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Price Formation in Call Auctions with Insider Information

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Abstract

Purpose: This study investigates -theoretically and empirically- if call auctions incorporate asymmetric information into prices.

Design/methodology/approach: First, this study introduces a new model of price formation in a call auction with insider information. In this call auction model, insider trading gives rise to an asymmetric information component of transaction costs. Next, this study estimates the model using twenty stocks from Euronext Paris and investigates if the asymmetric information component is present.

Findings: The theoretical analysis reveals that call auctions incorporate asymmetric information into prices. The empirical analysis finds strong evidence for the asymmetric information component. Testable implications provide further support for the model.

Practical implications: Call auctions have recently been proposed as an alternative to continuous limit order book markets to overcome problems associated with high frequency trading. However, it is still an open question whether call auctions efficiently aggregate asymmetric information. The findings of this study imply that call auctions facilitate price discovery and, therefore, are a viable alternative to continuous limit order book markets.

Originality/value: There is no generally accepted measure of trading costs for call auctions. Therefore, the measure introduced in this study is of great value to anyone who wants to (i) quantify trading costs in call auctions; (ii) understand the determinants of trading costs in call auctions; or (iii) compare trading costs and their components between continuous markets and call auctions. This study also contributes to the literature devoted to estimating the

probability of information-based trading.

JEL Classification: D82, G14, C11

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1 Introduction

During the last couple of years problems associated with high frequency trading have become a major concern. High frequency trading leads to excessive and inefficient investment in speed; it increases the cost of liquidity provision; and it is a cause of market instability. As a solution to these problems, several studies propose to replace the continuous limit order book market with frequent call auctions (Budish, Cramton, and Shim, 2014, Budish, Cramton, and Shim, 2015, Farmer and Skouras, 2012, Wah and Wellman, 2013). In a call auction, orders that arrive within a given time interval are accumulated in the order book. At the end of that time interval orders are executed at the same time and at the same price. This uniform transaction price is chosen to maximize the quantity of shares that are traded.

Whereas call auctions can solve the problems mentioned above, it is not clear if they perform as good as continuous limit order book markets in terms of price discovery. Price discovery is the process by which transaction prices adjust to new information. Imperfect price discovery favours traders with superior information at the expense of uninformed traders. In a continuous limit order book market there are two parties to each transaction: a liquidity trader who submits a limit order to the order book and a second trader who accepts the limit order. Liquidity traders are worried that their orders are picked up by traders with superior information. To protect themselves from this adverse selection problem, they adjust their limit prices to reflect the possibility that their counterpart in this transaction has superior information (Handa, Schwartz, and Tiwari, 2003).

In a call auction the transaction price and quantities are determined by the interplay of many market participants. It is therefore not obvious if liquidity traders face a similar adverse selection problem and if so, how they can protect themselves against it. According to Pagano and Schwartz (2003) 'the call auction is the least understood of the three major trading regimes' (p. 440). Empirical evidence from the opening auction at the London Stock Exchange suggests that the call auction is not suitable when information asymmetries are large (Ellul, Shin, and Tonks, 2005).

The aim of this study is to empirically assess the call auction's ability to aggregate asymmetric information. To this end we present a simple model of price formation in a call auction with insider trading. Based on this model, we derive a new measure of transaction costs in call auctions and decompose transaction costs into a difference in valuation part and an asymmetric information part. These components are similar to the ones obtained by Handa, Schwartz, and Tiwari (2003) for the bid-ask spread in continuous limit order book markets. The model provides the testable implication that the difference in valuation component is decreasing in liquidity whereas the asymmetric information component is not directly affected by liquidity.

We illustrate the estimation of the model using data from a trading category at Euronext Paris that comprises stocks that are only traded in morning and afternoon call auctions without a continuous trading phase inbetween.[1] This trading category has received little attention in the literature so far.[2]

The main result of the call auction model is that the asymmetric information impact is reflected in the liquidity traders' limit prices and thus translates into the transaction price. This will give rise to an asymmetric information component of transaction costs. The remaining part of transaction costs is the difference in valuation component.

The empirical analysis supports the results of the model. The call auction model with asymmetric information explains the data significantly better than a model that ignores the presence of insider information for 19 out of 20 stocks. The fact that the estimated difference in valuation component is greater than previous estimates for continuous limit order book markets indicates that liquidity traders incorporate the asymmetric information impact in their limit prices. The empirical analysis confirms the testable implication. The difference in valuation component is decreasing in liquidity but there is no relationship between the asymmetric information component and liquidity.

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[1] If call auctions are combined with continuous trading, traders –apart from selecting limit prices and order quantities– have the additional choice of the trading mechanism. Brooks and Su (1997) show that liquidity traders can reduce trading costs by trading at the opening call and not waiting for continuous trading to start.

[2] A notable exception is Venkataraman and Waisburd (2007).

