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Working Paper

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CFR Working Paper, No. 05-15

Provided in Cooperation with:

Centre for Financial Research (CFR), University of Cologne

Suggested Citation: Foucault, Thierry; Moinas, Sophie; Theissen, Erik (2005) : Does anonymity matter in electronic limit order markets?, CFR Working Paper, No. 05-15, University of Cologne, Centre for Financial Research (CFR), Cologne

This Version is available at:

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**Does Anonymity matter in
electronic Limit order markets?**

T. Foucault • S. Moinas • E. Theissen

centre for financial research
Look deeper

DOES ANONYMITY MATTER IN ELECTRONIC LIMIT ORDER MARKETS?¹

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This Draft: May, 2005

¹We are grateful to J.Angel, B.Biais, P.Bossaerts, D. Brown, C. Caglio, F. Declerk, G.Demange, J. Grammig, M. Kasch, D.Leschinski, S. Lovo, R. Lyons, F.deJong, M.O'Hara, F.Palomino, C.Spatt, B. Rindi, R.Roll, G. Saar, D. Seppi, A.Whol and one anonymous referee for providing very helpful comments. We also received useful comments from participants in various conferences (EFA03, WFA03, AFFI, INSEAD market microstructure workshop, the 6th ESC Toulouse-IDEI Finance Workshop, Oxford Symposium) and seminars (Bielefeld University, CORE, Frankfurt University, Duisburg University, HEC Montreal, Norwegian School of Business, University of Amsterdam, University of Rotterdam, Tilburg University and Séminaire Bachelier). We thank Euronext Paris for providing the data. Financial support from the Fondation HEC and the Deutsche Forschungsgemeinschaft through SFB/TR 15 is gratefully acknowledged. Of course, all errors or omissions are ours.

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Abstract

“Does Anonymity Matter in Electronic Limit Order Markets?”

As of April 23, 2001, the limit order book for stocks listed on Euronext Paris became anonymous. We study the effect of this switch to anonymity on market liquidity and the informational content of the limit order book. Our empirical analysis is based on a model of limit order trading in which traders have information on future price volatility. As limit orders have option-like features, this information is valuable for limit order traders. We analyze limit order traders' bidding strategies in 2 different market structures : (a) an anonymous market (limit order traders' IDs are concealed) and (b) a non-anonymous market (traders' IDs are disclosed). Limit order traders bid less aggressively when they expect volatility to rise. For this reason, in either market design, an increase in the bid-ask spread foreshadows increased volatility. Moreover, when information on future volatility is public, the informational content of the bid-ask spread and market liquidity are identical in each market structure. In contrast, when some traders possess superior information on future volatility, a switch to anonymity alters the informational content of the bid-ask spread and market liquidity. For our sample stocks, we find that the switch to anonymity in Euronext paris has significantly reduced the average quoted spread and the average effective spread. We also find that the size of the bid-ask spread is positively related the magnitude of future price movements. But the strength of this association is weaker after the switch to anonymity. Overall, the empirical findings are consistent with the version of our model in which traders possess private information about future volatility.

Keywords: Market Microstructure, Limit Order Trading, Anonymity, Transparency, Liquidity, Volatility Forecasts.

JEL Classification: G10, G14, G24

“Broker ids are an additional piece of information that can, in some circumstances, be useful in predicting future market activity. It is apparent that some traders attempt to second-guess future price movements based on trading by particular brokers [...] This activity has the ability to stifle and suppress natural liquidity, and imposes extra costs on participants when they try to disguise their trading strategies to protect their positions” (in “ASX market reforms-Enhancing the liquidity of the Australian equity markets” Consultation Paper of the Australian Stock Exchange (2003)).

1 Introduction

In the last decade, the security industry has witnessed a proliferation of electronic trading systems. These new trading venues (e.g. Island ECN, EuroSETS or Reuters D2000-2) are often organized as order-driven markets where traders can either post quotes (submit limit orders) or hit posted quotes (submit market orders). This development has spurred considerable interest and raises several questions about order-driven markets. In particular, how their design (transparency, priority rules etc...) affects market liquidity and the informational content of the limit order book are yet unsettled issues.¹

A case in point is the amount of information provided on traders’ identities. Some markets (e.g. the Hong Kong Stock Exchange or the Australian Stock Exchange) disclose, for each limit order standing in the limit order book, the issuing broker’s identification code. In other markets (e.g. Island, Euronext or the NYSE), brokers’ IDs are concealed. Does it matter? How is market liquidity affected by the disclosure of limit order traders’ identities? Is the informational content of the limit order book altered by anonymity? These questions are important as the effects of anonymity and the nature of information contained in limit order books are constantly debated by practitioners, regulators and researchers. On April 23, 2001, the limit order book for stocks listed on Euronext Paris became anonymous. We take advantage of this unique event to study empirically the effects of anonymity, using the guidance of a theoretical analysis developed in the first part of our article.

Central to this analysis is the idea that the limit order book contains information on the magnitude or the likelihood of future price changes (i.e. future price volatility). This follows from the fact that limit orders have option-like features. A trader who submits a sell (resp. buy) limit order for a security offers, for free, a call (resp. put) option on this security with a strike price equal to the price of the limit order. These options are valuable because speculators (e.g. day traders) can exercise them when there is a shift in the value of the security, by “picking off” stale limit orders. As option values depend on volatility, information on future price volatility is valuable for limit order traders. They should bid less aggressively in anticipation of increased volatility in order to reduce their exposure to the risk of being picked off (see Copeland and Galai (1983)).

¹Bloomfield, O’Hara and Saar (2005), Section 2, provide an excellent overview of the theoretical literature on limit order markets.

Building on this intuition, we develop a model in which some limit order traders have superior information on the likelihood of future price movements. Cautious bidding by informed traders, manifested by a large bid-ask spread, *signals* that the risk of being picked off is large. For this reason, a large spread deters uninformed traders from improving upon the offers posted in the book. In turn, this effect induces informed limit order traders to use “bluffing strategies”. They sometimes try to “fool” uninformed traders by bidding as if the risk of being picked off were large (they post non-aggressive limit orders) when indeed it is small. When their bluff is successful, i.e. deters competitors from free riding on their offers, informed traders earn larger profits.

We analyze these interactions in two different trading mechanisms : a *non-anonymous* market (limit order traders’ IDs are visible) and an *anonymous* market (limit order traders’ IDs are concealed). As a benchmark, we consider the case in which information on future volatility is public. In this case, anonymity does *not* matter : concealing limit order traders’ IDs does not alter market liquidity or the informativeness of the bid-ask spread. This irrelevance result breaks down when some limit order traders have private information on future volatility. Actually, in this case, uninformed traders form their beliefs about future volatility by observing the limit order book and the quality of their inferences depends on whether the limit order book is anonymous or not. Accordingly, a switch to anonymity changes traders’ bidding strategies. For instance, informed traders always bid more aggressively (i.e. bluff less frequently) when their identities are concealed because their attempt to manipulate uninformed traders’ beliefs is less effective in an anonymous environment.² Ultimately, the impact of anonymity on liquidity and the informational content of the bid-ask spread is determined by the proportion of informed traders. When it is small, a switch to anonymity reduces (i) the size of the quoted spread and (ii) the size of the effective spread, on average. In this case also, a switch to anonymity reduces the informativeness of the bid-ask spread about the likelihood of future price movements because best quotes are set more frequently by uninformed traders. Opposite results are obtained when the proportion of informed traders is large.

Until April 23, 2001 the identification codes for broker-dealers submitting limit orders on Euronext Paris (the French stock Exchange) were displayed to all brokerage firms. Since then, the limit order book is anonymous. Thus, using Euronext Paris data, we can run a natural experiment to study the effect of concealing liquidity suppliers’ identities. This is of particular interest as many electronic limit order markets (e.g. the Toronto Stock Exchange, the Stockholm Stock Exchange or Island) have a design which is very similar to the trading system used by Euronext Paris. Our data do not allow us to directly test the model predictions because we do not observe the proportion of informed limit order traders. However, we can study the impact of anonymity on measures of market liquidity and the informativeness of the bid-ask spread about future volatility.

To this end, we compare measures of market liquidity and the informativeness of the

²Several market observers have pointed out that non-anonymity facilitates market manipulation. This problem has played an important role in the decision of the Toronto Stock Exchange to switch to an anonymous trading system in July 2003. See “*TSE witholds broker names in bid to deter speculators*”, Financial Times, July, 1st, 2003. See also the opening quotation.

bid-ask spread before and after the switch to anonymity, using two different periods after the switch took place. The empirical findings are very similar for each post-event period. We find that the quoted spread and the effective spread for the stocks in our sample are significantly smaller after the switch to anonymity. These results are robust after controlling for the impact of other variables which are known to affect bid-ask spreads (such as volatility and trading volume). In order to study the informativeness of the bid-ask spread about future volatility, we divide each trading day into intervals of thirty minutes. We find that there is a positive and significant relationship between the bid-ask spread in one interval and the magnitude of the price change over the subsequent interval. We also find that the strength of this relationship is significantly smaller after the switch to anonymity. These results are robust when we model time-variations in conditional returns volatility using a GARCH(1,1) framework with the lagged bid-ask spread as explanatory variable.

To sum up, in line with the theoretical analysis, we find that the switch to anonymity has improved liquidity **and** reduced the informativeness of the bid-ask spread. We see these findings as providing support for the model because we are not aware of other explanations for the concomitance of these two observations (liquidity improves and the informativeness of the bid-ask spread decreases after the switch to anonymity). In particular, as shown in the paper, if information about future volatility is symmetric, then a switch to anonymity has no effect on market liquidity and the relationship between the bid-ask spread and future volatility. Our empirical findings reject this version of the model but not the version in which some traders are privately informed about future volatility.

Our study is related to the longstanding controversy regarding the desirability of transparency in security markets (see O'Hara (1995) for a review).³ The provision of information on traders' IDs' is obviously one dimension of market transparency. It can take place pre-trade and/or post-trade. Research on anonymity has primarily focused on the effects of providing pre-trade information. In general, researchers have shown that concealing pre-trade information about *liquidity demanders'* identities (e.g. block traders) impairs market liquidity.⁴ In contrast, we focus on the effects of disclosing pre-trade information about *liquidity suppliers'* (limit order traders) identities and our findings show that concealing this type of information can improve market liquidity. Waisburd (2003) empirically analyzes the effect of revealing traders' identities *post-trade*, using data from Euronext Paris. He considers a sample of stocks trading in two different regimes: one in which brokers' identities are revealed post-trade and one in which these identities are concealed. He finds that the average bid-ask spread is larger and quoted depth is smaller in the post-trade anonymous regime. Our empirical findings go in the opposite direction. Hence, post-trade and pre-trade anonymity have strikingly different effects. Overall, the differences between our results and those in the extant literature underscore the complex nature of the issues

³Recent papers have analyzed theoretically and empirically the effect of providing information on the prices and sizes of limit orders standing in the book (respectively Baruch (1999), Madhavan, Porter and Weaver (2002) and Boehmer, Saar and Yu (2005)). This type of information is distinct from information on liquidity providers' IDs.

⁴Papers on this topic include Seppi (1990), Forster and George (1992), Benveniste et al. (1992), Madhavan and Cheng (1997), Garfinkel and Nimalendran (2002), and Theissen (2003).

related to anonymity in financial markets.

Some articles analyze the effects of providing information on liquidity suppliers' identities. Rindi (2002) considers the effect of disclosing informed traders' demand in a rational expectations model (in the spirit of Grossman and Stiglitz (1980)). Our approach differs in many ways. Rindi (2002) analyzes a batch auction in which all orders are submitted simultaneously and clear at a uniform price. In contrast, in our model, liquidity suppliers submit their orders sequentially and market orders can execute at different prices (they can "walk up" or "walk down" the book). In this way, we can derive separate predictions for the effect of anonymity on quoted spreads and effective spreads. Another, more fundamental, difference is that limit order traders possess information on future volatility in our model. Simaan, Weaver and Whitcomb (2003) argue that non-anonymous trading facilitates collusion among liquidity suppliers. They find that dealers post more aggressive quotes in ECNs' than in Nasdaq, as predicted by the collusion hypothesis (as dealers' IDs are displayed on Nasdaq but not in ECNs'). Our model does not rely on collusion among liquidity suppliers and thereby it provides an alternative to the collusion hypothesis.⁵

Finally, our findings contribute to the recent literature on the informational content of the book (Irvine, Benston and Kandel (2000), Kalay and Wohl (2002), Harris and Penchappagesan (2003), Cao, Hansch and Wang (2003)). This literature has analyzed whether book information (e.g. order imbalances) could be used to predict the *direction* of future price changes. Our results show that limit order books may also convey information on the *magnitude* of future price changes.

The remainder of the paper is organized as follows. Section 2 describes a theoretical model of trading in a limit order market. In Section 3, we solve for equilibrium bidding strategies and we compare trading outcomes when liquidity suppliers' identities are disclosed and when they are concealed. Section 4 derives the empirical implications of our model. In Section 5, we empirically analyze the effect of concealing liquidity suppliers' identities using data from Euronext Paris. Section 6 concludes. The proofs are collected in the Appendix. The notation used in the theoretical model is listed in Table 1 just before the Appendix.

2 The Model

In this section, we present the model of limit order trading that we use to guide our empirical analysis. In contrast to the extant literature, some traders are privately informed about the likelihood of a change in the asset value. As they use this information to price their limit orders, the limit order book provides information on future price volatility. In particular, an increase in bid-ask spreads signals that informed limit order traders anticipate a large price change. This signaling role for the state of the book is key for our testable implications regarding the effect of anonymity.

⁵We do not allow dealers to choose between anonymous and non-anonymous trading venues. Reiss and Werner (2004) provides an empirical study of this choice.

2.1 Timing and Market Structure

We consider the market for a risky security. There are 3 dates, $t = 0, 1, 2$. At date 2, the final value of the security, \tilde{V}_2 , is realized. It is given by

$$\tilde{V}_2 = v_0 + \tilde{I} * \tilde{\epsilon}_1, \quad (1)$$

where the innovation $\tilde{\epsilon}_1$ is random and takes one of two values, $+\sigma$ or $-\sigma$, with equal probabilities. Variable \tilde{I} is equal to 1 if an information event occurs at date 1 and zero otherwise.⁶ An information event occurs with probability π_0 ($0 < \pi_0 < 1$). At date 0, the *expected* volatility of the security is therefore:

$$Var(\tilde{V}_2) = E((\tilde{V}_2 - v_0)^2) = \pi_0 \sigma^2. \quad (2)$$

The *realized* volatility is known at date 1. It is either large (equal to σ^2) if there is an information event or small, if there is no information event.

Liquidity suppliers post limit orders for the security at date 0. A sell (buy) limit order specifies a price and the maximum number of round lots a trader is willing to sell (buy) at this price. Liquidity demanders arrive at date 1 and submit market orders. We describe in more detail the decisions taken by these two types of participants in the rest of this section. Figure 1 depicts the tree diagram of the trading process at date 1.

Speculators and liquidity traders If no information event occurs at date 1, then market orders are submitted by liquidity traders. A market order can be a buy or a sell order with equal probabilities. Now, consider the situation in which an information event occurs. In this case, with probability α , a trader (henceforth a speculator) observes the innovation, ϵ_1 and decides to trade or not. The speculator submits a buy or a sell order depending on the direction of his information. If ϵ_1 is positive (negative), the speculator submits a buy (sell) market order so as to pick off all sell (buy) limit orders with a price below $v_0 + \sigma$ (resp. above $(v_0 - \sigma)$). With probability $(1 - \alpha)$, a liquidity trader arrives and submits a buy or a sell market order with equal probabilities.

Each order must be expressed in terms of a minimum unit (a round lot) which is equal to q shares. We normalize q to 1. The size of the order submitted by a liquidity trader is random. We denote it by Q_l . This size can be “small” (equal to 1 round lot) or “large” (equal to 2 round lots) with equal probabilities.

Liquidity Suppliers. Following Harris and Hasbrouck (1996), we assume that there are two kinds of liquidity suppliers: (a) risk-neutral *value traders* who post limit orders so as to maximize their expected profits and (b) *pre-committed traders* who have to buy or

⁶Uncertainty on the existence of an information event is a feature of other market microstructure models, in particular Easley and O’Hara (1992). An information event can be seen, for instance, as the arrival of public information (corporate announcements, price movements in related stocks, headlines news etc...).

to sell a given number of round lots. Value traders can be viewed as brokers who trade for their own account. Pre-committed traders represent brokers who seek to execute an order on behalf of a client (e.g. an institutional investor who rebalances his portfolio). Henceforth, we will refer to the value traders as being “the dealers”.

We assume that dealers are not equally informed on the likelihood of an information event. There are two types of dealers: (i) *informed dealers* who know whether or not an information event will take place at date 1 and (ii) *uninformed dealers* who do not have this knowledge. Therefore, informed dealers have private information on future price volatility. Observe that informed and uninformed dealers have the same estimate of the final payoff of the security, as $E(\tilde{V}_2) = E(\tilde{V}_2 | I = 1) = E(\tilde{V}_2 | I = 0) = v_0$.⁷ Hence it cannot be optimal for an informed dealer to trade against the book (since bid-ask quotes bracket v_0).

Yet, information on future price volatility is useful for limit order traders because it helps them to better assess the risk of being picked off and to price their limit orders accordingly. In particular, they should bid less aggressively when they know that an information event is pending as the the risk of being picked off is larger in this case. For this reason, the schedule of limit orders posted by informed dealers constitutes a *signal* about future price volatility. In turn, uninformed dealers should use this signal when they choose their order placement strategy.

Given these remarks, we model price formation in the limit order market as a signaling game. At date 0, dealers post their limit orders *sequentially*, in 2 stages denoted L (first stage) and F (second stage). Figure 2 describes the timing of this bidding game. With probability β , the price schedule (*the limit order book*) posted in the first stage is determined by an informed dealer ($0 < \beta < 1$). Otherwise the limit order book is chosen by pre-committed traders. In the second stage, an uninformed dealer observes the limit order book and decides to submit limit orders or not. We call the liquidity supplier acting in stage L : the *Leader* and the liquidity supplier acting in stage F : the *Follower*.⁸

At date 1, the incoming buy (sell) market order is filled against the sell (buy) limit orders posted in the book. Price priority is enforced and each limit order executes at its price. Furthermore, *time priority* is enforced. That is, *at a given price*, the limit order placed by the leader is executed before the limit order placed by the follower. Table 2 recaps the different types of traders in our model.

