14.2)
visible, %	100.0	100.0	55.0	54.5	54.5	55.0	55.5
	(0.0)	(0.0)	(0.6)	(0.4)	(0.5)	(0.5)	(0.6)
Buy depth	506.9	506.9	583.9	592.3	589.2	580.6	564.6
	(17.6)	(17.6)	(25.9)	(18.8)	(16.2)	(22.0)	(12.2)
visible, %	100.0	100.0	52.0	51.5	51.5	51.9	52.9
	(0.0)	(0.0)	(0.7)	(0.4)	(0.4)	(0.6)	(0.9)
Sell depth	321.4	321.4	343.7	326.9	333.4	312.2	319.9
	(6.7)	(6.7)	(8.4)	(9.2)	(6.8)	(13.2)	(6.5)
visible, %	100.0	100.0	60.1	60.0	59.9	60.9	60.3
	(0.0)	(0.0)	(0.5)	(0.6)	(0.7)	(0.8)	(0.5)