This study is related to Kyle (1989) and Madhavan (1992). Both of these studies show that in Bayes-Nash equilibrium call auction prices aggregate asymmetric information. Whereas Madhavan (1992) assumes that all traders hold different but equally valuable information, Kyle (1989) distinguishes between informed and uninformed traders, which is closer to the setup of the present study. The theoretical models of these two studies do not lend themselves to estimation and it is therefore not obvious that the positive properties of the Bayes-Nash equilibrium of these models also materialize in real world call auctions. The model in the present study shares the basic features of these two studies, but it goes further in that it allows for direct estimation of transaction costs as well as the decomposition of transaction costs into the difference valuation component and the asymmetric information component.

The empirical evidence on call auctions and their impact on price discovery is mixed. Pagano and Schwartz (2003) and Pagano, Peng, and Schwartz (2013) study the effect of the introduction of opening and closing call auctions on Euronext Paris and Nasdaq, respectively. Both studies find that the introduction of call auctions helped to improve price efficiency. Ellul, Shin, and Tonks (2005) study traders' choices between a dealership market and a call auction on the London Stock Exchange. They find that while trading costs are generally lower for the call auction, the dealership market has lower trading costs when the presence of insider information is large. This contradicts the theoretical result of Madhavan (1992). The present study is also related to the large literature devoted to estimating the probability of information-based trading in continuous markets (see, e.g., Easley, Kiefer, O'Hara, and Paperman, 1996; Duarte and Young, 2009; and Kryzanowski and Tran, 2018). The present study is the first to estimate the difference in valuation component and asymmetric information component in call auctions. The presence of a significant asymmetric information component implies that call auction prices incorporate insider information.

Finally, it should be noted that the insights of this study are not limited to stock markets. The question of whether a call auction, or a uniform-price auction, is preferable to sequential trade, or a discriminatory-price auction, is also important for electricity markets (Fabra, von der Fehr, and Harbord, 2006) and treasury auctions (Binmore and Swierzbinski, 2000). By extending our understanding of the role of asymmetric information in call auctions, this study contributes to this broader literature on the design of institutions.

2 A Stylized Model of a Call Auction

The precise design of call auction mechanisms can vary considerably. For this analysis, we consider the most basic call auction algorithm. Traders can place limit orders and market orders during the order accumulation phase. The order book is closed, i.e., traders do not observe orders made by other traders during the order accumulation phase.[3] While market orders are executed with certainty (provided there are orders on the other side of the order book), limit buy (sell) orders are only executed when the associated limit price is higher (lower) than the transaction price. The order accumulation phase ends at a specified time and the transaction price is determined such that: i) all market orders execute and ii) all limit sell orders with a limit price lower than the transaction price and all limit buy orders with a limit price higher than the transaction price execute. If there is a range of prices that satisfy these conditions the transaction price is the midpoint of this range. The asset traded in this call auction and the traders participating in the auction are described in the next subsection.

2.1 Model Assumptions

One risky asset is traded in the call auction. The asset's true value at time t, ν_t, follows a random walk with drift:

$$\nu_t = \mu + \nu_{t-1} + \varepsilon_t\,, \tag{1}$$

where μ is the drift parameter and $\varepsilon_t \sim N(0, \sigma^2)$ reflects news potentially available to an insider but unobservable to other market participants prior to the end of

[3]The assumption of a closed order book is not critical. The results of the theoretical analysis remain valid if the order book was open.

auction t.[4] After auction t, the realization of ε_t becomes common knowledge. The news shock, ε_t, is uncorrelated over time.

There are two types of risk-neutral liquidity traders: buyers and sellers. They differ in their valuation of the stock. Buyers are willing to pay a premium on the price of the stock while sellers demand a discount. These differences represent personal portfolio considerations such as individual tax brackets and liquidity shocks (see Foucault, 1999 and Handa, Schwartz, and Tiwari, 2003).[5] More specifically, buyer k is characterized by a premium k she is willing to pay, where k is uniformly distributed on the interval $[\underline{k}, \overline{k}]$. Hence, buyer k's personal valuation of the asset is $\nu_t + k$. Each buyer submits one limit buy order for one unit of the asset. The decision problem is to set an upper limit price b_t^k for the buy order to maximize the payoff

$$U_{b,t}^k = \begin{cases} \nu_t + k - p_t & \text{if } b_t^k \geq p_t, \\ 0 & \text{if } b_t^k < p_t \,, \end{cases} \tag{2}$$

where p_t is the transaction price determined according to the rules specified above.

Similarly, there is a continuum of sellers characterized by a discount on the value of the stock of size k.[6] Seller k's personal valuation of the asset is $\nu_t - k$. Each potential seller places one limit sell order for one unit of the stock with limit sell price s_t^k in order to maximize the payoff

$$U_{s,t}^k = \begin{cases} p_t - (\nu_t - k) & \text{if } s_t^k \leq p_t, \\ 0 & \text{if } s_t^k > p_t. \end{cases} \tag{3}$$

In addition, there is a potential insider. Dalko and Wang (2016) provide ample evidence that, despite insider trading law, insider trading is prevalent in financial

[4] The drift parameter μ is not important for the theoretical analysis and might be set equal to zero. However, it will later be useful as an interpretation of the intercept of the estimation model in the empirical part.