⁷This follows from the fact that informed dealers have no information *on the direction* of future price movements. As an example, consider the case of a dealer who knows that a merger announcement is pending. Numerous empirical studies have shown that this type of announcement has no impact on the price of the acquiring firm, *on average*. Thus, a dealer with this information can correctly anticipate that the announcement will trigger a price reaction for the acquiring firm without being able to predict its direction.

⁸In our model, the informed dealer always submits his limit orders before the follower. In a more general formulation, the sequence of moves could be random. This formulation however would obscure the presentation of our results without bringing new insights. Actually, the follower’s bidding strategy depends on the identity of the leader only when (i) the leader has a chance to be informed and (ii) the follower is uninformed. This configuration is therefore the only case in which concealing the leader’s identity has an effect, if any.

Table 2: Market Participants

Liquidity Suppliers (date 0)	Liquidity Demanders (date 1)
Precommitted Limit Order Traders	Liquidity Traders
Uninformed Dealers	Speculators
Informed Dealers	

Limit Order Book. Modeling price formation in limit order markets quickly becomes very complicated. In order to keep the model tractable, we make several simplifying assumptions.

First, for expositional convenience, we assume that the buy side and the sell side of the book are *segmented*. That is, traders intervening on each side are different and do *not* observe the offers on the opposite side (e.g. sell limit order traders do not observe buy limit orders). We can easily generalize our findings when this assumption is relaxed. However, the model becomes substantially more involved as we cannot treat *separately* the buy and the sell sides of the book. Actually the follower’s inferences depend on the entire state of the book and not only on the offers posted on one side. The informed dealer must therefore jointly determine his bidding strategy on both sides of the book. Despite this additional complexity, the economic intuitions uncovered by the model when the limit order market is segmented remain valid when it is not. In particular, less aggressive bidding by the informed dealer signals that an information event is impending.

Second, liquidity suppliers can post sell limit orders at prices A_1 and A_2 such that

$$A_2 - A_1 = A_1 - v_0 = \Delta. \tag{3}$$

Parameter Δ is the tick size, i.e. the minimum increment between two consecutive quotes: A_1 is the smallest eligible price above the unconditional expected value of the asset and A_2 is the second smallest eligible price above this value. We assume that $\Delta < \sigma < 2\Delta$. This means that limit orders at price A_1 are exposed to the risk of being picked off, as $A_1 < v_0 + \sigma$. In contrast, offers at price A_2 are immune to this risk as $v_0 + \sigma < A_2$.

The price schedule posted by the leader intervening on the sell side of the market is described by the pair (Q_1^s, Q_2^s) where Q_k^s denotes the number of round lots offered by the leader at price A_k . We assume that the leader must choose one of 3 price schedules : (a) schedule T : $(0, 2)$, (b) schedule S : $(1, 2)$ or (c) schedule D : $(2, 2)$.⁹ Hence, the limit order book posted by the leader can be : (a) “*thin*” if the leader posts schedule T , (b) “*shallow*” if the leader posts schedule S or (c) “*deep*” if the leader posts schedule D . In the first case, the quoted spread is wide (equal to $A_2 - v_0 = 2\Delta$) while in the 2 other cases, the quoted spread is small (equal to Δ). After observing the price schedule, $K \in \{T, S, D\}$, posted

⁹Note that the leader offers the maximum number of round lots (2) at price A_2 . This may appear restrictive as the leader could bid for only 1 round lot in order to induce the follower to match his offer at price A_2 (instead of improving upon it). However, this “cake splitting” strategy is never optimal if the number of followers is larger than 1. In order to obtain results which are robust to the number of potential followers (see remark at the end of Section 3.1), we assume directly that the leader chooses to offer 2 round lots at price A_2 .

by the leader, the follower chooses the number of round lots $n(K)$ that she decides to offer at price A_1 . Informed and uninformed dealers choose their bidding strategy to maximize their expected profits. Pre-committed traders' decisions are exogenous : they establish book K with probability Φ_K , (where $0 < \Phi_K < 1$).

We make symmetric assumptions on the buy side of the book. This implies that the equilibrium bidding strategies for the traders intervening on the buy side and the sell side are identical. Thus, from now on, we focus on the sell side of the book.

Anonymous and Non-Anonymous Limit Order Markets. In the non-anonymous limit order market, the follower observes the offers **and** the identity of the leader, that is she can distinguish between informative orders (those placed by an informed dealer) and non informative orders (those placed by pre-committed traders). In the anonymous market, she does not observe the identity of the leader and faces uncertainty on his type (informed/precommitted) as $0 < \beta < 1$. Our goal is to compare the liquidity and the informativeness of the limit order book in these two trading systems, for *fixed values* of the exogenous parameters $(\sigma, \pi_0, \beta, \Delta)$.

We compute two different measures of market liquidity: (a) the *small trade spread* which is the difference between the best ask price and the unconditional expected value of the security and (b) *the large trade spread* which is the difference between the marginal execution price of a market order for 2 round lots and the unconditional expected value of the security. For instance, if the first round lot executes at price A_1 and the second round lot executes at price A_2 , the large trade spread is $(A_2 - v_0)$. The large trade spread, denoted \tilde{S}_{large} , is a measure of price impact and is conceptually similar to the *effective spread* in our empirical analysis. The small trade spread, \tilde{S}_{small} , is the quoted (half) spread at the end of the bidding stage.

Let \tilde{Q}_1 be the number of round lots offered at price A_1 at the end of the bidding stage. The expected small trade spread in a given trading mechanism is given by:

$$\begin{aligned} E(\tilde{S}_{small}) &= \text{prob}(\tilde{Q}_1 \geq 1)A_1 + \text{prob}(\tilde{Q}_1 = 0)A_2 - v_0 \\ &= \Delta(1 + \text{prob}(\tilde{Q}_1 = 0)). \end{aligned} \tag{4}$$

The expected large trade spread is given by

$$E(\tilde{S}_{large}) = \text{prob}(\tilde{Q}_1 = 2)A_1 + (1 - \text{prob}(\tilde{Q}_1 = 2))A_2 - v_0,$$

which rewrites

$$E(\tilde{S}_{large}) = \Delta(2 - \text{prob}(\tilde{Q}_1 = 2)). \tag{5}$$

In our model, the bid-ask spread contains information about future price volatility. Intuitively, the bid-ask spread posted at the end of the bidding stage should be larger when there is an information event. This will induce a positive association between the bid-ask spread and the magnitude of future price movements. Accordingly, we measure

the informativeness of the bid-ask spread (*Infsread*) on future price volatility by the covariance between the size of the small trade spread (\tilde{S}_{small}) and the magnitude of the price movement between dates 0 and 2 (measured by the absolute value of $\tilde{V}_2 - v_0$):

$$Infsread \stackrel{def}{=} Cov\left(\left|\tilde{V}_2 - v_0\right|, \tilde{S}_{small}\right) = \sigma Cov(\tilde{I}, \tilde{S}_{small}). \quad (6)$$

3 Equilibria in Anonymous and Non-Anonymous Limit Order Markets

In this section, we analyze the nature of equilibria in the anonymous and in the non-anonymous market. As a building block, we first study the follower's optimal reaction in each possible state of the book, given her beliefs about the occurrence of an information event. Then, we study the benchmark case in which information about future price volatility is public. Finally, we consider the case in which some dealers have private information on future price volatility.

3.1 The Follower's Optimal Reaction

Let π_K be the follower's belief about the occurrence of an information event after observing the state of the book, K . Moreover let $\Pi^F(n; K, \pi_K)$ be the follower's expected profit when she offers n round lots at price A_1 . Of course, $\Pi^F(0; K, \pi_K) = 0$.

Consider the case in which the follower observes a thin book ($K = T$) at the end of the first stage. She can then decide to submit a limit order for 1 or 2 round lots at price A_1 or to stay put. Offering more than 2 round lots cannot be optimal as the maximal order size for the liquidity traders is 2 round lots. If she submits a sell limit order for one round lot then her expected profit in case of execution (i.e. *conditional on the arrival of a buy order at date 1*) is :

$$\begin{aligned} \Pi^F(1; T, \pi_T) &= \pi_T \underbrace{[\alpha(A_1 - (v_0 + \sigma))]}_{\text{Loss on speculators}} + \underbrace{(1 - \alpha)(A_1 - v_0)}_{\text{Profit on liquidity traders}} + \underbrace{(1 - \pi_T)(A_1 - v_0)}_{\text{Profit on liquidity traders}} \\ &= A_1 - (v_0 + \pi_T \alpha \sigma). \end{aligned} \quad (7)$$

Now, consider the case in which the follower offers 2 round lots at price A_1 . If a speculator intervenes at date 1, her order will certainly be executed as a speculator optimally consumes all the liquidity available at price A_1 . If instead, a liquidity trader intervenes at date 1, the follower's order will execute for 1 or 2 round lots, depending on the trader's order size (\tilde{Q}_l). Thus, the follower's expected profit is

$$\Pi^F(2; T, \pi_T) = \pi_T [2\alpha(A_1 - (v_0 + \sigma)) + E(\tilde{Q}_l)(1 - \alpha)(A_1 - v_0)] + (1 - \pi_T)E(\tilde{Q}_l)(A_1 - v_0).$$

As $E(\tilde{Q}_l) = \frac{3}{2}$, this equation rewrites (after some manipulations) as

$$\Pi^F(2; T, \pi_T) = \Pi^F(1; T, \pi_T) + \left(\frac{\alpha\pi_T + 1}{2}\right)\Pi^{mF}(2; T, \pi_T), \quad (8)$$

where

$$\Pi^{mF}(2; T, \pi_T) \stackrel{def}{=} (A_1 - (v_0 + (\frac{2\pi_T}{\alpha\pi_T + 1})\alpha\sigma)).$$

Thus, the follower's expected profit when she offers 2 round lots at price A_1 is equal to (i) her expected profit on the first round lot ($\Pi^F(1; T, \pi_T)$) plus (ii) her expected profit on the second round lot ($\Pi^{mF}(2; T, \pi_T)$), conditional on execution of this second round lot (which happens with probability $(\frac{\alpha\pi_T+1}{2})$). Observe that the follower expects a larger profit on the execution of the first round lot than on the execution of the second round lot (as $\Pi^F(1; T, \pi_T) > \Pi^{mF}(2; T, \pi_T)$). The intuition is simple. The informed speculator always exhausts the depth available at price A_1 . In contrast, a liquidity trader trades at least 1 round lot but not necessarily 2 round lots. Thus, the second round lot offered at price A_1 is *more exposed to the risk of being picked off* than the first round lot.¹⁰ This implies that it can be optimal for the follower to submit a limit order for just 1 round lot (this happens when $\Pi^F(1; T, \pi_T) > 0$ but $\Pi^{mF}(2; T, \pi_T) < 0$).

The optimal decision for the follower is the number of round lots, $n^*(\pi_T, T)$, which maximizes her expected profit, $\Pi^F(n; T, \pi_T)$. This decision is easily derived using equations (7) and (8). For instance, when

$$\pi_T\alpha\sigma < \Delta < (\frac{2\pi_T}{\pi_T\alpha + 1})\alpha\sigma,$$

the follower optimally submits an order for 1 round lot. When Δ is outside this interval, the optimal reaction is either to do nothing (this is optimal when $\Delta < \pi_T\alpha\sigma$) or to post an offer for 2 round lots (this is optimal if $\Delta \geq (\frac{2\pi_T}{\pi_T\alpha+1})\alpha\sigma$). When $\Delta = \pi_T\alpha\sigma$, the follower is indifferent between staying put or posting an offer for 1 round lot at price A_1 . Thus she plays a mixed strategy : she submits a limit order for 1 round lot at price A_1 with some probability denoted u_T .

We can follow a similar analysis when the follower observes a shallow or a deep book, substituting π_T by π_S or π_D . For brevity, we relegate the analysis of these cases to the Appendix. The next lemma describes the follower's optimal behavior in each possible state of the book.

Lemma 1 :

1. *When the follower observes a thin book, she submits a limit order at price A_1 for 2 round lots if $\frac{2\pi_T\alpha\sigma}{\pi_T\alpha+1} \leq \Delta$, 1 round lot if $\pi_T\alpha\sigma < \Delta < \frac{2\pi_T\alpha\sigma}{\pi_T\alpha+1}$, 1 round lot with probability u_T if $\Delta = \pi_T\alpha\sigma$ and does nothing otherwise.*
2. *When the follower observes a shallow book, she submits a limit order at price A_1 for 1 round lot if $\frac{2\pi_S\alpha\sigma}{\pi_S\alpha+1} \leq \Delta$ and does nothing otherwise.*

¹⁰In other words, execution of the second round lot is more indicative that an information event took place than execution of the first round lot. This implies that the follower's valuation conditional on execution of the second round lot is larger than her valuation conditional on execution of the first round lot. This is as in Glosten (1994).

3. *When the follower observes a deep book, she does nothing.*

The number of round lots offered by the follower at price A_1 decreases in her belief regarding the occurrence of an information event (i.e. $n^*(\pi_K, K)$ decreases in π_K). The risk of being picked off increases with the likelihood of an information event. Hence, the follower's inclination to add depth to the book is smaller when she assigns a large probability to the occurrence of an information event. This effect explains why, for a given state of the book, the follower bids less aggressively when she attaches a larger probability to an information event. This will play a crucial role in the rest of the analysis.

In the rest of the paper, we will focus on the case in which the following condition is satisfied :

$$\frac{2\pi_0\alpha\sigma}{\pi_0\alpha + 1} < \Delta < \alpha\sigma. \quad (9)$$

This condition on the exogenous parameters helps us to better illustrate how the information contained in the limit order book influences the follower's bidding strategy. Actually, under this condition, *in absence of additional information* (i.e. $\pi_K = \pi_0$), the follower would always fill the book in such a way that 2 round lots are offered at the end of the bidding stage (e.g. $n^*(\pi_0, T) = 2$ - see Lemma 1). We show below that this is not necessarily the case in equilibrium because a wide spread signals an impending information event and leads the follower to revise upward her belief about the occurrence of an information event. If this revision is large enough, she may eventually decide not to undercut the leader as $n^*(\pi_T, T) = 0$ for π_T large enough if $\Delta < \alpha\sigma$ (see Lemma 1).

Remark : It is worth stressing that the follower always chooses to fill the book at price A_1 in such a way that there are no remaining profit opportunities left in the book. That is, for each possible state of the book, the optimal action for the follower is such that another uninformed dealer cannot submit a limit order without making a loss. Hence, our conclusions are robust when several uninformed dealers submit limit orders sequentially, after observing the book chosen by the leader. We assume that there is a single follower to simplify the presentation of the game.

3.2 A Benchmark : Symmetric information.

The case in which information on future volatility is public constitutes an interesting benchmark. In this case, the state of the book and the identity of the leader do not convey any additional information to the follower. Indeed, her belief about the occurrence of an information event is entirely determined by public information. In this case, $\pi_K = 1$ if there is an information event at date 1 and $\pi_K = 0$ if there is no information event, whether the market is anonymous or not. The following proposition describes the equilibrium bidding strategies in this case.

Proposition 1 (*benchmark*) : *Suppose information on future volatility is public. In the anonymous and non-anonymous trading mechanisms, the unique subgame perfect equilibrium of the bidding game is as follows : (a) the dealer acting in stage L chooses schedule T*

if there is an information event and schedule D otherwise; (b) the follower acts as described in Lemma 1 with $\pi_K = 1$ if there is an information event at date 1 and $\pi_K = 0$, if there is no information event.

In this case, the equilibrium bidding strategies are identical in the anonymous regime and in the non-anonymous regime. Actually, when information on future volatility is public, the follower's belief about the occurrence of an information event is not determined by the information contained in the limit order book. Thus, she behaves in the same way in both market structures. Accordingly, the informed dealer also bids identically in both market structures. For this reason, market liquidity and the informativeness of the book are identical in each regime, as stated in the next corollary.

Corollary 1 (benchmark) : *When information on future volatility is public, market liquidity (i.e. the average small and large trade spread) is identical in the anonymous and non-anonymous trading mechanisms. Furthermore, the bid-ask spread is informative, i.e. $Cov(\left|\tilde{V}_2 - v_0\right|, \tilde{S}_{small}) > 0$, and the informativeness of the bid-ask spread is identical in the anonymous and non-anonymous trading mechanisms.*

Thus, when information on future volatility is public, anonymity has no effect. In the next subsection, we show that this irrelevance result breaks down when dealers have asymmetric information on future price volatility. In this case, anonymity matters.

Observe that there is a positive association between the bid-ask spread and the size of future price movements. In absence of an information event, the dealers bid in such a way that the book is deep with certainty at the end of the bidding stage. In contrast, when there is an information event, the dealers do not submit limit orders at price A_1 in equilibrium. Hence, the likelihood of observing a wide spread at the end of the bidding stage is greater when there is an information event. Thus, the size of the spread can be used to forecast the magnitude of future price movements. We will test this prediction in our empirical analysis.

3.3 The Anonymous Limit Order Market

Now we turn to the case in which there is asymmetric information among dealers. Throughout we focus on Perfect Bayesian equilibria of the bidding game, as usual in analyses of signaling games. This implies that (a) the follower's belief about the likelihood of an information event (i.e. π_K) must be consistent with the leader's bidding strategy (i.e. determined by Bayes Rule whenever possible) and (b) each dealer chooses the bidding strategy which maximizes his/her expected profit given other traders' bidding strategies. In this subsection, we derive the equilibrium bidding strategies when the limit order market is anonymous.

When the informed dealer knows that an information event is about to take place, he cannot profitably place a limit order at price A_1 (as $A_1 < v_0 + \alpha\sigma$). Yet, a limit order posted

at price A_2 is attractive as it executes against orders submitted by liquidity traders. For this reason, we shall focus on equilibria in which the informed dealer posts a wide spread (chooses schedule T) when there is an information event. When there is *no* information event, the informed dealer can profitably establish the deep book. He then obtains an expected profit equal to:

$$\Pi_{I=0}^L(D) \stackrel{def}{=} E(\tilde{Q}_I)(A_1 - v_0) = \frac{3(A_1 - v_0)}{2} > 0. \quad (10)$$

But he may also try to reap a larger profit by quoting a wide spread (the less competitive schedule T). If the informed dealer sometimes behaves in this way, we say that he follows a *bluffing strategy*.