[5] Alternatively, different premiums and discounts across liquidity traders can be thought of reduced-form representations of differences in risk tolerance or divergent expectations (see Davis, Pagano, and Schwartz, 2007).

[6] The assumption that there is a continuum of liquidity buyers and sellers is not crucial for our main result that liquidity traders adjust their limit prices for the presence of an insider.

markets around the world. With probabilities λ this trader learns the sign of the realization of ε_t. The interpretation of such a signal is that the insider knows some company-related news before it is revealed to the public, but she is uncertain about the reaction of the market and hence the exact impact on the asset's true value. With probability $1-\lambda$ the insider does not receive a signal. In this case the insider experiences a liquidity shock. A positive liquidity shock means the insider values the stock at a premium of k^i; a negative liquidity shock implies a discount of size k^i. Positive and negative liquidity shocks are equally likely.

The potential insider is assumed to be risk-neutral and trades an amount of α assets via market sell or market buy orders.[7] Assuming a premium of k^i her payoff is

$$U_{i,t} = \begin{cases} \alpha\left(\nu_t + k^i - p_t\right) & \text{for a market buy order,} \\ \alpha\left(p_t - (\nu_t + k^i)\right) & \text{for a market sell order.} \end{cases} \tag{4}$$

If the potential insider values the stock at a discount of k^i the sign of k^i in equation (4) is reversed.

The presence of the potential insider serves two purposes: Firstly, for $\lambda > 0$, it introduces asymmetric information into the model and secondly, it captures the randomness of the order flow.[8] While, on average, the number of buy and sell orders are the same, in each particular auction, there is a positive or negative order imbalance of size α. Hence λ measures the degree of information asymmetries and α can be interpreted as the volatility of the order flow and, thus, provides a measure for the liquidity of the market.

All traders are active for only one period. After an auction has ended a new, identical group of traders arrives at the market.

[7] We will later show that, given an upper bound on α, the assumption that the potential insider trades only via market orders can be dispensed with.

[8] In this sense the potential insider is very similar to the 'large traders' in Diamond and Verrecchia (1991).

3 Equilibrium Order Strategies and Implications

Given these three types of traders and the basic call auction algorithm described above we obtain the following equilibrium:

Proposition 1 *If the order imbalance is not too large, i.e., if*

$$\alpha \leq \min\{\frac{(1-\lambda)\sqrt{2/\pi}\,\sigma - \underline{k}}{2\,(\bar{k}-\underline{k})}, \frac{k^i - \underline{k} - \lambda\sqrt{2/\pi}\,\sigma}{2\,(\bar{k}-\underline{k})}\},$$

the following strategies constitute an equilibrium:

- $b_t^k = \nu_{t-1} + \mu + k + \lambda\sqrt{2/\pi}\,\sigma \quad, \forall k \in [\underline{k}, \bar{k}]$
- $s_t^k = \nu_{t-1} + \mu - k - \lambda\sqrt{2/\pi}\,\sigma \quad, \forall k \in [\underline{k}, \bar{k}]$
- *the insider places a market buy (sell) order when she observes a positive (negative) realization of the noise component or when she receives no information and has a positive (negative) liquidity shock.*

The upper bound on α ensures that the insider is indifferent between placing a limit order or a market order, i.e., if she were to place a limit order, her limit price would not be binding. The first part of the upper bound refers to situation where the insider received a signal about the stock's value. The second part corresponds to the situation where the insider has no superior information but faces a liquidity shock.

Proposition 1 shows that the liquidity traders' limit prices consist of three parts: (1) the asset's unconditional expectation, $E(\nu_t) = \nu_{t-1} + \mu$, (2) the personal premium or discount, k, and (3) the informational impact of the potential insider trading in the same direction, $\lambda\sqrt{2/\pi}\,\sigma$. Note that it is not important that a liquidity trader observes the order of the potential insider, because in equilibrium her limit price can only be binding when the potential insider trades in the same direction. This implies that the strategies in Proposition 1 are also an equilibrium when there is transparency of the order book during the order accumulation phase.

There exist multiple equilibria, e.g., a buyer of type $k > \underline{k} + (\bar{k} - \underline{k})\alpha$ can set any limit buy price greater than $\nu_{t-1} + \mu + \underline{k} + (\bar{k} - \underline{k})\alpha + \lambda\sqrt{2/\pi}\,\sigma$ since her order will always be executed and her limit price will never be binding. We are primarily interested in transaction prices resulting from these equilibrium strategies and since transaction prices are given by the limit prices of liquidity traders who know that their limit prices are binding, these prices are unique.