For the follower, a wide spread constitutes a warning : maybe the spread is large because the leader knows that an information event is pending. If this warning deters her from submitting a limit order within the best quotes then the informed dealer clears all market orders at price $A_2 > A_1$. His bluff has been successful. Formally, let m be the probability with which the informed dealer chooses schedule D when $I = 0$. With the complementary probability, he chooses schedule T when $I = 0$.¹¹ When $m > 0$, a wide spread is more likely to be observed when there is an information event. Actually, the informed dealer chooses the wide spread with probability 1 when there is an information event and with a smaller probability otherwise. Hence, a wide spread signals that an information event is impending. Let $\pi_T(m, \beta)$ be the follower's posterior belief conditional on observing a thin book (for given values of m and β). Bayesian calculus yields

$$\pi_T(m, \beta) \stackrel{def}{=} \text{prob}(I = 1 \mid K = T) = \left[\frac{(1 - \beta)\Phi_T + \beta}{(1 - \beta)\Phi_T + \beta(\pi_0 + (1 - \pi_0)(1 - m))} \right] \pi_0 \geq \pi_0, \quad (11)$$

with a strict inequality when $\beta > 0$. Thus, when she observes a wide spread, the follower revises upward the probability she assigns to an information event. As explained in Section 3.2, this reduces her incentive to submit a limit order at price A_1 . We refer to this effect as being the *deterrence effect*.¹²

The larger is the follower's posterior belief ($\pi_T(m, \beta)$), the larger is the deterrence effect. It is easily checked that $\pi_T(m, \beta)$ increases in m and β . Actually, these two parameters control the quality of the signal conveyed by a wide spread. A large β , for instance, increases the likelihood that quotes are informative because they have been set by an informed dealer. A large value of m also reinforces the deterrence effect as it makes bluffing less likely. In the next proposition, we show that there exists an equilibrium with

¹¹We focus on the class of equilibria in which the informed dealer chooses the thin book when there is an information event. This is natural because a limit order submitted at price A_1 cannot break even when there is an information event (as $\Delta < \alpha\sigma$). For this class, it is easily shown that there is no equilibrium in which the informed dealer chooses a shallow book when there is no information event. Equilibria in which the informed dealer chooses a shallow book arise when $\alpha\sigma < \Delta$. See the remark at the end of Section 4.2.

¹²In our model, a wide bid-ask spread signals to potential competitors that the profitability of limit orders within the best quotes is small. This signal reduces potential competitors' incentive to enter more competitive orders in the book. This line of reasoning is reminiscent of Milgrom and Roberts (1982) or Harrington (1986)'s studies of limit pricing by a monopolist or oligopolists.

bluffing (i.e. $0 \leq m < 1$) when β is large enough. Let $\beta^* \stackrel{def}{=} \frac{\Phi_T(r-\pi_0)}{(1-r)\pi_0 + \Phi_T(r-\pi_0)}$ and $r \stackrel{def}{=} \frac{\Delta}{\alpha\sigma}$. Observe that Condition (9) implies that $\pi_0 < r < 1$.

Proposition 2 : *When $\beta > \beta^*$, the following bidding strategies constitute a perfect bayesian equilibrium:*

1. *When there is an information event, the informed dealer posts schedule T. When there is no information event, the informed dealer posts schedule D with probability $m^*(\beta) = \left(\frac{(\beta+(1-\beta)\Phi_T)}{\beta}\right)\left(\frac{r-\pi_0}{r(1-\pi_0)}\right)$ and schedule T with probability $(1 - m^*(\beta))$, with $0 < m^*(\beta) < 1$.*
2. *When the book is thin, the follower submits a limit order for 1 round lot at price A_1 with probability $u_T^* = \frac{3}{4}$ and else does nothing. When the book is shallow, the follower adds 1 round lot at price A_1 . When the book is deep, the follower does nothing.*

The set of parameters for which this equilibrium is obtained is non-empty as $\beta^* < 1$ since $r < 1$. Moreover, observe that $m^*(\beta) > 0$ because $r > \pi_0$. On the other hand, the condition $\beta > \beta^*$ guarantees that bluffing occurs in equilibrium, i.e. $m^*(\beta) < 1$. Hence, bluffing strategies can be sustained in equilibrium. Observe that the dealers use mixed strategies in the equilibrium described in Proposition 2. We now explain why this is the case.

In equilibrium, the follower correctly anticipates the bluffing strategy used by the leader. Thus, the follower's posterior belief is given by $\pi_T(m^*(\beta), \beta)$. Substituting $m^*(\beta)$ by its expression given in Proposition 2 in $\pi_T(m^*(\beta), \beta)$, it is easily shown that :

$$\alpha\sigma\pi_T(m^*(\beta), \beta) = \Delta. \quad (12)$$

Thus, in equilibrium, the follower holds a posterior belief about the likelihood of an information event which makes her indifferent between undercutting the wide spread or not (see Lemma 1). For this reason, she follows a mixed strategy. She improves upon the wide spread sometimes but not always. When there is no information event, the leader is then confronted with a trade off between *certain execution* at a profitable price A_1 and *uncertain execution* at an even more profitable price, A_2 . The informed dealer's expected profit if he posts a thin book is:

$$\Pi_{I=0}^L(T) \stackrel{def}{=} (1 - u_T)E(\tilde{Q}_l)(A_2 - v_0) + \frac{u_T}{2}(A_2 - v_0) = \left((1 - u_T)\frac{3}{2} + \frac{u_T}{2}\right)(A_2 - v_0), \quad (13)$$

where u_T is the probability that the follower undercuts the thin book with a limit order for 1 round lot at price A_1 . In contrast, if the informed dealer chooses the deep book, he obtains an expected profit equal to

$$\Pi_{I=0}^L(D) = \frac{3(A_1 - v_0)}{2}. \quad (14)$$

It is immediate that the informed dealer is strictly better off choosing a thin (resp. a deep) book iff $u_T < \frac{3}{4}$ (resp. $u_T > \frac{3}{4}$). For $u_T = \frac{3}{4}$, he is just indifferent and therefore he uses a mixed strategy, as described in the proposition. It is worth stressing that this mixed strategy equilibrium is the unique equilibrium when $\beta^* < \beta < 1$.¹³

Recall that a decrease in β relaxes the deterrence effect (see the discussion following equation (11)). Accordingly, in order to sustain the equilibrium with bluffing, the probability with which the informed dealer chooses schedule D (i.e. m^*) must increase when β decreases (i.e. $m^*(\beta)$ decreases with β). Thus, the informed dealer bids more aggressively when β decreases. When $\beta \leq \beta^*$, the follower cannot be deterred from submitting a limit order for 1 round lot at price A_1 , even if $m = 1$. The equilibrium bidding strategies for this case are described in the following proposition. Let $\beta^{**} \stackrel{def}{=} \frac{\Phi_T(r(\alpha\pi_0+1)-2\pi_0)}{\pi_0(2-r(1+\alpha))+\Phi_T(r(\alpha\pi_0+1)-2\pi_0)} > 0$.

Proposition 3 : *When $\beta^{**} < \beta \leq \beta^*$, the following bidding strategies constitute a perfect bayesian equilibrium:*

1. *No bluffing : When there is an information event, the informed dealer chooses schedule T . When there is no information event, the informed dealer chooses schedule D , i.e. $m^*(\beta) = 1$.*
2. *When the book is thin or shallow, the follower submits a limit order for 1 round lot at price A_1 . When the book is deep, the follower does nothing.*

In this case, the follower's posterior belief about the likelihood of an information event after observing a thin book is given by $\pi_T(1, \beta)$. The revision in the follower's belief (i.e. $\pi_T(1, \beta) - \pi_0$) is too small to deter her from submitting a limit order for 1 round lot at price A_1 . However, it is large enough to deter her from posting a larger size. Actually, it is easily checked that :

$$\pi_T(1, \beta)\alpha\sigma \leq \Delta < \left(\frac{2\pi_T(1, \beta)}{\pi_T(1, \beta)\alpha + 1}\right)\alpha\sigma, \text{ for } \beta^{**} < \beta \leq \beta^*, \quad (15)$$

which implies that the follower optimally submits 1 round lot but not 2 when she observes a thin book (see Lemma 1). The next proposition derives the equilibrium in the remaining case ($0 < \beta \leq \beta^{**}$).

Proposition 4 : *When $0 < \beta \leq \beta^{**}$ then the following bidding strategies constitute a perfect bayesian equilibrium:*

¹³To see this point suppose that the informed dealer chooses a deep book with probability $m > m^*$. In this case, $\alpha\sigma\pi_T(m, \beta) > \Delta$ as $\pi_T(\cdot, \beta)$ increases with m . But this implies that the follower is better off staying put when she observes a thin book (Lemma 1). Anticipating this reaction, the informed dealer is better off always posting a thin book, which means that $m > m^*$ is not an equilibrium. A similar argument shows that $m < m^*$ is not possible in equilibrium.

1. *No bluffing* : When there is an information event, the informed dealer chooses schedule T . When there is no information event, the informed dealer chooses schedule D .
2. When the book is thin, the follower submits a limit order for 2 round lots at price A_1 . When the book is shallow, the follower submits a limit order for 1 round lot at price A_1 and when the book is deep, the follower does nothing.

When β is smaller than β^{**} , there is a small probability that the leader has information. Hence the follower's belief about the occurrence of an information event is only weakly influenced by the orders placed in the book. The deterrence effect is then too weak to prevent the follower from behaving as if she had no information. In this case, she fills the book so that eventually 2 round lots are offered at price A_1 . Anticipating this behavior, the leader establishes a deep book whenever this is profitable.

3.4 The Non-Anonymous Limit Order Market

In the non-anonymous market, we must consider two cases separately : (i) the leader is informed and (ii) the leader is uninformed. The equilibrium in each case is readily obtained by considering limiting cases of the analysis for the anonymous market. First, consider the case in which the leader is a pre-committed trader in the non-anonymous market. This situation is identical to the situation in which $\beta = 0$ in the anonymous market. We deduce that the equilibrium of the non-anonymous market when the leader is uninformed is identical to the equilibrium of the anonymous market when β goes to zero. Hence, it is described by Proposition 4. Next, consider the case in which the leader is informed in the non-anonymous market. This situation is identical to the case in which $\beta = 1$ in the anonymous market. Thus, the equilibrium course of actions in this case is as described in Proposition 2 when β goes to 1.¹⁴ These remarks yield the following corollary.

Corollary 2 : *The following bidding strategies form a perfect bayesian equilibrium in the non-anonymous market:*

1. *When the leader is informed, the dealers behave as described in Proposition 2 when $\beta = 1$. In particular, the informed dealer uses a bluffing strategy: when there is no information event, he chooses schedule D with probability $m^*(1) = \frac{r-\pi_0}{r(1-\pi_0)} < 1$.*

¹⁴The informed dealer never chooses a shallow book in the equilibria described in Section 3.3. Thus, for $\beta < 1$, the follower's posterior belief after observing a shallow book is equal to her prior belief ($\pi_S(m^*, \beta) = \pi_0$). When $\beta = 1$, the follower's belief conditional on observing a shallow book cannot be determined by Bayes rule because a shallow book is out-of-the equilibrium path (an observation with a zero probability of occurrence). But the equilibrium obtained by taking β to 1 in Proposition 2 is sustained by the following specification for the follower's belief after observing a shallow book : $\pi_S(m, 1) = \pi_0$. This specification is natural because $\pi_S(m, \beta) = \pi_0, \forall \beta < 1$.

2. When the leader is a pre-committed trader, the follower behaves as described in Proposition 4.

It is useful to analyze in detail how dealers' bidding behavior differs in the anonymous market and in the non-anonymous market. Ultimately this helps understanding the effects of a switch to anonymity in our model. For a given value of β , the informed dealer chooses to establish a deep book with probability $(1 - \pi_0)m^*(\beta)$ in the anonymous market and probability $(1 - \pi_0)m^*(1)$ in the non-anonymous market. As $m^*(\beta) > m^*(1)$, the informed dealer behaves more aggressively in the anonymous market.

The effect of anonymity on the uninformed dealer's bidding behavior is more complex. Consider the case in which the uninformed dealer faces a wide spread (for the other states of the book, the uninformed dealer's behavior is not affected by the anonymity regime). In the non-anonymous market, the uninformed dealer undercuts the wide spread with probability $u_T^* = \frac{3}{4}$ if the leader is informed and with probability 1 if the leader is a precommitted trader. Thus, in the non-anonymous market, the probability of observing a limit order improving upon the wide spread is:

$$\beta u_T^* + (1 - \beta) = \frac{(4 - \beta)}{4}. \quad (16)$$

In the anonymous market, the uninformed dealer's behavior depends on *her belief* on the identity of the leader. If the leader is informed with a large probability ($\beta > \beta^*$), then the uninformed dealer behaves cautiously : she undercuts the wide spread with probability $u_T^* = \frac{3}{4}$. If the leader is informed with a small probability ($\beta \leq \beta^*$) then the uninformed dealer improves upon the wide spread with probability 1. As $\frac{3}{4} < \frac{(4-\beta)}{4} < 1$, we conclude that the likelihood that the uninformed dealer improves upon a wide spread can be smaller or larger in the anonymous market, depending on the value of β .

Another measure of the follower's aggressiveness is the probability that she will offer two round lots (instead of 1) *if* she undercuts a wide spread. This probability is $(1 - \beta)$ in the non-anonymous market. In the anonymous market, this probability is equal to zero if $\beta > \beta^{**}$ and 1 otherwise. Thus, conditional on undercutting the wide spread, the follower can offer more or less depth at price A_1 in the anonymous market, depending on the value of β . To sum up, the follower is unambiguously more (resp. less) aggressive in the anonymous market if $\beta \leq \beta^{**}$ (resp. $\beta > \beta^*$). For $\beta \in (\beta^{**}, \beta^*]$, she undercuts the thin book more frequently in the anonymous market but with smaller orders than in the non-anonymous market.

4 Testable Predictions : The Effects of a Switch to Anonymity

Suppose that market organizers decide to switch from a non-anonymous market to an anonymous market. What are the effects of this switch to anonymity on market liquidity

and the informational content of the bid-ask spread? Using the results of the previous sections, we can now address these questions and derive predictions that we test in the next section.

4.1 Anonymity and Market Liquidity

We compute the equilibrium values of the small and the large trade spreads (as defined in Equations (4) and (5)) in the anonymous market and in the non-anonymous market. We obtain the following result.

Corollary 3 : *A switch to an anonymous limit order book reduces the expected small and large trade spreads when β is small enough ($\beta \leq \beta^{**}$). When β is large ($\beta > \beta^*$), a switch to an anonymous limit order book enlarges the expected small and large trade spreads. When $\beta^{**} < \beta \leq \beta^*$, a switch to anonymity: (i) reduces the expected small trade spread and (ii) increases the expected large trade spread.*

In contrast with the benchmark case, anonymity does matter when some dealers have private information about future volatility. Actually, in this case, uninformed dealers extract information from observing the limit order book and the quality of their inferences depend on whether the book is anonymous or not. For this reason, a switch to anonymity changes the equilibrium bidding strategies.

The impact of a switch to anonymity on liquidity is ambiguous and depends on the proportion of informed dealers (i.e. β). Recall that the informed trader behaves more aggressively in the anonymous market. However, when the proportion of informed dealers is large (i.e. $\beta > \beta^*$), the uninformed trader bids less aggressively (undercuts a thin book less frequently) in the anonymous market (see the previous section). These two effects have opposite impacts on market liquidity and the second effect dominates when $\beta > \beta^*$. When β is small enough (i.e. $\beta \leq \beta^{**}$), a switch to anonymity makes both the informed dealer and the uninformed dealer more aggressive. This explains why it reduces the small and the large trade spread.

For intermediate values of β ($\beta^{**} < \beta \leq \beta^*$), a switch to anonymity is beneficial to traders who submit small market orders (since it reduces the average small trade spread) but not to traders who submit large orders. Actually, for these intermediate values the switch to anonymity reduces the probability that no round lots will be offered at price A_1 (i.e. $prob(\tilde{Q}_1 = 0)$ decreases). But, simultaneously, it reduces the probability that the uninformed dealer will offer 2 round lots at price A_1 (see previous subsection for an explanation). Overall, the probability that 2 round lots will be offered at price A_1 (i.e. $prob(\tilde{Q}_1 = 2)$) is smaller. Accordingly, the probability that a large market order will walk up the book is greater after the switch to anonymity when $\beta^{**} < \beta \leq \beta^*$ and the large trade spread widens.

4.2 Anonymity and the Informational Content of the Bid-Ask Spread

Recall that we measure the informativeness of the bid-ask spread by the covariance between the size of the quoted spread at date 1 (i.e. \tilde{S}_{small}) and the magnitude of the change in the value of the security between date 0 and date 2 (i.e. $|\tilde{V}_2 - v_0|$). Let $Infspread^a(\beta)$ and $Infspread^{na}(\beta)$ be the value of this covariance in the anonymous market and in the non-anonymous market, respectively. We obtain the following result.

Corollary 4 : *In the non-anonymous market and in the anonymous market, the size of the bid-ask spread is informative about future price volatility : $Infspread^{na}(\beta) > 0$ (for $\beta > 0$) and $Infspread^a(\beta) \geq 0$ (the inequality is strict for $\beta > \beta^*$). However, the informational content of the bid-ask spread is different in the anonymous and the non-anonymous market. It is smaller (resp. larger) in the anonymous market when $\beta \leq \beta^*$ (resp. $\beta > \beta^*$).*

When an information event is about to take place, an informed dealer posts a wide spread and uninformed dealers do not necessarily improve upon this wide spread. In contrast, when the informed dealer does not expect an information event, he sometimes posts a narrow spread. This explains why there is a positive association between the size of the spread at the end of the bidding stage and future price volatility. A switch to anonymity can weaken or strengthen this relationship as claimed in the second part of the corollary. The intuition for this result is as follows. Observe that the quoted spread at the end of the bidding stage results from the actions chosen both by the leader and the follower. When the follower does not intervene, the quoted spread is informative as it is sometimes set by an informed dealer. In these cases, the quoted spread is more informative in the anonymous market because the informed dealer is less likely to bluff in this market structure. This effect works to increase the informativeness of the quoted spread. However, when $\beta \leq \beta^*$, the uninformed dealer undercuts the leader more frequently in the anonymous regime and, doing so, she reduces the informativeness of the bid-ask spread. When $\beta \leq \beta^*$, this effect dominates and a switch to anonymity reduces the informativeness of the bid-ask spread.

Corollary 4 yields two testable predictions. In time-series, the size of the spread in a given period should be positively correlated with the magnitude of price movements in subsequent periods (future price volatility). This correlation arises under two (non exclusive) hypotheses : (a) information on future volatility is public or (b) information on future volatility is (at least in part) private. The second part of Corollary 4 gives us a way to distinguish between these hypotheses. If information on future volatility is not entirely public then the strength of the association between the size of the spread in one period and price volatility in a subsequent period should be altered by a switch to anonymity. This is not the case if limit order traders use only public information (Corollary 1). Moreover, when a switch to anonymity unambiguously improves liquidity ($\beta \leq \beta^*$), the association between the size of the spread and subsequent price volatility should be weaker under anonymity.