[Figure 1 about here.]

3.1 The Transaction Price

Given the equilibrium strategies in Proposition 1, the order book of auction t can be illustrated by one of the two panels in Figure 1. Figure 1(a) depicts the situation where the potential insider places a market buy order. The market order shifts the orders of the buyers α units to the right so that the last limit buy order that can be executed is that of buyer $\underline{k} + (\bar{k} - \underline{k})\alpha$. The limit price of this buyer determines the transaction price. Figure 1(b) shows the case where the potential insider sells. Here the transaction price is the limit price of the seller with discount $\underline{k} + (\bar{k} - \underline{k})\alpha$. We represent the two possible constellations of the order book with the indicator variable q_t: $q_t = 1$ denotes a market buy order by the insider, $q_t = -1$ denotes a market sell order by the insider. Hence, the transaction price of auction t can be written as

$$p_t = \nu_{t-1} + \mu + (\underline{k} + (\bar{k} - \underline{k})\alpha)\, q_t + \lambda\sqrt{2/\pi}\,\sigma\, q_t\,. \tag{5}$$

Equation (5) highlights that transaction prices in a call auction incorporate asymmetric information. They are a function of the probability that a trader has superior information, λ, and of the value of that information, $\sqrt{2/\pi}\,\sigma$. If $q_t = 1$, the transaction price p_t exceeds the unconditionally expected true value of the asset; if $q_t = -1$, p_t falls below that value by the same amount. This symmetry of the transaction price around the unconditional expectation of the asset's true value leads to our definition of transaction costs.

3.2 Measures of Transaction Costs

In continuous limit order book markets, transaction costs are measured by the bid-ask spread. But there is no such generally accepted concept of transaction costs for call auctions. In call auctions, the bid-ask spread is defined as the difference of the prices corresponding to the lowest limit sell and highest limit buy orders that were not executed. Since, usually, no trade takes place at these prices, this concept of the bid-ask spread is not appropriate for measuring actual transaction costs. As an alternative, some studies use the measure proposed by Roll (1984) to estimate transaction costs in call auctions (e.g. Haller and Stoll, 1989 and Stoll and Whaley, 1990).

We define transaction costs as the difference in the transaction price that would result from a buy order by the potential insider and the price corresponding to a market sell order. Of course, for each particular auction only one of these two prices is observed.

Definition 1 *Transaction costs in a call auction are defined as the difference between the two transaction prices that would result from a market buy order and a market sell order, respectively:*

$$S = p_t(q_t = 1) - p_t(q_t = -1)\,.$$

It should be stressed that this measure does not capture the transaction costs faced by an individual trader.[9] It reflects the deviation of transaction prices from the unconditional expectation of the asset's true value caused by order imbalances and asymmetric information.

Plugging the expression for the transaction price (equation (5)) in our definition of transaction costs we obtain an expression for transaction costs in call auctions.

Proposition 2 *Transaction costs in a call auction are given by*

$$S = 2(\underline{k} + (\bar{k} - \underline{k})\alpha) + 2\lambda\sqrt{2/\pi}\,\sigma\,. \tag{6}$$

Transaction costs consist of a 'difference in valuation' component, $2(\underline{k} + (\bar{k} - \underline{k})\alpha)$, *and an 'asymmetric information' component,* $2\lambda\sqrt{2/\pi}\,\sigma$.

Thus, in a call auction market, transaction costs consist of two components. The first component is the difference in valuation of the buyer with the lowest limit buy

[9] This is also pointed out in Theissen (2000).

price and the seller with the highest limit sell price whose orders are being executed. The second component is the asymmetric information component which is a positive function of the impact of private information on the order book, λ, and the variance of the potentially available news, σ^2 (see, e.g., Glosten and Milgrom, 1985). These two components of transaction cost in a call auction have similar interpretations as those Handa, Schwartz, and Tiwari (2003) find for the bid-ask spread in continuous limit order book markets. Note, however, that transaction costs in a call auction are minimized for $\alpha = 0$, whereas Handa, Schwartz, and Tiwari (2003) show that the bid-ask spread in continuous limit order book markets is *largest* for a zero order imbalance.

Proposition 3 *The difference in valuation component is increasing in the order imbalance (α).*
The asymmetric information component is increasing in (1) the probability that the potential insider receives information, λ, and (2) the uncertainty of the asset's value, σ.

Proposition 2 and 3 are supported by empirical evidence from opening and closing auctions at the London Stock Exchange. Ellul, Shin, and Tonks (2005) find that transaction costs in these auctions are increasing in the order imbalance and asymmetric information.

Madhavan (1996) and Kehr, Krahnen, and Theissen (2001) define trading costs as the difference between the two hypothetical transaction prices which result from adding an additional market buy order and an additional market sell order of the same size, say Δ, respectively. For an order size equal to the order imbalance, $\Delta = \alpha$, this definition is equal to the measure proposed in the present study.

3.3 The Transaction Return Process

We can use the expression of transaction prices in equation (5) to obtain the transaction returns. Taking the first difference of equation (5) and substituting equation (1) yields

$$p_t - p_{t-1} = \mu + (\underline{k} + (\bar{k} - \underline{k})\,\alpha)(q_t - q_{t-1}) + \lambda\sqrt{2/\pi}\,\sigma\,(q_t - q_{t-1}) + \varepsilon_{t-1}\,. \tag{7}$$

Letting $r_t = p_t - p_{t-1}$ and using the expression of transaction costs in equation (6) we obtain

$$r_t = \mu + \frac{S}{2}(q_t - q_{t-1}) + \varepsilon_{t-1}\,. \tag{8}$$

Equation (8) implies negative serial correlation between successive transaction returns. The result that order imbalances lead to negative serial correlation in call auction returns has been previously noted by Ho, Schwartz, and Whitcomb (1985); in the present model this negative correlation is further augmented by the asymmetric information component.

Roll (1984) uses a return process similar to equation (8) together with the assumption that ε_{t-1} is uncorrelated with q_t and q_{t-1} to derive the implicit bid ask spread

$$S^{Roll} = 2\sqrt{-COV(r_t, r_{t-1})}. \tag{9}$$

In a call auction with asymmetric information, the insider's behaviour introduces a correlation between ε_{t-1} and q_{t-1}. Suppose the insider placed a buy order in auction t. By Proposition 1 there are two possibilities: The insider learned that ε_t is positive or the insider experienced a positive liquidity shock. Liquidity shocks are uncorrelated with ε_t. But when the insider receives a signal, which happens with probability λ, a buy order coincides with a positive realization of ε_t. Similarly, with probability λ a market sell order ($q_t = -1$) coincides with a negative realization of ε_t. As a result, ε_t and q_t are positively correlated. Thus, the Roll measure cannot be used to measure transaction costs in call auctions when $\lambda > 0$.

The next section shows how equation (8) can be used to estimated transaction costs and decompose them into a difference in valuation component and asymmetric information component.

4 Estimation

When estimating equation (8) it should be noted that conditional on q_t, ε_t is no longer normally distributed. The distribution of ε_t given q_t is normal with probability $(1-\lambda)$ and truncated normal with probability λ, i.e.

$$\varepsilon_t|\, q_t = \begin{cases} q_t \cdot \varepsilon_t|(\varepsilon_t > 0) & \text{with prob. } \lambda\,, \\ \varepsilon_t & \text{with prob. } (1-\lambda)\,. \end{cases} \tag{10}$$

Therefore, we estimate equation (8) using the following mixture model

$$r_t = \mu + \frac{S}{2} \cdot (q_t - q_{t-1}) + \zeta_{t-1} \cdot q_{t-1} \cdot \varepsilon_{t-1}|(\varepsilon_{t-1} > 0) + (1-\zeta_{t-1}) \cdot \varepsilon_{t-1}\,, \tag{11}$$

where, for each t, the latent variable ζ_t equals 1, if the insider received a signal about the direction of ε_t, and zero otherwise. In this mixture model specification, λ is a hyperparameter that represents the probability that $\zeta_t = 1$. Using the estimates for λ and σ, we can calculate the asymmetric information component. Subtracting the asymmetric information component from the estimated transaction costs, S, we obtain the difference in valuation component.

The generalization that the order imbalance might be zero for a particular auction is easy to accommodate in our model. Although liquidity traders will adjust their limit prices if they are able to observe that the potential insider does not trade, equation (5) still holds if in the case of a zero order imbalance the transaction price is the mid-point between the lowest limit buy and the highest limit sell price which are being executed.

We estimate the mixture model of equation (11) with this extension. Of course, ζ_t cannot equal 1 when $q_t = 0$ and thus λ is the proportion of informed trades relative to the total number of trades by the potential insider.

The prior distributions of the unknown parameters μ, S, λ and σ are chosen to be noninformative. The joint prior of μ, S and σ is $p(\mu, S, \sigma) \propto \sigma^{-2}$ and $\lambda \sim beta(1,1)$.

Since the posterior distribution is not analytically tractable, we use numerical techniques to draw inferences. Random draws from the joint posterior distribution of the parameters are obtained using a Gibbs sampler with 3000 iterations, where the draws of the first 1000 iterations are discarded. Tests with simulated data and repeated estimation with different starting values have shown that this number of iterations is enough for the Gibbs sampler to converge.

For each draw of S, λ and σ we calculate the asymmetric information component $\Lambda = \lambda\sqrt{2/\pi}\,\sigma$ and difference in valuation component $K = \frac{S}{2} - \Lambda$. The mean and standard deviation of the marginal distributions of these parameters are presented in Table 2.