Remark. We have analyzed in detail the case in which $\frac{2\pi_0\alpha\sigma}{\pi_0\alpha+1} < \Delta < \alpha\sigma$. Analysis of other parameter values yields similar conclusions. In particular, consider the case in which $\alpha\sigma < \Delta < \frac{2\alpha\sigma}{\alpha+1}$.¹⁵ In this case, it is profitable to offer one round lot (but no more) at price A_1 if there is an information event. Thus, the informed dealer posts a shallow book (rather than a thin book) when there is an information event. For β large enough, the informed dealer uses a bluffing strategy : he sometimes posts the shallow book when there is no information event. Thus, in this case, the shallow book (rather than the thin book) signals that an information event is pending. The implications are qualitatively identical to those we derived when $\Delta < \alpha\sigma$. In particular the lack of liquidity in the book (manifested by an increase in the large-trade spread) foreshadows an informational event. Furthermore, a switch to anonymity decreases the size and the informativeness of the large-trade spread if β is small enough.¹⁶

5 Empirical Analysis

In this section, we study empirically the switch to anonymity of the trading system operated by Euronext Paris (the French stock exchange). We analyze whether it had an impact on liquidity as predicted by Corollary 3 and, if so, whether liquidity increased or decreased. Second, we study the impact of the switch to anonymity on the informational content of the bid-ask spread. Corollary 4 predicts that the size of the bid-ask spread is informative about future volatility and that, given certain parameter restrictions, the informational content of the spread is smaller in the anonymous regime. This prediction can, at least to the best of our knowledge, not be derived from the extant literature and therefore provides a sharp empirical test of our model.

5.1 Institutional Background and Dataset

5.1.1 Euronext Paris

In March 2000, the Amsterdam Stock Exchange, the Brussels Stock Exchange and the Paris Bourse decided to merge. This merger (which took place in September 2000) gave birth to Euronext, a holding with 3 subsidiaries: Euronext Amsterdam, Euronext Brussels and Euronext Paris. The 3 exchanges have then strived to create a unique trading platform called “Nouveau Système de Cotation” (NSC). Euronext Paris was first to adopt the new trading platform on April 23, 2001, followed by Brussels on May 21, 2001 and Amsterdam on October 29, 2001. The Lisboa Stock Exchange joined Euronext in 2002. For Euronext

¹⁵The case in which $\frac{2\alpha\sigma}{\alpha+1} \leq \Delta$ is not interesting. In this case, the tick size is so large that it is profitable to offer two round lots at price A_1 even if an information event occurs with probability one. Clearly, in this situation, the deterrence effect has no bite.

¹⁶For these parameter values, the small trade spread is not affected by the switch to anonymity. But this is an artifact of the condition $\alpha\sigma < \Delta$. We have focussed on the case $\Delta < \alpha\sigma$ to show that a switch to anonymity affects both the small trade spread and the large trade spread in general.

Paris, the trading rules were very similar before and after the switch to NSC. Indeed, for CAC40 stocks, the switch to an anonymous limit order book was the only significant change (see below).

NSC is an electronic limit order market (see Biais, Hillion and Spatt (1995) for a complete description of this market). Trading occurs continuously for most of the stocks.¹⁷ The opening and the closing prices are determined by a call auction. All orders are submitted through brokers who trade for their own account or on behalf of other investors. Traders primarily use two types of orders: (a) limit orders and (b) market orders. Limit orders specify a limit price and a quantity to buy or to sell at the limit price. They are stored in the limit order book and are executed in sequence according to price and time priority. If a limit order is marketable (i.e., its price crosses a limit on the opposite side of the book) then it is immediately executed. If the size of a buy (resp sell) marketable order exceeds the depth available at the best ask (resp. bid) price, then the order walks up (resp. down) the book until it is filled (entirely or partially, depending on its limit price and size). Market orders on NSC are treated as marketable orders with a price limit equal to the best price on the opposite side of the book.

All limit orders must be priced on a pre-specified grid. The tick size is a function of the stock price level. At the time of our study, the tick size was 0.01 Euros for prices below 50 Euros, 0.05 Euros for prices between 50.05 and 100 Euros, 0.1 Euros for prices between 100.1 Euros and 500 Euros and 0.5 Euros for prices above 500 Euros.¹⁸

The transparency of the market is quite high. Broker-dealers observe (on their computer terminals) all the visible limit orders (price and associated depth) standing in the book at any point in time. Remaining market participants observe the 5 best limits on each side of the book, the total depth visible at these limits and the number of orders placed at each limit. NSC enables traders to display only a portion of their limit order by submitting hidden orders. This implies that the depth available in the book can be larger than the visible depth.

The identification code of the issuing broker was displayed for each order standing in the book since the inception of electronic trading in the Paris Bourse (i.e. 1986). This ceased to be the case on April 23, 2001. The motivation for making brokers' IDs invisible was to harmonize trading rules in Euronext Paris and Euronext Amsterdam (where traditionally, trading had been anonymous). The switch to anonymity applied to **all** stocks listed on Euronext Paris.

At the time of our study, Euronext Paris classifies stocks which trade continuously in 2 different groups, called "Continu A" and "Continu B". Stocks are assigned to one group based on measures of market activity (transaction and order frequency, trading volume). Stocks in Continu A feature a higher level of market activity. For stocks in Continu B, counterparty IDs used to be disclosed immediately after completion of a transaction until April 23, 2001. This is not the case anymore since this date. Thus, stocks in Continu B

¹⁷Less liquid stocks trade in call auctions which take place at fixed points in time during the trading day. All stocks in our sample are traded continuously.

¹⁸In April 2001, the value of the euro in dollar was approximately 0.86 Dollar / Euro.

have experienced a change in both pre-trade and post-trade anonymity. For this reason, it is difficult to isolate the effects of a switch to pre-trade anonymity for these stocks. Fortunately, counterparty IDs have always been concealed for stocks in Continu A and our study uses CAC40 stocks, which all belong to the Continu A group. The constituent stocks of the CAC40 index account for 84% of the total market capitalization of the Continu A group (at the time of our study).

5.1.2 The Dataset

The data (trades, quotes and orders) are obtained from the BDM database provided by Euronext Paris. Our dataset contains a time stamped record of all transactions and orders (prices and quantities) submitted to the market for the constituent stocks of the CAC40 index. Some marketable limit orders exhaust the quantity offered at the best quotes and walk up or down the limit order book. In our dataset these orders are reported as multiple trades occurring at the same time but at different prices. Following Biais, Hillion and Spatt (1995), we aggregate these multiple trades to a single transaction at the weighted average price. We drop one stock from the sample because it was delisted from the index during the sample period. Our final data set thus comprises 39 stocks.

We use a 14 trading day pre-event sample (March 26 to April 12, 2001) and a 14 trading day post-event sample (April 30 to May 20, 2001). The two weeks of observations around April 23, 2001 are dropped in order to avoid contamination of our findings due to the proximity of the event date. The empirical analysis is based on the assumption that in the post-event sample period investors have already learned how to trade in the new market environment. The market may, however, not have reached its new equilibrium one week after the structural change. We therefore repeat our analysis using a second post-event sample, also containing 14 trading days and extending from July 2 to July 19, 2001.¹⁹

Additional but minor changes in trading rules took place for the stocks in our sample on April 23, 2001. Firstly, the Bourse changed some of the criteria which are used to select the opening price when there is a multiplicity of clearing prices at the opening. Secondly, it advanced the end of the continuous trading session from 5:35 p.m. to 5:30 p.m. in order to facilitate the organization of the closing call auction. In our empirical analysis, we exclude all observations collected during the first 5 minutes of the continuous trading period (9:00 a.m. to 9:05 a.m.) and those collected after 5:25 p.m. Thus our findings should not be contaminated by changes which affect the determination of opening and closing prices. The Bourse also changed the treatment of orders which can trigger a trading halt. Trading halts occur when price changes exceed pre-specified thresholds. Before April 23, 2001 traders had the possibility to submit marketable limit orders resulting in a halt without partial execution of their order. Thus, traders could suspend the trading process without bearing any direct cost. In contrast, as of April 23, 2001 marketable limit orders triggering a halt

¹⁹There is a caveat, however. Euronext Brussels adopted the new trading platform on May 21, 2001. Arguably, this facilitated the access of Belgian traders to the French market and may have increased the number of participants in Euronext Paris. Therefore, results for the second post-event period may be contaminated.

are partially executed up to the threshold price. This change in the handling of trading halts applies to all stocks. Hence, there is no obvious way to control for its possible effects.

Table 3 presents some summary statistics (number of trades, average trade price, trading volume, average trade size, daily return volatility and market capitalization) for our sample stocks. Separate figures are given for the pre-event period and the two post-event periods. We further report t-values for a test for equality of the means and z-values for a Wilcoxon test for equality of the medians. The figures reveal a high level of trading activity for the stocks in our sample. The average daily number of transactions is slightly lower after the switch to anonymity but exceeds 1,200 in all three sample periods. The share trading volume and the average trade size are higher in the post-event periods. The Euro trading volume increases between the pre-event period and the first post-event period but subsequently decreases. All differences are insignificant, however, with the exception of the average trade size which is significantly higher in the second post-event period as compared to the pre-event period. Return volatility, defined as the standard deviation of 30 minute midquote returns, is significantly lower in the post-event periods. Thus, in our empirical analysis we control for the possible effect of lower volatility on measures of market liquidity.

5.2 Empirical Findings

5.2.1 Anonymity and Market Liquidity

Our model implies that measures of market liquidity such as the quoted spread and the effective spread should be different in the pre and in the post-event periods. The direction of the impact should be determined by the proportion of informed dealers, β (see Corollary 3). It is difficult to design a direct test of this prediction because β is not observed. Moreover, our model is too stylised for structural estimation. A natural proxy for β is the proportion of limit orders placed by brokers for their own account. Unfortunately, we cannot identify principal and agency orders. For CAC40 stocks, Declerck (2001) finds that the 6 intermediaries which handled 71% of all principal trades accounted for only 39% of all orders during her study period. Furthermore, principal trading accounted for 27% of the trading volume, on average. These findings suggest that β is relatively small for CAC40 stocks (which constitute our sample). Thus, we expect a decrease in the quoted spread and in the effective spread (a proxy for the large-trade spread in our theoretical analysis) after the switch to anonymity.

Univariate Analysis.

In order to analyze the effect of the switch to anonymity on the spread we calculate average spreads for each stock and each trading day. We then average over the 14 days of the pre-event period and the 14 days of each post-event period. This results in three observations for each stock, one pre-event observation and two post-event observations. Finally, we average over the sample stocks. We use two measures of the quoted bid-ask

spread, namely, the quoted spread in Euro and the quoted percentage spread.²⁰ The results are shown in Table 4. Spreads in both post-event periods are lower than those in the pre-event period. This holds irrespective of the spread measure used. The quoted spread in Euro decreases from 0.177 Euros to 0.146 Euros on average from the pre-event period to the first post-event period (a decline of 17.5%), and it decreases further to 0.112 Euros in the second post-event period. Percentage spreads decrease between the pre-event period and the first post-event period but there is no further decrease between the first and the second post-event period. This suggests that the lower Euro spread in the second post-event period could be due to the lower stock prices in that period (see Table 3).

We apply a t-test and a Wilcoxon test to investigate whether the reduction in spreads is significant. The test statistics, also shown in Table 4, indicate that the reduction between the pre-event period and the first post-event period is significant at the 5% level for the percentage quoted spread but not for the quoted spread in Euro. A potential explanation is that, as documented in Table 3, average prices were slightly higher in the first post-event period. This reinforces the decrease in percentage spreads. Additionally, the minimum tick size is frequently binding for CAC40 stocks which prevents a decrease in the Euro spread. In the multivariate analysis, we will control for the effect of the price level and the tick size. The reduction in quoted spreads between the pre-event period and the second post-event period is significant irrespective of the measure used.

The effective spread is the absolute difference between the (average) price at which a market order executes and the quote midpoint prior to the trade multiplied by two:

$$Effective\ Spread = 2 * | P - m |,$$

where m is the quote midpoint 5 seconds prior to the transaction and P is the transaction price. In electronic limit order markets, the effective spread differs from the (half) quoted spread when a marketable order executes at multiple prices because the number of shares offered at the best quotes is insufficient to fill the order in full. Thus, the effective spread is *indirectly* a measure of the overall depth of the limit order book. Actually, the larger the quantities offered at given prices in the book, the smaller will be the price impact of a marketable order with a given trade size. Table 4 reports the results. The average effective spread decreases from 0.154 Euro to 0.129 Euro in the first post-event period and decreases further to 0.097 Euro in the second post-event period.²¹ The difference between the pre-event period and the second post-event period is significant.

A decrease in the effective spread can be due both to an increase in the overall depth of the book and a decrease in trade size. In order to better identify the cause for the reduction

²⁰In order to compute the quoted spread, we sample the bid-ask spread each time there is a change in the size of the inside spread or in the quantities offered at the best quotes. We use two weighting schemes for computing the quoted spreads. The first gives each observation equal weight. The second assigns each observation a weight that corresponds to the time span during which the respective spread was valid. As the results for the two weighting schemes are virtually identical we restrict the presentation to the equally-weighted spread measures.

²¹Note that the average effective spread is smaller than the average quoted spread, in each period. This observation indicates that traders strategically submit their market orders when the quoted spread is smaller than average. It is not due to price improvements as there are no such improvements in electronic limit order markets like Euronext Paris.

in the effective spread, we need to control for the impact of trade size. To this end, we sort the transactions by size, form deciles and then calculate the average effective spread for each decile per stock and per trading day. We then average over the 14 days of the pre- and the post-event periods and finally aggregate over the sample stocks. The results are presented in Figure 3. Overall, the effective spread has decreased for each trade size decile and in each post-event period. The decrease, however, is statistically insignificant in the first post-event period and significant in the second post-event period.

These results suggest that the depth of the book has increased after the switch to anonymity. We cannot provide a more detailed analysis of this question because we do not have data on the quantities offered behind the best quotes. However, we can study the effect of the switch to anonymity on the number of shares and the Euro volume offered at the best quotes (the “quoted depth”). The results are shown in the last two lines of Table 4. They indicate that quoted depth has indeed increased after the switch to anonymity. The increase is not statistically significant, however.²² It is well-known that quoted depth tends to be larger, other things equal, at larger spreads (see Lee et al. (1993)). Hence, we also compare the quoted depth in the pre-event period and in the post-event periods controlling for the level of the quoted spread. For each level of the quoted spread (between 1 and 9 ticks), we first calculate the average depth at the best bid and ask prices per stock and per trading day, then average over the 14 days of the pre-event period and the two post-event periods and finally aggregate over the sample stocks. The results (omitted from the paper to conserve space) indicate that quoted depth is larger in the post-event periods than in the pre-event period for all nine quoted spread sizes. However, the change in quoted depth is generally not significant.

Overall the results of the univariate analysis indicate that market liquidity has improved after the switch to anonymity. The quoted spread and the effective spread have declined while the quoted depth is larger (though not significantly so). At this stage of the analysis, however, it is premature to conclude that this improvement is due to the switch to anonymity. Actually, changes in other variables may explain this observation. In particular, Table 3 reveals that volatility is systematically lower in both post-event periods. Furthermore, effects due to the tick size or differences in price levels between the sample periods limit the conclusions which can be drawn from the univariate analysis.

Multivariate Analysis.

In order to address these problems and isolate the impact of the switch to anonymity on the quoted spread and the effective spread, we use a regression framework. Numerous empirical studies find that spreads depend on trading volume, the price level, and return volatility (see Stoll (2000)). We therefore include the log of the trading volume (in euro), the average price level and the standard deviation calculated from 30-minute midquote returns as control variables. As noted previously, the minimum tick size is a function of the price level of the stock. As the tick size potentially affects the size of the spread, we

²²Quoted depth measured in shares is significantly larger in the second post-event period as compared to the pre-event period. This might just reflect lower price levels in the second period (so that quoted depth in euros is unchanged).

include the effective average tick size for stock i as explanatory variable.²³ Our regression model is

$$s_{i,t} = \gamma_0 + \gamma_1 \log(\text{Vol}u_{i,t}) + \gamma_2 TS_{i,t} + \gamma_3 P_{i,t} + \gamma_4 \sigma_{i,t} + \gamma_5 D_i^{\text{post}} + \varepsilon_{i,t}, \quad (17)$$

where $s_{i,t}$ is a measure of the spread, $\text{Vol}u_{i,t}$ is the Euro trading volume, $TS_{i,t}$ is the average tick size, $P_{i,t}$ is the price level and $\sigma_{i,t}$ is the standard deviation of 30-minutes midquote returns. Indices i and t identify the stock and the trading day, respectively. D^{post} is a dummy variable which captures the effect of the switch to anonymity on the bid-ask spread (it takes on the value 1 for the observations in the anonymous regime). All variables are calculated for each stock and each day. We thus have one observation for each stock and each trading day.

We estimate separate regressions for the two post-event periods and for the three spread measures described above. The results are reported in Table 5 (under the label “Regression 1”). To account for potential autocorrelation in the residuals, we compute t-statistics using Newey-West standard errors. The independent variables explain a large part of the variation in bid-ask spreads, as evidenced by R^2 s ranging from 0.63 to 0.87. All spread measures are negatively related to volume and are positively related to volatility. Quoted spreads measured in Euros and effective spreads are positively related to the price level whereas quoted percentage spreads are negatively related to the price level. Finally, we find a significant positive relation between the spread measures and the effective tick size. This supports our conjecture that, for CAC40 stocks, the tick size may often be a binding restriction on the inside spread.

The coefficient on the post-event dummy is negative and significant in each case, indicating that spreads are lower after the switch to anonymity. The magnitude of the coefficient on the dummy variable indicates that the switch to anonymity has reduced the quoted spread and the effective spread by about 0.02 Euros in each post-event period. When compared to the average pre-event quoted and effective spread of 0.177 Euros and 0.154 Euros, respectively, the reduction in spreads appears to be economically significant.

As we work with panel data, a possible concern is that the residuals in our regression are correlated across time and across firms. The coefficient estimates are still unbiased and consistent in the presence of correlation in error terms. However, estimates for standard errors of the coefficients might be biased. The presence of a fixed stock effect can be a source of correlation in the residuals of a given stock. We therefore allow for fixed stock effects in our regression by including stock-specific dummy variables. The results are also presented in Table 5 (“Regression 2”; we omit the coefficients on the stock-specific dummy variables to conserve space). Upon inclusion of the dummy variables the regression R^2 increases. The coefficient on the dummy variable capturing the impact of a switch to anonymity remains significantly negative and equal to about -0.02 euros for the quoted spread and the effective spread.