5 Empirical Analysis

5.1 Data

To illustrate estimation of the model we use data from the "Fixing" trading category at Euronext Paris that consists of stocks that trade in two call auctions per day only. As of January 2017 this trading category comprised 118 stocks, which make up approximately 21% of all firms listed at Euronext Paris.[10] For the analysis we randomly chose twenty of the most actively traded companies. Data on transaction prices as well as best bid and ask prices and trading volume are taken from the *Paris Intraday BBO-2006* data set which was purchased from Euronext NextHistory. Table 1 presents summary statistics for these stocks for the period between 1/01/2006 and 31/12/2006.

There were 255 trading days in 2006. Thus, with two call auctions a day there were 510 possible observations per stock. However, not all auctions had sufficient demand and supply to facilitate trade. If the limit buy and limit sell orders of a particular auction could not be matched, i.e., if there was no transaction price that generated positive trading volume, this observation is discarded. Therefore only auctions that resulted in a transaction price are considered. The number of auctions varies across stocks between 45 and 488 (see the first column of Table 1).

The indicator variable q_t is set to 1, if the transaction price of auction t is closest to the best ask price that remains in the order book after the auction, and it is set to -1, if the transaction price is closest to the best bid price.[11] In some instances

[10]Euronext Paris assigns less actively traded stocks (fewer than 2,500 order book transactions per year) to the "Fixing" category; presumably because these stocks would have very wide bid-ask spreads, if they were traded continuously. Muscarella and Piwowar (2001), however, fail to find significant improvements in liquidity for less actively traded stocks that move from continuous trading to call auction trading.

[11]This procedure is analogous to trade indicator classification in continuous markets (see, e.g.,

these three prices coincide. This can be interpreted as the potential insider not participating in that day's auction and thus all orders being executed. In these cases the indicator variable is set to zero.

The second column of Table 1 shows the volatility of the transaction returns. Volatility varies between 0.68 and 9.46 with an average of 2.44. Average prices vary from €1.55 to €6118.35. Column four provides average bid-ask spreads in 2006, where the bid-ask spread is defined as the difference between the lowest limit sell and the highest limit buy price that remained in the order book after the auction had cleared divided by their midpoint. Average bid-ask spreads range from 0.53% to 15.81% with a cross-section average of 3.25%.

[Table 1 about here.]

5.2 Results

5.2.1 Transaction Costs

Table 2 shows the results of the estimation for each of the twenty assets. The first column shows the estimated transaction costs. They vary between 0.40 and 5.45 with an average of 1.85. As expected, these actual transaction costs are, on average, lower than the bid-ask spreads. The only two stocks for which transaction costs exceed the bid-ask spread are *Banque de la Reunion* and *Credit Agricole Oise*. This provides additional support for the claim that bid-ask spreads are not a good measure of trading costs in call auctions since they overestimate actual costs.

[Table 2 about here.]

Kehr, Krahnen, and Theissen (2001) apply their measure of transaction costs to the opening call auction of fifteen stocks on the Frankfurt Stock Exchange in 1996 and find average transaction costs of 0.33 and 2.37 for small and large order sizes, respectively.[12] Thus, the estimates of transaction costs we obtain are roughly com-

Finucane (2000) for a discussion).

[12]Kehr, Krahnen, and Theissen (2001) also calculate transaction costs for the noon and closing

parable with the previously-documented transaction costs in call auctions, especially those for large order sizes.

5.2.2 The Difference in Valuation Component

The second column of Table 2 shows the difference in valuation component $K = \underline{k} + (\bar{k} - \underline{k})\alpha$. The average difference in valuation component is 0.74 across the twenty stocks. If traders within each group are relatively homogeneous, i.e., $\bar{k} - \underline{k}$ is small, differences in valuation are largely attributable to personal portfolio considerations and thus do not depend on the details of the trading mechanism. With this assumption we can, therefore, check the results of our decomposition by comparing the estimates of the difference in valuation with the estimates obtained by Handa, Schwartz, and Tiwari (2003) for the continuous limit order book market. The average difference in valuation in the call auction mechanism is higher than the estimates of the difference in valuation Handa, Schwartz, and Tiwari (2003) find for the continuous limit order book market on Euronext Paris but the difference is not statistically significant.[13]

The decomposition of transaction costs by subtracting $\lambda\sqrt{2/\pi}\,\sigma$ from $\frac{S}{2}$ is only correct if liquidity traders assess the asymmetric information component correctly. If liquidity traders underestimate the informational impact of the potential insider by underestimating λ or σ, transaction costs will be too low. As a result the decomposition attributes too large a component of transaction costs to asymmetric information and the estimated difference in valuation component will be too small. The fact that our estimate of the difference in valuation is comparable to and even higher than the difference in valuation component found by Handa, Schwartz, and Tiwari (2003) suggests that, on average, liquidity traders correctly incorporate asymmetric

auction but the opening auction is the most appropriate auction to compare with pure call auction trading, since it is preceded by the longest interval where no trading takes place.