²³As the minimum tick size is a function of the price level, it changes whenever the price of a stock crosses a threshold level. If the bid and the ask straddle a threshold price the minimum tick size is different on the bid and the ask side of the book. Our effective tick size measure takes this into account. It is simply the average minimum tick size calculated from all bid and ask quotations for stock i on day t .

The residuals in our regressions may also be contemporaneously correlated across stocks because the switch to anonymity affects all stocks at the same time. In order to address that concern, we include separate dummy variables for each day of the post-event period, as in Boehmer, Saar and Yu (2005). We also allow for stock fixed effects by including a dummy variable for each stock. Testing the median of the 14 post-event dummy variables against zero provides a robust test of the hypothesis that spreads are lower in the post-event period.²⁴ Results are shown in the last 3 columns of Table 5 (“Regression 3”). Each of the post-event dummy variable is negative. Furthermore, the median of these post event dummy variables is negative and significantly different from zero at the 5% level. Again, the value of the median of the post-event dummy variables indicates that the switch to anonymity has reduced quoted and effective spreads by about 0.02 euros.

To sum up, the multivariate analysis indicates that the switch to anonymity has reduced both quoted spreads and effective spreads by about 0.02 euros. This reduction is consistent with our model when beta is small.

5.2.2 The Spread as a Signal of Future Price Changes.

Corollaries 1 and 4 predict that the size of the bid-ask spread is positively related to the magnitude of future (short-term) price movements. Corollary 4 further predicts that the strength of this relationship should be altered by the switch to anonymity when some traders have private information about future volatility. Specifically, this relationship should be weaker in the anonymous regime if beta is small. As the previous empirical findings suggest that this is the case, we expect a loosening of the relationship between the bid-ask spread and future volatility after the switch to anonymity.

Baseline Methodology and Findings

In order to test these predictions, we use the following methodology. For each stock in our sample we partition each trading day into fifteen 30-minute intervals and two 25-minute intervals (the first and last interval). As in our model, we measure the magnitude of the price change in interval $\tau \in \{1, 2, \dots, 17\}$ for stock i by $Vol_{i,\tau} = |m_{i,\tau} - m_{i,\tau-1}|$ where $m_{i,\tau}$ is the midquote (the midpoint of the best bid and the best ask price) at the end of interval τ .²⁵ We then estimate the following regression model :

$$\begin{aligned}
 Vol_{i,\tau+1} &= a_0 + a_1 Vol_{M,\tau} + a_2 Vol_{i,\tau} + a_3 N_{i,\tau} + a_4 ATr_{i,\tau} + (a_5 + a_6 D^{post}) s_{i,\tau} \\
 &+ \sum_{k=3}^{k=17} b_k T_{k,\tau} + \sum_{i=2}^{k=39} c_i D_i + \varepsilon_{i,\tau}
 \end{aligned} \tag{18}$$

²⁴Another way to control for contemporaneous correlation (also proposed by Boehmer, Saar and Yu (2005)) is to aggregate the data across stocks. This results in a time-series regression with 28 observations, one for each trading day. We estimate this model (results are not shown) and found the post-event dummy to be negative and significant. The results are thus fully consistent with those presented in the text.

²⁵For the first interval of each trading day, the change in midquote over this interval is calculated as the difference between the last midquote of the interval and the first midquote of the interval (rather than the last midquote of the previous interval) in order to exclude the overnight return from the sample.

where, for stock i and interval τ , $N_{i,\tau}$ is the number of transactions, $ATr_{i,\tau}$ is the average trade size and $s_{i,\tau}$ is the quoted bid-ask spread in Euros. $Vol_{M,\tau}$ is the market volatility, defined as the absolute change in the value of an equally weighted index of the sample stocks (calculated using midquotes). D^{post} is a dummy variable equal to 1 in the post event-period and zero in the pre-event period. $T_{k,\tau}$ is a trading interval dummy equal to 1 if $k = \tau$ and the D_i are stock-specific dummy variables allowing for stock fixed effects. We have partitioned each trading day into seventeen intervals but we only have sixteen intradaily observations per stock since we use lagged variables as regressors. Furthermore, we drop one trading interval dummy and one stock dummy to avoid perfect multicollinearity.

Variable $Vol_{i,\tau+1}$ is a measure of ex-post volatility in interval $\tau + 1$. Many other studies develop measures of ex-post volatility based on absolute returns (e.g. Jones, Kaul and Lipson (1994) or Ahn, Bae and Chan (2001)). We only include lagged variables in the set of explanatory variables in Equation (18) in order to avoid a simultaneity bias. It is well-known that there are systematic intraday patterns in price volatility and clustering in volatility (e.g. large changes in prices tend to be followed by large changes). We include the trading interval dummies, $T_{k,\tau}$, and the lagged volatility, $Vol_{i,\tau}$, in the set of independent variables to control for these effects. According to the mixtures of distributions hypothesis (Tauchen and Pitts (1983)), the rate at which new information arrives determines both price volatility and trading activity. Moreover, serial dependence in the news arrival process should induce serial correlation between volatility and trading volume (see Bollerslev, Engle and Nelson (1994)). Several authors have therefore used measures of trading activity (e.g. number of transactions) to forecast future price volatility (for instance Bollerslev and Domowitz (1993)). Here, we use the number of trades and the average trade size as measures of trading activity as Jones, Kaul and Lipson (1994) suggest that these two variables may not have the same informational content for future volatility. Finally, Black (1976) argues that there are commonalities in volatily changes across stocks. Thus, we include a measure of market volatility, $Vol_{M,\tau}$, in the set of explanatory variables.

The last explanatory variable is the lagged quoted spread in a given period ($s_{i,\tau}$).²⁶ In this way, we can study the relationship between the size of the bid-ask spread in a given period and the magnitude of price changes in the subsequent period ($Vol_{i,\tau+1}$). In order to evaluate the impact of the switch to anonymity on the strength of this relationship, we interact the coefficient on the quoted spread with a dummy variable (D^{post}) equal to 1 after the switch to anonymity. Recall that our hypothesis is that a wide spread in a given period foreshadows a large price movement in the subsequent period. Thus, we expect $a_5 > 0$. But the switch to anonymity should reduce the informativeness of the spread for future price volatility, i.e. $a_6 < 0$.

The two first columns of Table 6 report the results for each post-event period. The coefficients for the trading intervals and stock specific dummy variables are jointly significant. We do not report their estimates to save space. Consistent with our hypothesis, for both post-event periods, we find that the size of the spread in the pre-event period is positively and significantly related to future volatility (e.g. $a_5 = 0.64$ when we estimate

²⁶Our empirical findings are similar when we use the effective spread instead of the quoted spread as a proxy for the book liquidity.

the model with data from the second post-event period). Furthermore, the sensitivity of future price volatility to the size of the spread is significantly smaller in the anonymous regime (e.g. $a_6 = -0.57$ for the second post event period). The R^2 of the regression falls when the bid-ask spread is not used as an explanatory variable, especially for the second post event period (see the 2 last lines of Table 6). This indicates that the lagged bid-ask spread explains part of the variation in the magnitude of future changes in midquotes.

We also estimate individual regressions for all sample stocks. The findings are summarized in Columns 3 and 4 of Table 6. Our main result is confirmed in these individual regressions. When comparing the pre-event period to the first [second] post-event period the coefficient on the lagged spread, a_5 , is positive in 39 [38] out of 39 cases and significant at the 10% level or better in 22 [23] cases. The mean of the coefficient values is 0.63 [0.63]. The coefficient on the interaction term, a_6 , is negative in 37 [37] cases and significantly so in 22 [31] cases. The mean value is -0.36 [-0.80].²⁷

Overall the results provide support for the hypothesis that the size of the spread is positively related to the magnitude of future price changes. This prediction is not in itself specific to our model. It is a natural implication of the fact that traders should bid less aggressively when, based on public information, they expect large price movements. However, we also find that the strength of the association between the size of the spread and the magnitude of future price changes is smaller after the switch to anonymity. This finding provides a more compelling evidence in favor of our framework as it cannot be explained if traders react to public information only (see Corollary 1). Rather, it is consistent with a situation in which some limit order traders possess private information (Corollary 4). Thus, our findings suggest that the limit order book contains information on future price volatility over and above other public sources of information.

Robustness Tests

Alternative Measures of Volatility. It is well known that various market microstructure effects induce transient deviations of midquotes from the fair value of the security. At high-frequency, these transient deviations result in a negative correlation in midquote returns (see Hasbrouck (1993)). This implies that mean changes in midquotes are partly predictable. In order to account for this possibility, we modify our baseline methodology as follows. We run the following regression for each stock:

$$\Delta m_{i,\tau+1} = a_i + b_i \Delta m_{i,\tau} + u_{i,\tau+1}, \quad (19)$$

where $\Delta m_{i,\tau}$ is the change in midquotes for stock i in interval τ . We then use the absolute value of the residuals in each interval ($|u_{i\tau}|$) as our measure of ex-post volatility in interval τ . Using this alternative measure of volatility we repeat our previous analysis. The results are provided in Columns 4 and 5 of Table 6. Clearly, they are very similar to those presented earlier (Columns 1 and 2 in Table 6). We also repeat our baseline analysis with ex-post volatility measured by (a) the squared changes in midquotes or (b) the absolute

²⁷A possible concern is that there may be contemporaneous correlation among the residuals for different stocks. To address this issue we analyze the residuals from the separate regressions for each stock. The mean of the 741 pairwise correlations is 0.059 [0.057], suggesting that contemporaneous correlation of the residuals does not pose problems.

change in the logarithm of midquotes. The results are qualitatively unchanged but the regressions R^2 are smaller. We do not report the results in these cases for brevity.

Transitory vs. Permanent Volatility. Our model predicts that the bid-ask spread contains information on the magnitude of future changes in the “efficient price”. However, empirically, we observe changes in midquotes, not changes in the efficient price of the security. Thus, we cannot discard the possibility that the bid-ask spread contains information on transitory price changes rather than permanent price changes. There is no obvious method to circumvent this problem because the volatility of the efficient price cannot be directly observed. However, there is a quick way to gauge the fraction of the volatility of midquote changes due to transitory volatility. Consider the following simple model for the changes in midquotes (in the spirit of Hasbrouck (1993)).²⁸ Let $\tilde{m}_{i\tau}$ and $\tilde{v}_{i\tau}$ be respectively the midquote and the efficient price at the end of interval τ for stock i . We have $\tilde{m}_{i\tau} = \tilde{v}_{i\tau} + \tilde{d}_{i\tau}$ where $\tilde{d}_{i\tau}$ is the deviation between the midquote and the efficient price due to market microstructure effects. The efficient price, $\tilde{v}_{i\tau}$, follows a random walk while the $\tilde{d}_{i\tau}$ are i.i.d with variance σ_{id}^2 . Innovations in the efficient price, $\tilde{\omega}_{i\tau} \stackrel{def}{=} \Delta\tilde{v}_{i\tau}$ and the $\tilde{d}_{i\tau}$ are independent. In this case, the volatility of midquote changes is given by $Var(\Delta m_{i\tau}) = \sigma_{i\omega}^2 + 2\sigma_{id}^2$. This is simply the sum of the variance of the efficient price, $\sigma_{i\omega}^2$, and transitory volatility ($2\sigma_{id}^2$). Moreover, the first order autocorrelation between midquote changes is:

$$corr(\Delta m_{i\tau}, \Delta m_{i\tau-1}) = -\frac{2\sigma_{id}^2}{2Var(\Delta m_{i\tau})},$$

Thus, $|2 * corr(\Delta m_{i\tau}, \Delta m_{i\tau-1})|$ is equal to the fraction of total volatility due to transitory volatility. We estimate $2 * corr(\Delta m_{i\tau}, \Delta m_{i\tau-1})$ (the first order autocorrelation of midquote changes multiplied by two) in our sample for each stock separately. Then we test whether our estimates are significantly different from zero. For the sample defined over the pre-event period and the first post-event period, we find that even at a 10% level of significance only 9 out of a total of 39 correlations are significant. We obtain the same result for the sample defined over the pre-event and the second post-event period. This suggests that permanent volatility accounts for a large fraction of the volatility of midquote changes, at least at the data frequency we use. Note also that we account for this problem when we use $|u_{i\tau}|$ as a proxy for ex-post volatility. We observe that the estimates of the coefficients in our baseline regression and the regression in which ex-post volatility is measured by $|u_{i\tau}|$ are very similar. Thus, the effect of autocorrelation in midquote returns seems to be of second order importance at the half-hour frequency.

GARCH specification. Many empirical studies model time-varying conditional variances of returns using the generalized autoregressive conditional heteroskedastic (GARCH) framework (see Bollerslev, Engle and Nelson (1994) for a survey). As this framework has been widely used to forecast volatility, it is of interest to check whether our findings are

²⁸Hasbrouck (1993) considers transactions prices instead of midquotes. He does not require pricing errors due to market microstructure errors to be independent from innovations in the efficient price as we do here.

robust within this framework. To this end, we estimate the following GARCH(1,1) model:

$$\begin{aligned}\Delta q_{i,\tau+1}^a &= \mu_i + \theta_i \Delta q_{i,\tau}^a + \eta_{i,\tau+1} \\ \sigma_{i,\tau+1}^2 &= \omega_i + \lambda_i \eta_{i,\tau}^2 + \gamma_i \sigma_{i,\tau}^2 + \delta_1 Vol_{M,\tau}^a + \delta_2 N_{i,\tau} + \delta_3 ATr_{i,\tau} + (\delta_4 + \delta_5 D^{post}) s_{i,\tau} \\ \eta_{i,\tau+1} &| \Psi_\tau \sim N(0, \sigma_{i,\tau+1}^2).\end{aligned}\tag{20}$$

The formulation for the conditional mean equation aims at capturing first order autocorrelation in the changes in midquotes. Equation (20) models movements in conditional volatility using a GARCH(1,1) with exogenous explanatory variables (e.g. $s_{i,\tau}$). These are the same explanatory variables as in our baseline regression model. As for the effect of the bid-ask spread, we expect to find that $\delta_4 > 0$ and $\delta_5 < 0$. There are some differences to the baseline model. First, in order to be closer to the standard specification in GARCH modeling, we focus on percentage returns for the midquotes by taking a logarithmic transformation of the midquotes series (i.e. $\Delta q_{i,\tau+1} = \log(m_{i,\tau+1}) - \log(m_{i,\tau})$). Second, we control for intraday seasonalities by using *adjusted returns*. That is, we regress the midquote returns on a set of time-of-day dummies and retain the fitted values of the regression. Then, in each interval, we divide the actual midquote return by the fitted value to obtain the adjusted midquote return, $\Delta q_{i,\tau}^a$. This procedure is suggested by Engle (2000). Market volatility, $Vol_{M,\tau}^a$, is also measured using adjusted returns.

We estimate the model for each post-event period and for each stock separately. We summarize the main findings in Table 7. When comparing the pre-event period to the first [second] post-event period, the coefficient on the lagged spread, δ_4 , is positive in 26 [31] out of 39 cases and significant at the 10% level or better in 16 [20] cases. The mean of the coefficient values is 2.86 [2.56]. The coefficient on the interaction term, δ_5 , is negative in 36 [34] cases and significantly so in 17 [19] cases. The mean value is -1.96 [-1.77]. These results confirm the conclusions of the baseline regressions. The lagged bid-ask spread is positively related to future price volatility but the strength of this relationship is smaller in the anonymous trading environment.²⁹

Bollerslev and Domowitz (1993) estimate a GARCH(1,1) model in the deutsche mark-dollar market.³⁰ Interestingly, they also find a positive and significant contribution of the bid-ask spread to movements in conditional volatility. Our findings go in the same direction. Bollerslev and Domowitz (1993) point out, p.1436, that they are not aware of a theoretical model “*that provides a causal link between the magnitude of the spread and returns volatility*”. According to our model, the relationship between the bid-ask spread and future volatility is due to the fact that some traders possess information on future volatility. Moreover, the alteration of this relationship after the switch to anonymity suggests that this information is private.

²⁹Besides the GARCH specification we also estimate an EGARCH (1,1) model. This alternative specification has the advantage that the estimate of the conditional variance is guaranteed to be positive. Conclusions are similar to those reported in the paper and are omitted for brevity.

³⁰The GARCH(1,1) model estimated in Bollerslev and Domowitz (1993) is conceptually close to our GARCH(1,1) model. The main differences are as follows : (i) they do not control for intraday effects as they consider a market operating round-the-clock, (ii) they control for trading activity by the duration between trades and the number of quote updates instead of the number of trades due to data limitations and (iii) they work with 5 minutes intervals.

Alternative Length of Time Interval. All our empirical results are based on 30-minute intervals (except the first and the last interval of each trading day). We re-estimate all our models using 15-minute intervals. Results are qualitatively similar to those reported for intervals of thirty minutes and are omitted for brevity.

Overall, the robustness tests reinforce the findings in the baseline analysis : (i) the bid-ask spread predicts future volatility and (ii) the forecasting power of the spread is lower in the anonymous regime.

5.2.3 Other Explanations

Three empirical findings emerge : (i) the switch to anonymity has been followed by an improvement in various measures of liquidity, (ii) the size of the spread contains information on future price volatility but (iii) its informativeness has declined after the switch to anonymity. These findings are consistent with our model. Are there alternative explanations?

Simaan et al. (2003) argue that it is more difficult for liquidity providers to collude in an anonymous environment. This hypothesis implies that a switch to anonymity should result in more competitive bid-ask spreads, as we find. However, collusion among liquidity suppliers is unlikely in a limit order market like Euronext because a large number of intermediaries compete in supplying liquidity. For instance, for the CAC40 stocks (our sample stocks), Declerk (2001) reports that there were 59 active broker-dealers in 1999. Furthermore the collusion hypothesis does not explain why the informativeness of the bid-ask spread for future price volatility should be affected by the switch to anonymity.

Non-anonymity also facilitates the search for counterparties in block trades. For instance, consider an upstairs broker who must buy a block of shares for a client. Non-anonymity enables the broker to locate traders with large sell orders standing in the book. Then he can contact these traders directly (by phone) and arrange the trade without executing the order against the limit order book. If upstairs brokers use brokers' IDs for this purpose, a switch to anonymity will increase their search costs. We should thus expect that volume in the upstairs market is lower in the anonymous regime. This reduction in market fragmentation may then result in a deeper limit order book. We call this the "search cost hypothesis".

In order to investigate this hypothesis further, we compute the average daily number of block trades negotiated upstairs before and after the switch to anonymity. We also compute the number of block trades executed downstairs, that is, executed directly against the book. For each stock in our sample, Euronext Paris defines a "normal block size" (NBS). All orders larger than one NBS are considered as blocks and as such are eligible for special block trading rules. In particular, they can be negotiated upstairs and do not need to be executed at prices equal to or within the best bid and offer quotes.³¹ Hence we consider that a transaction is a block if its size exceeds one NBS. The NBS in our sample varies

³¹See Bessembinder and Venkataraman (2003) for a detailed analysis of block trading on Euronext Paris.

between 2,000 and 100,000 shares with an average value of 19,410.26 shares. If the “search cost hypothesis” is valid, the number of upstairs trades should decrease and the number of downstairs trades should increase after the switch to anonymity.

Table 8 reports the results. The average daily number of upstairs trades initially decreased after the switch to anonymity (from 3.7 trades per day to 2.4 trades in the first post-event period) but then increased again, reaching its original level in the second post-event period. The average daily trading volume negotiated upstairs decreased, but not significantly. The number and the volume of downstairs trades have increased. The increase is significant only for the second post-event period. Overall these mixed results are not very supportive of the search cost hypothesis. We also note that this hypothesis cannot explain why the informativeness of the spread for future price volatility has changed after the switch to anonymity.

6 Conclusions

On April 23, 2001, the limit order book for stocks listed on Euronext Paris became anonymous. We analyze the effect of this switch to anonymity on market liquidity and the informational content of the limit order book. In order to guide our empirical analysis, we develop a model of limit order trading in which traders have information on the likelihood of future price movements (information events). Limit order traders bid more conservatively when they expect a large price movement. For this reason, a wide bid-ask spread signals an impending price movement. This effect creates a positive relationship between the size of the bid-ask spread and future volatility.

We show that when information on future volatility is public, a switch to anonymity does not affect market liquidity and the relationship between the bid-ask spread and future volatility. In contrast, when information on future volatility is private, anonymity does matter. Actually, in this case, uninformed traders extract information on future volatility from observing limit orders posted in the book. Now, the amount of information released by the limit order book is not the same when the book is anonymous and when it is not. For this reason, a switch to anonymity alters uninformed traders’ bidding strategies and thereby it also affects informed traders’ bidding strategies. In particular, informed traders are less prone to engage into bluffing strategies in the anonymous environment. Thus, when information on future volatility is asymmetric, a switch to anonymity changes both market liquidity and the informativeness of the bid-ask spread. More specifically, a switch to anonymity reduces (resp. enlarges) the average trading costs for small and large orders when the proportion of informed limit order traders is small (resp. large). We also find that it reduces (resp. increases) the informational content of the bid-ask spread when the proportion of informed limit order traders is small (resp. large).

The decision of Euronext Paris to conceal limit order traders’ IDs’ in April 2001 constitutes a unique opportunity to test these predictions. We compare bid-ask spreads before and after the switch to anonymity in Euronext Paris for a sample of 39 actively traded stocks. We find that quoted and effective spreads are significantly smaller after the switch

to anonymity, after controlling for the effects of other variables affecting bid-ask spreads. Moreover, the quoted depth has increased after the switch to anonymity (albeit not significantly). Overall the results suggest that the switch to anonymity has improved market liquidity. We also study the intraday relationship between price volatility and the size of the bid-ask spread. We divide each trading day in intervals of thirty minutes. Using various methodologies, we find that there is a positive and significant relationship between the magnitude of the price movement in one period and the size of the bid-ask spread in the previous period. The association is significantly weaker after the switch to anonymity. Thus, the bid-ask spread contains information about future price volatility but its informativeness is weaker after the switch to anonymity.

Overall, the version of the model in which information about future volatility is public is rejected by our empirical findings. In contrast, these empirical findings are consistent with a scenario in which some traders possess private information about future volatility, partially revealed by the limit order book. One may find other plausible explanations for the impact of anonymity on market liquidity or for the positive relationship between the bid-ask spread and future volatility. However, unlike our model, these alternative explanations fail to explain why the switch to anonymity also affects the informativeness of the bid-ask spread for future volatility.

Our findings suggest several interesting venues for future research. Our model is based on a simple intuition : a lack of liquidity in the book foreshadows an information event. This lack of liquidity manifests itself by a large spread but more generally by a steeper book. This suggests that the slope of the book, in addition to the size of the spread, may also contain information on future price volatility.³² This could be tested with more detailed data. Our empirical findings also show that anonymity affects the predictive power of variables such as the bid-ask spread in models of the conditional volatility. It would be interesting to analyze whether other features of market design are important for modeling time variations in conditional volatility. On another front, the analysis raises intriguing questions about the relationships between changes in option prices and the liquidity of the underlying securities. Options contain information on the price volatility of the underlying security (see, for instance, Lamoureux and Lastrape (1993)). How does this information affect limit order prices in the market for the underlying security? Conversely, how does information on future price volatility contained in the limit order book affect option prices?

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³²Naes and Skjeltorp (2003) find empirically a negative relationship between volatility and the slope of the book. Their results however are not directly comparable to ours because they analyze the contemporaneous (instead of the lagged) relationship between volatility and the slope of the book at the daily frequency (instead of considering intraday relationships).

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Table 1: Main Notations

\tilde{V}_2	Final value of the security at Date 2
ϵ_1	Innovation at date 1
v_0	Unconditional expected value of the security
α	Probability of order submission by a speculator if information event
q	Size of 1 round lot
π_0	Prior probability of an information event
σ	Size of an innovation
β	Probability that the leader is an informed dealer
Δ	Tick size
A_j	j^{th} ask price on the grid above the unconditional expected value
K	State of the book at the end of the first stage
Φ_K	Probability that the state of the book is K if the leader is a pre-commited trader
Q_1	Depth of the book at price A_1
Q_s	Size of the market order submitted by a speculator
Q_l	Size of the market order submitted by a liquidity trader
π_K	Follower's belief about the occurrence of an information event
I	Indicator variable (0 if there is no information event; 1 otherwise)

7 Appendix

Proof of Lemma 1.

The first part of the lemma follows from the arguments in the text. Let $\Pi^F(n; S, \pi_S)$ be the follower's expected profit if she offers n round lots at price A_1 conditional on the book being shallow at the end of stage L and *conditional on the arrival of a buy order at date 1*. The follower's optimal reaction when she observes a shallow book is the value of n which maximizes $\Pi^F(n; S, \pi_S)$. We obtain

$$\begin{aligned}\Pi^F(1; S, \pi_S) &= \pi_S[\alpha(A_1 - (v_0 + \sigma)) + \frac{1}{2}(1 - \alpha)(A_1 - v_0)] + \frac{1}{2}(1 - \pi_S)(A_1 - v_0) \\ &= \left(\frac{\alpha\pi_S + 1}{2}\right)(A_1 - v_0 - \left(\frac{2\pi_S}{\pi_S\alpha + 1}\right)\alpha\sigma).\end{aligned}\quad (21)$$

Now suppose that the follower offers $n > 1$ round lots. Her expected profit is

$$\begin{aligned}\Pi^F(n; S, \pi_S) &= \pi_S[n\alpha(A_1 - (v_0 + \sigma)) + \frac{1}{2}(1 - \alpha)(A_1 - v_0)] + \frac{1}{2}(1 - \pi_S)(A_1 - v_0) \\ &= \Pi^F(1; S, \pi_S) + (n - 1)\pi_S\alpha(A_1 - (v_0 + \sigma)).\end{aligned}$$

As $A_1 < (v_0 + \sigma)$, we deduce that $\Pi^F(1; S, \pi_S) > \Pi^F(n; S, \pi_S)$. Thus, offering more than 1 round lot cannot be optimal for the follower when she observes a shallow book. Moreover $\Pi^F(1; S, \pi_S) > 0$ iff $\Delta > \left(\frac{2\pi_S}{\pi_S\alpha + 1}\right)\alpha\sigma$. Thus, $n^*(S) = 1$ if $\Delta > \left(\frac{2\pi_S}{\pi_S\alpha + 1}\right)\alpha\sigma$ and $n^*(S) = 0$, otherwise.

Now consider the case in which the book is deep at the end of stage L . Suppose that the follower submits a limit order for $n > 0$ round lots. Then, her order will be executed **iff** the trader submitting market orders is a speculator because (i) the maximum trade size for liquidity traders is 2 round lots and (ii) time priority is enforced (hence the limit order placed by the leader always executes before the follower's limit order). But this implies that the follower cannot break even on her limit orders. Thus, she is strictly better off doing nothing when she observes a deep book. ■

Proof of Proposition 1. We denote by $\Pi_{I=i}^L(K)$, the leader's expected profit if he posts schedule K , when the indicator variable \tilde{I} is equal to $i \in \{0, 1\}$.

Consider first the case in which there is an information event. In this case, the follower's reaction is given in Lemma 1 for $\pi_S = \pi_T = 1$ (since dealers have perfect information). *Given the follower's reaction*, we deduce that

$$\Pi_{I=1}^L(T) = \frac{3}{2}(1 - \alpha)(A_2 - v_0) > 0, \quad (22)$$

$$\begin{aligned}\Pi_{I=1}^L(S) &= [\alpha(A_1 - (v_0 + \sigma)) + (1 - \alpha)((A_1 - v_0) + 0.5(A_2 - v_0))] \\ &= (A_1 - (v_0 + \alpha\sigma)) + 0.5(1 - \alpha)(A_2 - v_0)\end{aligned}\quad (23)$$

$$\begin{aligned}
\Pi_{I=1}^L(D) &= 2\alpha(A_1 - (v_0 + \sigma)) + \frac{3}{2}(1 - \alpha)(A_1 - v_0) \\
&= \Pi_{I=1}^L(S) + \frac{\alpha + 1}{2}(A_1 - (v_0 + \frac{2\alpha\sigma}{\alpha + 1})),
\end{aligned} \tag{24}$$

As $\Delta < \alpha\sigma$, it immediately follows that

$$\Pi_{I=1}^L(D) < \Pi_{I=1}^L(S) < \Pi_{I=1}^L(T),$$

which proves that the dealer acting in stage L chooses schedule T when there is an information event.

Now consider the case in which there is no information event. In this case, the follower's reaction is given in Lemma 1 for $\pi_S = \pi_T = 0$ (since dealers have perfect information). Given this reaction, we deduce that :

$$\begin{aligned}
\Pi_{I=0}^L(T) &= 0, \\
\Pi_{I=0}^L(S) &= A_1 - v_0, \\
\Pi_{I=0}^L(D) &= \frac{3}{2}(A_1 - v_0).
\end{aligned}$$

It immediately follows that

$$\Pi_{I=0}^L(D) > \Pi_{I=1}^L(S) > \Pi_{I=1}^L(T),$$

which proves that the dealer acting in stage L chooses schedule D when there is no information event. ■

Proof of Corollary 1.

Part 1. Liquidity. The expected small trade spread in a given trading mechanism is given by:

$$E(\tilde{S}_{small}) = \Delta(1 + \text{prob}(\tilde{Q}_1 = 0)). \tag{25}$$

and the expected large trade spread is given by:

$$ES_{large} = \Delta(2 - \text{prob}(\tilde{Q}_1 = 2)). \tag{26}$$

The likelihood of observing no offer at price A_1 or an offer for 2 round lots at price A_1 is entirely determined by traders' bidding strategies. As these strategies are identical in the anonymous and the non-anonymous trading mechanism, we deduce that $\text{prob}(\tilde{Q}_1 = 0)$ and $\text{prob}(\tilde{Q}_1 = 2)$ are identical in both trading mechanisms. This implies that market liquidity is identical in the anonymous and the non-anonymous trading system when information on future volatility is public.

Part 2. Informativeness. By definition :

$$Cov(\left| \tilde{V}_2 - v_0 \right|, \tilde{S}_{small}) = \sigma Cov(\tilde{I}, \tilde{S}_{small}) = \sigma [E(\tilde{I}\tilde{S}_{small}) - E(\tilde{I})E(\tilde{S}_{small})].$$

We deduce, after some straightforward manipulations, that :

$$Cov(\left| \tilde{V}_2 - v_0 \right|, \tilde{S}_{small}) = \sigma \pi_0 (1 - \pi_0) [E(\tilde{S}_{small} \mid \tilde{I} = 1) - E(\tilde{S}_{small} \mid \tilde{I} = 0)].$$

Finally, as \tilde{S}_{small} is either equal to Δ or 2Δ , we obtain that :

$$Cov(\left| \tilde{V}_2 - v_0 \right|, \tilde{S}_{small}) = \sigma \pi_0 (1 - \pi_0) \Delta [prob(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 1) - prob(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 0)]. \quad (27)$$

Now, given the bidding strategies described in Proposition 1, we deduce that

$$prob(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 1) = (1 - \beta)\Phi_T + \beta,$$

and

$$prob(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 0) = 0,$$

in **both** the anonymous and the non-anonymous trading system. This implies :

$$Cov(\left| \tilde{V}_2 - v_0 \right|, \tilde{S}_{small}) = \sigma \pi_0 (1 - \pi_0) \Delta [(1 - \beta)\Phi_T + \beta] > 0,$$

in both the anonymous and the non-anonymous trading system. Thus, the bid-ask spread is informative and its informativeness does not depend on the anonymity regime. ■

Proof of Proposition 2.

Step 1. We show that the follower's bidding strategy is a best response to the informed dealer's bidding strategy. First consider the case in which the book is thin at the end of the first stage. Substituting $m^*(\beta)$ by its expression in $\pi_T(m, \beta)$ (given by Eq.(11)), it is easily checked that

$$\Delta = \pi_T(m^*(\beta), \beta) \alpha \sigma \quad \text{and} \quad \Delta < \left(\frac{2\pi_T(m^*(\beta), \beta)}{\pi_T(m^*(\beta), \beta) \alpha + 1} \right) \alpha \sigma.$$

Using Lemma 1, we conclude that when she observes a thin book, the follower's optimal reaction is either to submit a limit order for 1 round lot or to do nothing. As she is indifferent, the mixed strategy given in the proposition is a best response for the follower. In equilibrium, the informed dealer never chooses a shallow book (whether $I = 1$ or not). Thus, a shallow book does not contain information, which implies $\pi_S = \pi_0$. Therefore :

$$\left(\frac{2\pi_S}{\pi_S \alpha + 1} \right) \alpha \sigma < \Delta.$$

Using Lemma 1, we deduce that the follower submits a limit order for 1 round lot at price A_1 when she observes a shallow book. When the follower faces a deep book, she optimally does nothing, independently of her beliefs about the occurrence of an information event, as shown in the last part of the proof of Lemma 1. These arguments establish the second part of the proposition.

Step 2. We show that the informed dealer's bidding strategy is a best response. Recall that $\Pi_{I=i}^L(K)$ denotes the leader's expected profit in state I if he posts schedule K . When $I = 0$, straightforward computations yield (taking into account the follower's reaction):

$$\Pi_{I=0}^L(T) = (1 - u_T^*)E(\tilde{Q}_u)(A_2 - v_0) + \frac{u_T^*}{2}(A_2 - v_0) = \frac{3}{2}(1 - u_T^*)(A_2 - v_0) + \frac{u_T^*}{2}(A_2 - v_0).$$

and

$$\Pi_{I=0}^L(S) = A_1 - v_0,$$

and

$$\Pi_{I=0}^L(D) = E(\tilde{Q}_u)(A_1 - v_0) = \frac{3}{2}(A_1 - v_0).$$

Using the fact that $u_T^* = \frac{3}{4}$, we obtain

$$\Pi_{I=0}^L(D) = \Pi_{I=0}^L(T) > \Pi_{I=0}^L(S).$$

Thus when $I = 0$, the leader optimally chooses schedule D or schedule T . As she is indifferent between these two schedules, choosing schedule D with probability $m^*(\beta)$ and schedule T with probability $(1 - m^*(\beta))$ is a best response.

Now we consider the informed dealer's optimal reaction when $I = 1$. Given the follower's reaction and the informed trader's behavior, we deduce that:

$$\Pi_{I=1}^L(T) = (1 - \alpha)\left[\frac{3}{2}(1 - u_T^*)(A_2 - v_0) + \frac{u_T^*}{2}(A_2 - v_0)\right] > 0.$$

Furthermore,

$$\Pi_{I=1}^L(S) = \alpha(A_1 - (v_0 + \sigma)) + (1 - \alpha)(A_1 - v_0) = A_1 - v_0 - \alpha\sigma < 0,$$

and $\Pi_{I=1}^L(D)$ is as given by Equation (24). Hence, we deduce that

$$\Pi_{I=1}^L(T) > 0 > \text{Max}\{\Pi_{I=1}^L(S), \Pi_{I=1}^L(D)\}.$$

Thus, when $I = 1$, the leader optimally chooses schedule T . ■

Proof of Proposition 3.

Part 1. We first show that the follower's bidding strategy is a best response. First consider the case in which the book is thin. From Eq.(11), we obtain :

$$\pi_T(1, \beta) = \text{prob}(I = 1 \mid K = T) = \left[\frac{(1 - \beta)\Phi_T + \beta}{(1 - \beta)\Phi_T + \beta\pi_0}\right]\pi_0.$$

It is then easily checked that

$$\alpha\pi_T(1, \beta)\sigma \leq \Delta,$$

if $\beta \leq \beta^*$. Moreover

$$\Delta < \left(\frac{2\pi_T(1, \beta)}{\pi_T(1, \beta)\alpha + 1}\right)\alpha\sigma. \quad (28)$$

if $\beta > \beta^{**}$. We deduce from Lemma 1 that the follower's best response when she observes a thin book is to submit a limit order for 1 round lot. In the other possible states of the book, the optimal reaction of the follower is derived as in Part 1 in the proof of Proposition 2.

Part 2. Next we show that the informed dealer's bidding strategy is a best response. Recall that $\Pi_{I=i}^L(K)$ denotes the leader's expected profit in state I if he posts schedule K . When $I = 1$, the argument is identical to the argument developed in the proof of the previous proposition (with $u_T^* = 1$). When $I = 0$, given the follower's reaction, straight forward computations yield :

$$\Pi_{I=0}^L(T) = \frac{1}{2}(A_2 - v_0) = \Delta.$$

and

$$\Pi_{I=0}^L(S) = A_1 - v_0 = \Delta,$$

and

$$\Pi_{I=0}^L(D) = E(\tilde{Q}_u)(A_1 - v_0) = \frac{3}{2}(A_1 - v_0) = \frac{3}{2}\Delta.$$

Thus the informed dealer's best response when there is no information event is to post schedule D . ■

Proof of Proposition 4

The proof is identical to the proof of Proposition 3. The only difference is that the inequality in equation (28) is reversed, i.e.

$$\Delta \leq \left(\frac{2\pi_T(1, \beta)}{\pi_T(1, \beta)\alpha + 1} \right) \alpha \sigma,$$

since $0 \leq \beta \leq \beta^{**}$. This means that the follower optimally submits a limit order for 2 round lots when she observes a thin book (see Lemma 1). ■

Proof of Corollary 2. It follows immediately from the arguments in the text. ■

Proof of Corollary 3.