[13]Handa, Schwartz, and Tiwari (2003) assume two types of traders: one type values the stock at V_h the other at V_l. The difference $V_h - V_l$ relative to the mid-quote corresponds to $2K$ in the present model. The average difference in valuation for their sample of 40 stocks on Euronext Paris CAC40 index amounts to 1.04% compared to $2K = 1.48\%$ for the 20 stocks in the present study.

information in their limit prices.

5.2.3 Asymmetric Information Component

Column 3 reports the average asymmetric information component $\Lambda = \lambda\sqrt{2/\pi}\,\sigma$. The average over the twenty stocks is 0.18. It varies between 0.03 and 0.93. Since λ is restricted to lie between 0 and 1 and σ is strictly positive, the asymmetric information component, Λ, cannot be negative. Thus, we cannot assess the significance of the asymmetric information component by looking at the t-statistics. But clearly, Λ is significantly greater than zero, whenever λ is significantly greater than zero.

The average probability that the potential insider has superior information is 17% across the twenty stocks. For *Credit Foncier Communal d'Alsace* only 4% of the orders submitted by the potential insider were triggered by inside information. For *Banque de la Reunion* the potential insider was informed in 64% of the auctions she participated in. Handa, Schwartz, and Tiwari (2003) estimate the probability of trading with an informed investor to be 34%, on average, ranging from 10% to 57%. The large average probability seems to be specific to the sample of stocks considered in their study. Handa, Schwartz, and Tiwari (2003) focus on stocks in the CAC40 index, 40 of the most liquid stocks traded at the Paris Stock Exchange, for the period January and February 1995. Lai, Ng, and Zhang (2014) estimate the probability of informed trading (PIN) for 829 stocks traded on the Paris Stock Exchange during the period from 1996 to 2010 using the procedure proposed by Duarte and Young (2009). They find an average PIN of 20.6% with half of the values between 14.9% and 25.0%.

5.2.4 Model Comparison

By assumption, λ is continuously distributed between 0 and 1. Hence, the probability that λ is exactly equal to zero is zero. We can, however, assess the significance of λ by evaluating the Bayes Factor for the mixture model versus the restricted model with $\lambda = 0$. Note that the restricted model is a simple regression of r_t on a constant and $q_t - q_{t-1}$ with normally distributed disturbances. This is precisely the transaction return process that Roll (1984) uses to derive his measure for the implicit spread. Thus, for $\lambda = 0$ our model collapses to the Roll model and Roll's measure for the implicit spread could be used to measure transaction costs in call auctions.

If we ascribe equal prior probabilities to the competing models, the mixture model and the restricted model, the Bayes Factor, $B_{M,R}$, is the posterior odds ratio. Then, $B_{M,R}/(1+B_{M,R})$ is the implied posterior probability that the mixture model is the correct model, i.e., $\lambda > 0$. This probability is reported in the last column of Table 2.[14] The probability that λ is positive exceeds 85% for all stocks in the sample. For nineteen stocks, λ is significantly positive at a 10%-level and seventeen stocks show significant insider trading at a 5%-level.

Since the asymmetric information component is a linear function of the probability of inside information in an auction, λ, the asymmetric information component is significantly positive whenever λ is significantly positive. This shows that the asymmetric information component should not be neglected, and thus, the Roll measure does not fully reflect transaction costs in call auctions.

6 Determinants of Transaction Costs

Proposition 3 states that the difference in valuation component is an increasing function of the relative order imbalance, α. The order imbalance is closely related to liquidity. The more liquid the market, the smaller the relative size of the insider's order. We, therefore, expect a negative relationship between the difference in valuation component and liquidity.

We use the following proxies for liquidity:[15] trading volume in 2005, the number of days in 2005 with zero returns (Zeros), the Roll measure defined in equation (9)

[14] We simulate the Bayes factor with the bridge sampling technique proposed by Meng and Wong (1996).

[15] For a discussion of these and other liquidity measures and their performance see Goyenko, Holden, and Trzcinka (2009). Czauderna, Riedel, and Wagner (2015) provides a good treatment of the limitations of the Amihud illiquidity measure.

and the Amihud illiquidity measure, defined as

$$Amihud = Average(\frac{|r_t|}{Volume_t}).$$

The liquidity measures for the 20 stocks are presented in columns 5 to 8 in Table 1.

Table 3 shows the correlations of the difference in valuation component, K, with these proxies for liquidity. The number of trading days with zero returns and the Amihud measure are strongly correlated with the difference in valuation component; the correlation coefficients are 0.753 and 0.657, respectively. The correlation between the Roll measure and the difference in valuation component is only marginally significant. The correlation coefficient for trading volume has the expected sign but fails to be significant.

[Table 3 about here.]