In what follows, a superscript "a" (resp. "na") indexes the value of a variable in the anonymous (resp. non-anonymous) market.

Part 1. The Small Trade Spread. The expected small trade spread is given by:

$$E(\tilde{S}_{small}^j) = \Delta(1 + \text{prob}(\tilde{Q}_1^j = 0)), \text{ for } j \in \{a, na\}.$$

We deduce that the difference between the expected small trade spread in the anonymous market and the expected small trade spread in the non-anonymous markets is:

$$E(\tilde{S}_{small}^a) - E(\tilde{S}_{small}^{na}) = \Delta(\text{prob}(\tilde{Q}_1^a = 0) - \text{prob}(\tilde{Q}_1^{na} = 0)).$$

When $\beta \leq \beta^*$, we have $prob(\tilde{Q}_1^a = 0) = 0$. This follows from Propositions 3 and 4. Furthermore, we deduce from Corollary 2 that:

$$prob(\tilde{Q}_1^{na} = 0) = \beta(1 - u_T^*)[\pi_0 + (1 - \pi_0)(1 - m^*(1))] > 0. \quad (29)$$

Thus for $0 \leq \beta \leq \beta^*$, $E(\tilde{S}_{small}^a) < E(\tilde{S}_{small}^{na})$. When $\beta > \beta^*$, using the equilibrium bidding strategies described in Proposition 2, we obtain:

$$prob(\tilde{Q}_1^a = 0) = (1 - \beta)\Phi_T(1 - u_T^*) + \beta(1 - u_T^*)(\pi_0 + (1 - \pi_0)(1 - m^*(\beta))). \quad (30)$$

Thus

$$prob(\tilde{Q}_1^a = 0) - prob(\tilde{Q}_1^{na} = 0) = (1 - u_T^*)[(1 - \beta)\Phi_T + \beta(1 - \pi_0)(m^*(1) - m^*(\beta))].$$

Using the expression for $m^*(\beta)$, we rewrite this equation:

$$prob(\tilde{Q}_1^a = 0) - prob(\tilde{Q}_1^{na} = 0) = (1 - u_T^*)(1 - \beta)\Phi_T(1 - (1 - \pi_0)m^*(1)) > 0,$$

which means that $E(\tilde{S}_{small}^a) - E(\tilde{S}_{small}^{na}) > 0$ when $\beta > \beta^*$.

Part 2. The Large Trade Spread. The expected large trade spread is given by

$$E(\tilde{S}_{l\arg e}^j) = \Delta(2 - prob(\tilde{Q}_1^j = 2)), \text{ for } j \in \{a, na\}.$$

We deduce that the difference between the expected large trade spread in the anonymous market and the expected large trade spread in the non-anonymous markets is:

$$ES_{l\arg e}^a - ES_{l\arg e}^{na} = \Delta(prob(\tilde{Q}_1^{na} = 2) - prob(\tilde{Q}_1^a = 2)).$$

Using Corollary 2, we obtain

$$prob(\tilde{Q}_1^{na} = 2) = (1 - \beta) + \beta(1 - \pi_0)m^*(1) < 1.$$

When $\beta \leq \beta^{**}$, we have $prob(\tilde{Q}_1^a = 2) = 1$ (see Proposition 4). Thus $ES_{l\arg e}^a < ES_{l\arg e}^{na}$ for $\beta \leq \beta^{**}$. For $\beta^* < \beta$, we deduce from Proposition 2 that:

$$prob(\tilde{Q}_1^a = 2) = (1 - \beta)(\Phi_S + \Phi_D) + \beta(1 - \pi_0)m^*(\beta).$$

Hence,

$$prob(\tilde{Q}_1^{na} = 2) - prob(\tilde{Q}_1^a = 2) = (1 - \beta)\Phi_T + \beta(1 - \pi_0)(m^*(1) - m^*(\beta)).$$

Using the expression for $m^*(.)$ and rearranging, we rewrite this equation:

$$prob(\tilde{Q}_1^{na} = 2) - prob(\tilde{Q}_1^a = 2) = \beta\Phi_T(1 - (1 - \pi_0)m^*(1)) > 0.$$

We deduce that $ES_{l\arg e}^a - ES_{l\arg e}^{na} > 0$ for $\beta > \beta^*$.

For $\beta^{**} < \beta \leq \beta^*$, we deduce from Proposition 3 that:

$$prob(\tilde{Q}_1^a = 2) = (1 - \beta)(\Phi_S + \Phi_D) + \beta(1 - \pi_0).$$

Thus,

$$prob(\tilde{Q}_1^{na} = 2) - prob(\tilde{Q}_1^a = 2) = (1 - \beta)\Phi_T + \beta(1 - \pi_0)(m^*(\beta) - 1).$$

Hence,

$$ES_{l_{arg e}}^a - ES_{l_{arg e}}^{na} = \Delta[(1 - \beta)\Phi_T + \beta(1 - \pi_0)(m^*(1) - 1)].$$

Substituting $m^*(1)$ by its expression, it is readily shown that $ES_{l_{arg e}}^a - ES_{l_{arg e}}^{na} > 0$ when $\beta^{**} < \beta \leq \beta^*$. ■

Proof of Corollary 4.

Recall that (see Eq. (27)):

$$Cov(\left| \tilde{V}_2 - v_0 \right|, \tilde{S}_{small}) = \sigma\pi_0(1 - \pi_0)\Delta[prob(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 1) - prob(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 0)].$$

1) In the Non-Anonymous Regime. Using the bidding strategies described in Corollary 2 and Bayesian calculus, we obtain :

$$prob^{na}(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 1) = \beta(1 - u_T^*),$$

and

$$prob^{na}(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 0) = \beta(1 - u_T^*)(1 - m^*(1)).$$

We deduce that

$$Cov(\left| \tilde{V}_2 - v_0 \right|, \tilde{S}_{small}) = \sigma\pi_0(1 - \pi_0)\beta(1 - u_T^*)m^*(1) > 0. \quad (31)$$

Hence : $Infspread^{na}(\beta) > 0$ for $\beta > 0$.

2) In the Anonymous Regime. If $\beta > \beta^*$, using the bidding strategies described in Proposition 2 , we obtain :

$$prob^a(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 1) = ((1 - \beta)\Phi_T + \beta)(1 - u_T^*),$$

and

$$prob^a(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 0) = ((1 - \beta)\Phi_T + \beta(1 - m^*(\beta)))(1 - u_T^*)$$

Hence we deduce that :

$$Cov(\left| \tilde{V}_2 - v_0 \right|, \tilde{S}_{small}) = \sigma\pi_0(1 - \pi_0)\beta(1 - u_T^*)m^*(\beta) \quad (32)$$

Comparing Equation (31) and (32), we conclude that $Infspread^a(\beta) > Infspread^{na}(\beta) > 0$ when $\beta > \beta^*$ because $m^*(\beta) > m^*(1)$. If $\beta \leq \beta^*$, using the bidding strategies described in Propositions 3 and 4 , we obtain :

$$prob^a(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 1) = prob^a(\tilde{S}_{small} = 2\Delta \mid \tilde{I} = 0) = 0,$$

Hence

$$Cov(\left| \tilde{V}_2 - v_0 \right|, \tilde{S}_{small}) = 0 \quad (33)$$

Comparing Equation (31) and (33), we conclude that $Infspread^a(\beta) < Infspread^{na}(\beta)$ when $\beta \leq \beta^*$. ■

Table 3**Descriptive Statistics**

The table reports averages for the variables listed in the first column. For each variable, we first calculate averages for each stock and each day. Then, we average over the 14 days of the pre-event period and the post-event period, respectively, for both post-event periods. The pre-event period includes data from March 26, 2001 to April 12, 2001. The two post-event periods include data from April 30, 2001 to May 18, 2001, and from July 2, 2001 to July 19, 2001, respectively. In order to compute the number of trades, the trade price and the average trade size, we treat transactions occurring at the same time as a single trade. The trade price is thus the volume-weighted price of all transactions occurring at the same time. Volatility is measured by the standard deviation of 30-minute midquote returns. For each post-event period, the last two columns report the test statistics (a t-test and a z value for the Wilcoxon test) of the null hypothesis that the differences in means and medians, respectively, are zero.

	Pre-event	Post-event 1			Post-event 2		
	Mean	Mean	t-value	z-value	Mean	t-value	z-value
Number of trades	1 435	1 371	0,28	0,15	1 248	0,84	0,75
Trade price	85,30	89,80	0,34	0,61	67,85	1,54	1,46
Trading volume (shares)	1 323 177	1 433 757	0,26	0,91	1 532 290	0,48	1,26
Trading volume (€ mio)	83	99	0,73	1,00	83	0,01	0,24
Average trade size (shares)	718	834	1,13	1,16	998	2,42	2,38
Daily return volatility	0,0063	0,0047	5,21	4,46	0,0048	4,38	4,23
Market capitalization (€ mio)	26 431	33 843	1,00	0,64	25 977	0,08	0,06

Table 4**Univariate Analysis of the Spread**

The table reports averages for the variables listed in the first column. We first calculate averages for each stock and each day. Then, we average over the 14 days of the pre-event period and the post-event period, respectively, for both post-event periods. The pre-event period includes data from March 26, 2001 to April 12, 2001. The two post-event periods include data from April 30, 2001 to May 18, 2001, and from July 2, 2001 to July 19, 2001, respectively. Standard deviations of each variable (dispersion of the daily spread and depth across days and stocks) are given in parentheses. For each post-event period, the last two columns report the test statistics (respectively a t-test and a Wilcoxon test) of the null hypothesis that the differences in means and medians, respectively, are zero.

	Pre-event		Post-event 1		Post-event 2		
	Mean	Mean	t-value	z-value	Mean	t-value	z-value
quoted spread €, equally-weighted	0,177 (0,12)	0,146 (0,10)	1,36	1,34	0,112 (0,07)	3,12	3,16
quoted percentage spread, equally-weighted	0,22% (0,08%)	0,17% (0,06%)	3,67	3,35	0,17% (0,05%)	3,63	3,15
effective spread, equally-weighted	0,154 (0,11)	0,129 (0,08)	1,27	1,10	0,097 (0,06)	3,13	3,30
depth (in number of shares)	1 016 (759)	1 211 (850)	1,16	1,41	1 680 (6 803)	2,05	2,45
depth (in euros)	74 176 (55 165)	93 556 (71 810)	1,45	1,50	98 342 (327 850)	1,33	1,04

Table 5 **Multivariate Analysis of the Quoted Spread**

This table presents estimates of the regression defined in Equation (17), and reported below, for various measures of the bid-ask spread.

$$s_{i,t} = \gamma_0 + \gamma_1 \log(\text{Volu}_{i,t}) + \gamma_2 \text{TS}_{i,t} + \gamma_3 \text{P}_{i,t} + \gamma_4 \sigma_{i,t} + \gamma_5 \text{D}_t^{\text{post}} + \varepsilon_{i,t}$$

For all regressions we use daily averages for the dependent and independent variables. Panel A [B] reports the results of the regressions for the pre-event period and the post-event 1 [post-event 2] period. The pre-event period includes data from March 26, 2001 to April 12, 2001. The two post-event periods include data from April 30, 2001 to May 18, 2001, and from July 2, 2001 to July 19, 2001, respectively.

In Regression 1, we report the results of an OLS regression of each spread measure on a set of control variables. Volume is measured in mio€. The tick size variable measures the average effective tick size. The tick size is 1€-Cent (5 Cents, 10 Cents, 50 Cents) for stocks trading at prices below 50 € (between 50 and 100 €, between 100 and 500 €, above 500€). The effective tick size can take on intermediate values if a stock trades at prices in more than one tick size range. Volatility is measured by the standard deviation of 30-minute midquote returns.

In Regression 2, we allow for stock-specific intercepts.

In Regression 3, we control for cross-correlation by introducing 14 dummy variables \mathbb{T}_t that equal one if the day is t (in the post-event period) and 0 otherwise. We omit the estimates of the intraday dummies and the fixed effects. However, in Regression 3, we report the median of the day dummy variables. We compute Newey-West standard errors with lag two to control for heteroskedasticity and autocorrelation. Corresponding t -statistics are reported in parentheses. A "*" denotes significance at the 5% level.

Panel A: Pre-event and Post-event 1	Regression 1 : Baseline regression			Regression 2: Fixed effects			Regression 3: Fixed effects and day dummies for the post-sample period		
	quoted spread in €	quoted percentage spread	effective spread in €	quoted spread in €	quoted percentage spread	effective spread in €	quoted spread in €	quoted percentage spread	effective spread in €
Constant	0,101 *	0,343 *	0,053 *	0,128 *	0,297 *	0,074 *	0,122 *	0,296 *	0,071 *
	(16,85)	(38,50)	(7,26)	(11,19)	(22,04)	(7,30)	(10,40)	(21,25)	(6,88)
Log(volume)	-0,031 *	-0,047 *	-0,019 *	-0,020 *	-0,027 *	-0,011 *	-0,018 *	-0,027 *	-0,009 *
	(-23,39)	(-28,06)	(-13,77)	(-8,21)	(-8,54)	(-4,51)	(-6,59)	(-7,53)	(-3,57)
Ticksize	0,561 *	0,563 *	0,681 *	1,152 *	0,824 *	1,064 *	1,149 *	0,810 *	1,075 *
	(4,58)	(5,50)	(5,27)	(6,17)	(3,72)	(6,51)	(6,23)	(3,67)	(6,58)
Trade Price	0,0015 *	-0,0003 *	0,0011 *	0,0004 *	-0,0004 *	0,0004 *	0,0004 *	-0,0004 *	0,0004 *
	(15,74)	(-5,21)	(14,98)	(2,28)	(-2,27)	(2,36)	(2,20)	(-2,15)	(2,04)
Volatility	7,295 *	9,680 *	7,008 *	5,471 *	7,689 *	4,417 *	5,522 *	7,765 *	4,378 *
	(13,74)	(13,04)	(10,27)	(10,12)	(10,41)	(7,57)	(9,60)	(10,07)	(7,12)
Post-Event 1 (Median of the daily dummies for Specification 3)	-0,024 *	-0,027 *	-0,018 *	-0,025 *	-0,034 *	-0,021 *	-0,026 *	-0,032 *	-0,022 *
	(-7,81)	(-8,52)	(-5,60)	(-10,56)	(-12,28)	(-5,49)			
Number of negative daily dummies							14	14	14
Number of significantly negative daily dummies at 5%							13	14	11
Adj. R2	0,86	0,64	0,71	0,89	0,73	0,75	0,90	0,74	0,75

Panel B: Pre-event and Post-event 2	Regression 1 : Baseline regression			Regression 2: Fixed effects			Regression 3: Fixed effects and day dummies for the post-sample period		
	quoted spread in €, equally-weighted	quoted percentage spread, equally-weighted (in %)	effective spread in €, equally-weighted	quoted spread in €, equally-weighted	quoted percentage spread, equally-weighted (in %)	effective spread in €, equally-weighted	quoted spread in €, equally-weighted	quoted percentage spread, equally-weighted (in %)	effective spread in €, equally-weighted
Constant	0,092 *	0,345 *	0,050 *	0,089 *	0,304 *	0,040 *	0,091 *	0,303 *	0,039 *
	(14,45)	(36,09)	(7,36)	(9,42)	(22,97)	(3,01)	(8,70)	(20,50)	(2,66)
Log(volume)	-0,030 *	-0,047 *	-0,020 *	-0,020 *	-0,030 *	-0,009 *	-0,021 *	-0,030 *	-0,009 *
	(-21,44)	(-24,81)	(-16,39)	(-8,55)	(-8,72)	(-2,86)	(-7,74)	(-7,52)	(-2,40)
Ticksize	0,308 *	0,528 *	0,476 *	-0,040 *	0,387 *	0,218 *	-0,044 *	0,379 *	0,211 *
	(2,33)	(4,87)	(3,51)	(-0,25)	(3,56)	(1,23)	(-0,27)	(3,38)	(1,19)
Trade Price	0,0017 *	-0,0003 *	0,0013 *	0,0018 *	-0,0003 *	0,0014 *	0,0018 *	-0,0003 *	0,0014 *
	(16,06)	(-4,97)	(16,39)	(14,28)	(-4,07)	(14,05)	(14,17)	(-3,74)	(13,98)
Volatility	7,029 *	10,071 *	6,756 *	5,815 *	8,771 *	4,498 *	5,825 *	8,721 *	4,453 *
	(14,45)	(14,06)	(9,68)	(11,16)	(11,42)	(8,30)	(10,91)	(11,10)	(7,96)
Post-Event 1 (Median of the daily dummies for Specification 3)	-0,023 *	-0,033 *	-0,019 *	-0,026 *	-0,035 *	-0,024 *	-0,026 *	-0,035 *	-0,023 *
	(-9,10)	(-10,49)	(-8,01)	(-11,74)	(-12,04)	(-9,62)			
Number of negative daily dummies							14	14	14
Number of significantly negative daily dummies at 5%							14	14	14
Adj. R2	0,87	0,63	0,73	0,90	0,70	0,76	0,90	0,71	0,77

Figure 3: Effective spread
Panel A: Pre-event and Post-event 1

Figure 3(A) reports the average daily effective spread by trade size decile (trade size is measured in euro). We first calculate the average effective spread for each stock and each day. Then, we average over the 14 days of the pre-event period and the first post-event period, respectively. The pre-event period includes data from March 26, 2001 to April 12, 2001. The post-event 1 period includes data from April 30, 2001 to May 18, 2001. We also report the test statistics (a t-value and z value for a Wilcoxon test) of the null hypothesis that the differences in means and medians, respectively, are zero.

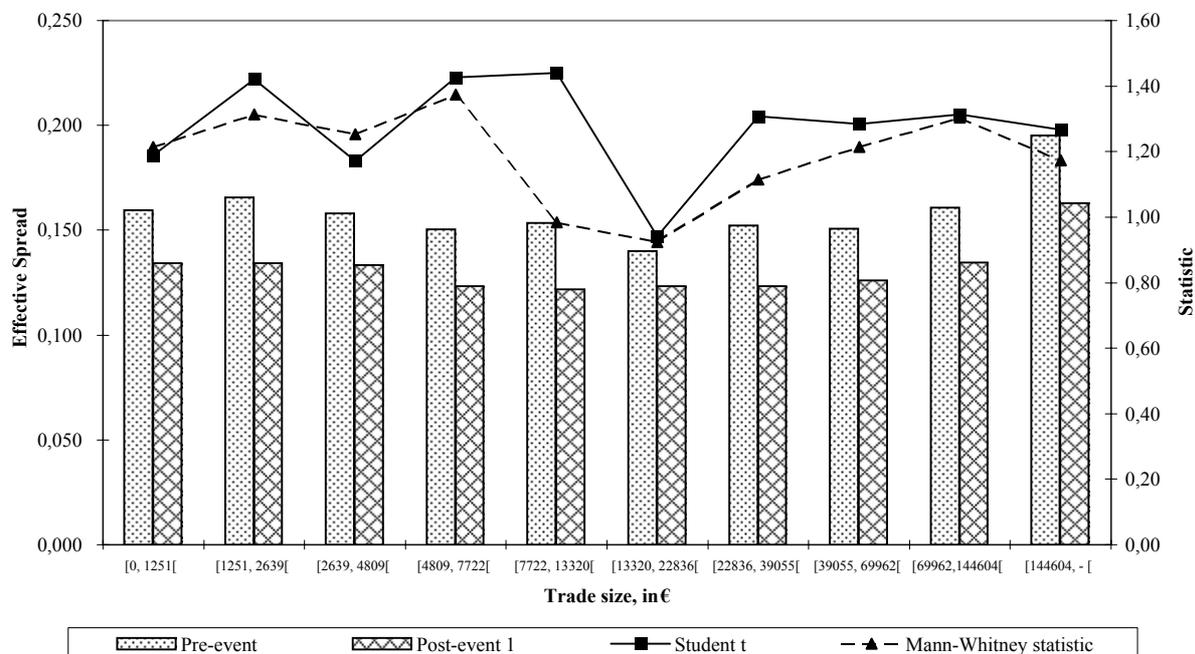


Figure 3: Effective spread
Panel B: Pre-event and Post-event 2

Figure 3(B) reports the average daily effective spread by trade size decile (trade size is measured in euro). We first calculate the average effective spread for each stock and each day. Then, we average over the 14 days of the pre-event period and the second post-event period, respectively. The pre-event period includes data from March 26, 2001 to April 12, 2001. The post-event 2 period includes data from July 2, 2001 to July 19, 2001. We also report the test statistics (a t-value and z value for a Wilcoxon test) of the null hypothesis that the differences in means and medians, respectively, are zero.

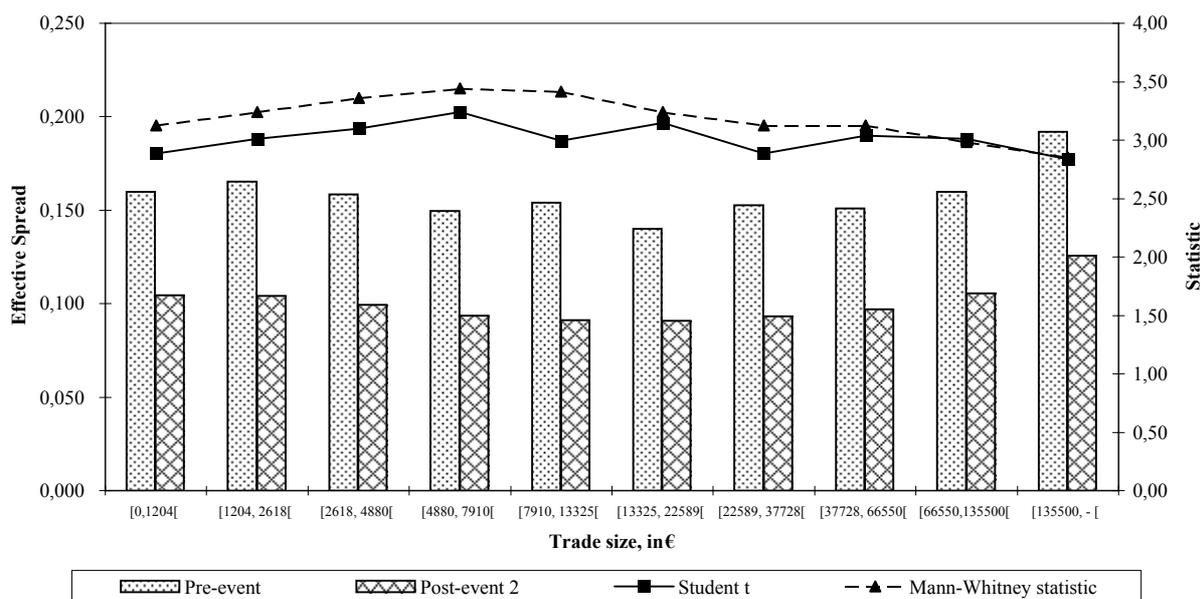


Table 6**Regression model for the volatility**

For each stock in our sample, we partition each trading day into fifteen 30-minutes intervals and two 25-minutes intervals. Using two measures of volatility, we estimate the following regression model :

$$\text{Vol}_{i,\tau+1} = a_0 + a_1 \text{Vol}_{M,\tau} + a_2 \text{Vol}_{i,\tau} + a_3 N_{i,\tau} + a_4 \text{ATr}_{i,\tau} + (a_5 + a_6 D^{\text{post}}) s_{i,\tau} + \sum_{k=3}^{17} b_k T_{k,\tau} + \sum_{i=2}^{39} c_i D_i + \varepsilon_{i,\tau}$$

where $s_{i,\tau}$ is the average quoted spread in interval τ , D^{post} is a dummy variable equal to 1 in the post event-period and zero in the pre-event period, $N_{i,\tau}$ is the number of transactions in interval τ , $\text{ATr}_{i,\tau}$ is the average trade size in interval τ and $\text{Vol}_{M,\tau+1}$ is a proxy for the market volatility in interval τ defined as:

$$\text{Vol}_{M,\tau} = \frac{1}{39} \left| \sum_{i=1}^{39} (m_{i,\tau} - m_{i,\tau-1}) \right|$$

D_i is a dummy variable equal to one when the stock is i and zero otherwise, and $T_{k,\tau}$ is a dummy variable which is 1 when the interval is k and zero otherwise, which account for fixed effects.

Panel A [B] reports the results of the regressions for the pre-event period and the post-event 1 [post-event 2] period. The pre-event period includes data from March 26, 2001 to April 12, 2001. The two post-event periods include data from April 30, 2001 to May 18, 2001, and from July 2, 2001 to July 19, 2001, respectively.

In Regression 1, we measure price volatility in any interval $[t-1,t]$ for stock i by $\text{Vol}_{i,t} = |m_{i,t} - m_{i,t-1}|$ where $m_{i,t}$ is the midquote at the end of interval t . Columns 1 and 2 show the results of the pooled regression. Columns 3 and 4 summarize the results obtained when estimating the model separately for each stock. Regression coefficients are cross-sectional averages of the coefficients across the 39 stocks. For the bid-ask spread and the spread interacted with the dummy post, we report in brackets first the number of coefficients whose signs are as expected (positive for the spread, negative for the interaction term), and second the number of coefficients whose signs are as expected and which are significant at the 10% level or better.

In Regression 2, $\text{Vol}_{i,t}$ is the absolute value of the residual of a regression of the changes in midquotes on its lagged value (see Equation (19)). Otherwise the specification is as in columns 1 and 2. t-statistics are reported in parentheses. A "*" denotes significance at the 5% level. To save space, we omit the estimates of the intraday dummies and the fixed effects.

	Regression 1: Volatility in $[t-1,t]$ defined as $ m_{i,t} - m_{i,t-1} $				Regression 2 : Volatility in $[t-1,t]$ defined as $ u_{i,t} $	
	Pooled regression		Summary of individual regressions		Pooled regression	
	Panel A : Pre-event and Post- event 1	Panel B : Pre-event and Post- event 2	Panel A : Pre-event and Post- event 1	Panel B : Pre-event and Post- event 2	Panel A : Pre-event and Post- event 1	Panel B : Pre-event and Post- event 2
Volatility in $[\tau,\tau+1]$						
Constant	0,19 * (9,05)	0,14 * (6,87)	0,21	0,24	0,11 * (6,45)	0,22 * (11,01)
Volatility in $[\tau-1,\tau]$	0,11 * (7,23)	0,13 * (7,70)	0,07	0,08	0,10 * (6,18)	0,11 * (6,04)
Average spread in $[\tau-1,\tau]$	0,37 * (6,84)	0,64 * (11,95)	0,63 [39 / 22]	0,63 [38 / 23]	0,44 * (7,43)	0,76 * (13,13)
Average spread in $[\tau-1,\tau]$ * Dummy Post	-0,38 * (-9,30)	-0,57 * (-13,73)	-0,36 [37 / 22]	-0,80 [37 / 31]	-0,38 * (-8,48)	-0,59 * (-13,10)
Number of trades in 1,000 in $[\tau-1,\tau]$	0,237 * (3,75)	0,287 * (4,51)	0,597	0,359	0,208 * (3,29)	0,266 * (4,05)
Average trade size in 1,000 shares in $[\tau-1,\tau]$	0,005 (1,67)	-0,004 * (-3,67)	-0,000	-0,000	0,005 (1,79)	-0,003 * (-3,26)
Market volatility in $[\tau-1,\tau]$	0,07 * (3,44)	0,04 (1,50)	0,083	0,062	0,07 * (3,44)	0,04 (1,71)
R ² of the regression with spread and interaction term	0,2596	0,2554	0,1255	0,1490	0,2581	0,2527
R ² of the regression without spread and interaction term	0,2465	0,2186			0,2451	0,2112

Table 7**GARCH**

For each stock in our sample, we partition each trading day into fifteen 30-minutes intervals and two 25-minutes intervals. We estimate the following GARCH(1,1) model for individual stocks:

$$(1) \Delta q_{i,t+1}^a = \mu_i + \theta_i \Delta q_{i,t}^a + \eta_{i,t+1}$$

$$(2) \sigma_{i,t+1}^2 = \omega_i + \lambda_i \eta_{i,t}^2 + \gamma_i \sigma_{i,t}^2 + \delta_1 \text{Vol}_{M,t}^a + \delta_2 N_{i,t} + \delta_3 \text{ATr}_{i,t} + (\delta_4 + \delta_5 D^{\text{post}}) s_{i,t}$$

$$(3) \eta_{i,t+1} | \psi_t \sim N(0, \sigma_{i,t+1}^2)$$

The dependent variable is the (adjusted) midquote return. To compute it, we first take a logarithmic transformation of the midquotes series. Second, to control for intraday seasonalities we regress the midquote returns on a set of time-of-day dummies and we retain the fitted values of the regression. Then, in each interval, we divide the actual midquote return by the fitted value to obtain the adjusted midquote return.

The mean equation (1) includes the lagged midquote return.

The variance equation (2) includes the same explanatory variables as our baseline model, i.e. the variables of interest (the lagged quoted spread and an interaction term) and a set of control variables (lagged market volatility, measured by the adjusted midquote return of an equally weighted portfolio of the sample stocks, the lagged number of trades and the lagged average trade size).

Panel A [B] reports the results of the regressions for the pre-event period and the post-event 1 [post-event 2] period. The pre-event period includes data from March 26, 2001 to April 12, 2001. The two post-event periods include data from April 30, 2001 to May 18, 2001, and from July 2, 2001 to July 19, 2001, respectively.

The table presents summary statistics for the variables of interest.

		Panel A :	Panel B :
		Pre-event and Post-event 1	Pre-event and Post-event 2
spread(-1)	mean	2,8570	2,5595
	median	1,1459	1,2414
	# >0	26	31
	# > 0 and significant 10%	16	20
	# < 0	13	8
	# < 0 and significant 10%	0	1
post*spread(-1)	mean	-1,9669	-1,7738
	median	-0,9011	-0,5976
	# <0	36	34
	# < 0 and significant 10%	17	19
	# >0	3	5
	# > 0 and significant 10%	2	1

Table 8

For each day and each stock, we compute the number and the Euro volume of block trades taking place in the upstairs market and in the downstairs market. A block trade is a trade larger than one "normal block size" . Then we average across days and across stocks. For each post-event period, the last column reports the test statistic of the null hypothesis that the difference in means is zero. A "*" denotes significance at the 5% level.

	Pre-event	Post-event 1	Diff. Post1-Pre	t-value	Post-event 2	Diff. Post2-Pre	t-value
Downstairs Trades							
Daily Number of block trades	2,6	3,4	0,7	1,45	8,3	5,7	5,84 *
Daily Volume of block trades (in 1,000 €)	2 426	3 281	854,4	1,82	4 061	1 635,0	4,22 *
Upstairs Trades							
Daily Number of block trades	3,7	2,4	-1,3	1,98 *	3,7	-0,0	0,06
Daily Volume of block trades (in 1,000 €)	10 947	7 056	-3 890	1,75	8 156	-2 791	0,94

Figure 1

Date 1 : Tree Diagram of the Trading Process.

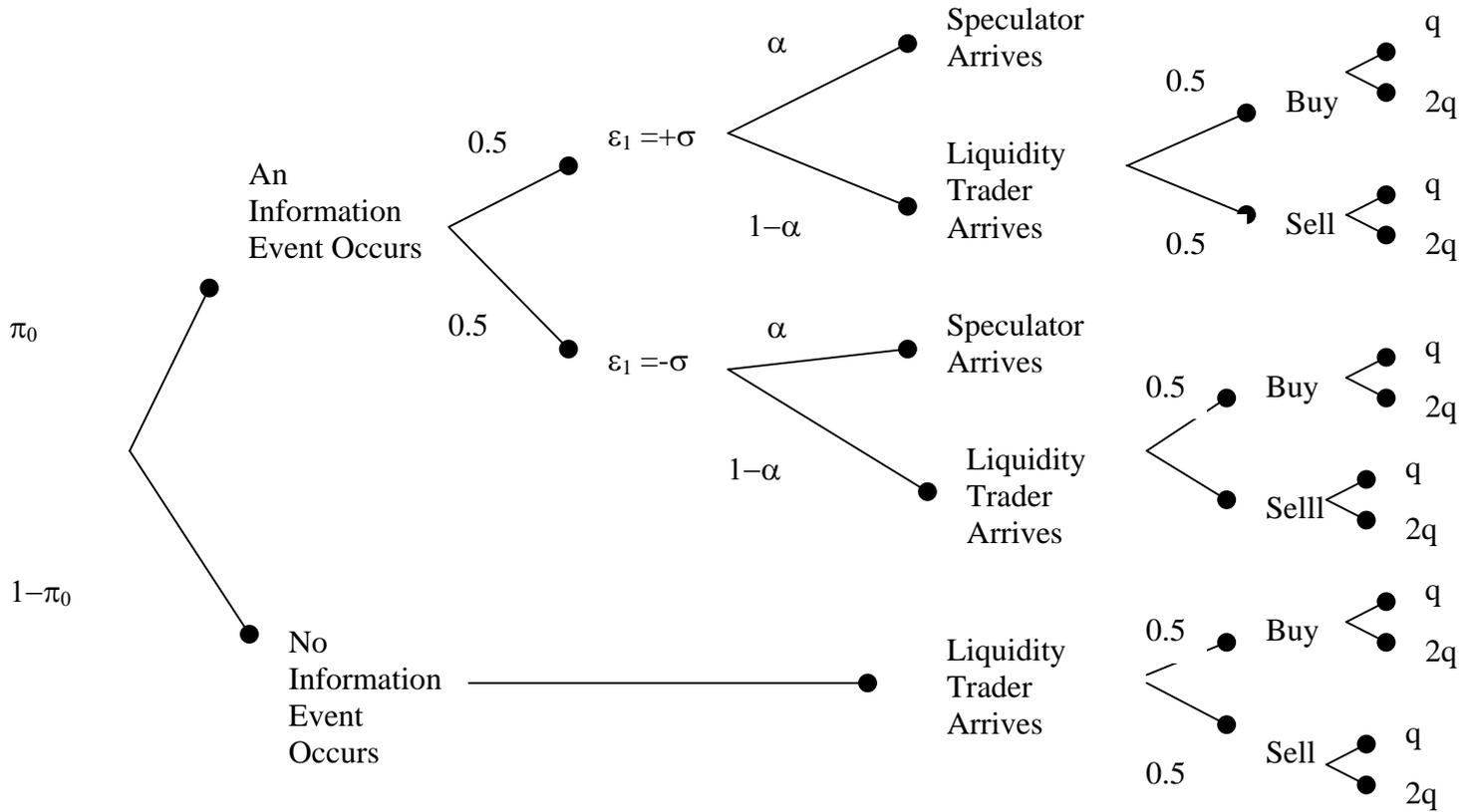
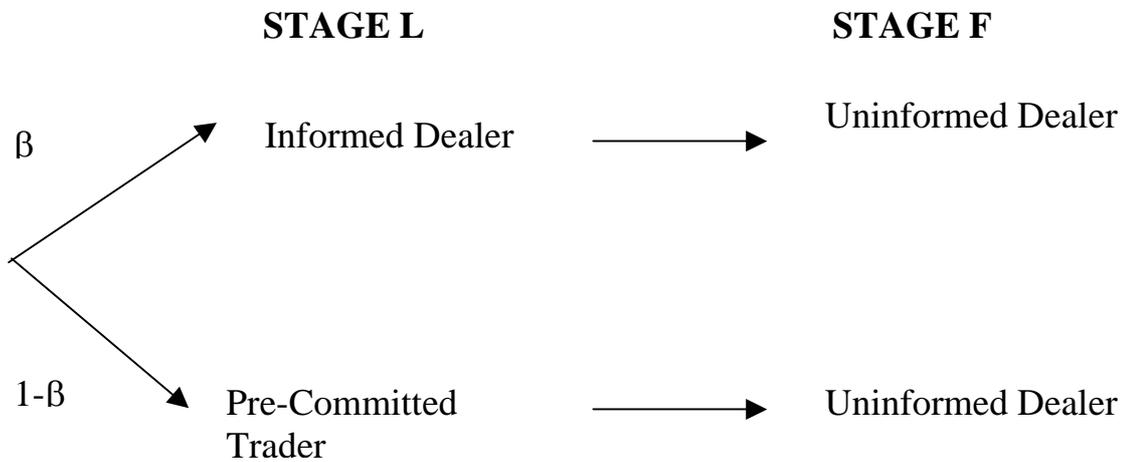


Figure 2 : Building the Limit Order Book



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