By Proposition 3, the asymmetric information component should not be directly affected by liquidity. Table 3 confirms that the asymmetric information component (Λ) is not related to any of the proxies for liquidity. As predicted by our model this implies that the relation between liquidity and transaction cost is largely attributable to the difference in valuation component. This is in contrast to Easley, Kiefer, O'Hara, and Paperman (1996), who find that, for continuous trading on the NYSE, the probability of informed trade was decreasing in trading activity. A possible explanation for these conflicting results is that an increase in the number of liquidity traders increases the number of trades in a continuous market, but not the number of auctions in a call auction market. Holding the trading activity of insiders constant, an increase in trades that are initiated by liquidity traders will then reduce the probability of informed trading in continuous markets, but it will not change the number of call auctions with insider information.

7 Conclusions

The analysis in this study shows that asymmetric information is reflected in the liquidity traders' limit prices and therefore affects transaction prices. Furthermore, our call auction model implies that, just as in continuous limit order book markets, the presence of an insider gives rise to an asymmetric information component of transaction costs. The empirical analysis finds strong support for our call auction model with asymmetric information. The asymmetric information component forms a substantial and significant part of transactions costs.

Based on these findings we conclude that call auctions are well equipped to deal with asymmetric information. Liquidity traders are aware of asymmetric information problems and they adjust their limit prices to prevent themselves from being systematically exploited by traders with superior information.

Appendix

Proof 1 *To see that Proposition 1 constitutes an equilibrium, consider a buyer of type k^* and suppose that all other traders play the equilibrium strategies given in Proposition 1. If the limit order of buyer k^* is binding, i.e. if buyer k^*'s limit price determines the transaction price, the insider must have placed a market buy order. Let q_t be an indicator variable which is 1 if the insider places a buy order and -1 if the insider places a sell order. The conditional expectation of ε_t given the insider's market buy order is $E(\varepsilon_t | q_t = 1) = \lambda E(\varepsilon_t | \varepsilon_t > 0) = \lambda\sqrt{2/\pi}\,\sigma$.[16] Therefore the maximum price buyer k^* is willing to pay is $\nu_{t-1} + \mu + k^* + \lambda\sqrt{2/\pi}\,\sigma$. If the buyer chose a higher limit price, she might incur an expected loss, with a lower price she might forgo expected profits. Thus, a limit buy price of $\nu_{t-1} + \mu + k^* + \lambda\sqrt{2/\pi}\,\sigma$ is buyer k^*'s best response.*

A symmetric argument applies for sellers.

Now consider the potential insider who receives the signal $\varepsilon_t > 0$ and assume that all liquidity traders follow the equilibrium strategies. If the insider chooses a market buy order of size α the transaction price is the limit buy price of the buyer with premium $k = \underline{k} + (\bar{k} - \underline{k})\alpha$, i.e. $b_t^* = \nu_{t-1} + \mu + \underline{k} + (\bar{k} - \underline{k})\alpha + \lambda\sqrt{2/\pi}\,\sigma$.

[16] To see this, observe that the density of ε_t conditional on $\varepsilon_t > 0$ is $f(\varepsilon_t | \varepsilon_t > 0) = f(\varepsilon_t)/P(\varepsilon_t > 0) = 2f(\varepsilon_t)$. Then, $E(\varepsilon_t | \varepsilon_t > 0) = 2\int_0^\infty \varepsilon_t f(\varepsilon_t)\, d\varepsilon_t = \sqrt{2/\pi}\,[-\sigma \exp\{-\varepsilon_t^2/(2\sigma^2)\}]_0^\infty = \sqrt{2/\pi}\,[0 - (-\sigma)] = \sqrt{2/\pi}\,\sigma$.

(See also Figure 1.) Therefore, the insider's utility from a market order is $U^m_{i,t} = \alpha\,[E(\nu_t|\varepsilon_t > 0) - b^*_t] = \alpha[(1-\lambda)\sqrt{2/\pi}\,\sigma - \underline{k} - (\bar{k} - \underline{k})\alpha]\,.$

If the potential insider chooses a limit order her utility is the same as for a market order, whenever her limit price exceeds b^*_t*, and utility is zero for limit prices lower than* $b^{\underline{k}}_t = \nu_{t-1} + \mu + \underline{k} + \lambda\sqrt{2/\pi}\,\sigma$ *, because these orders will not execute. If the insider chooses a limit price between these two prices her order is only partially executed. The potential insider's utility from a limit buy order with limit price* b^i *is*

$$U^l_{i,t} = \begin{cases} \alpha((1-\lambda)\sqrt{2/\pi}\,\sigma - \underline{k} - (\bar{k} - \underline{k})\alpha), & b^i \geq b^*_t, \\ \frac{b^i - \nu_{t-1} - \mu - \lambda\sqrt{2/\pi}\,\sigma - \underline{k}}{\bar{k} - \underline{k}}(E(\nu_t|\varepsilon_t > 0) - b^i), & b^{\underline{k}}_t \leq b^i < b^*_t, \\ 0, & b^i < b^{\underline{k}}_t\,. \end{cases} \tag{12}$$

Maximizing equation (12) with respect to b^i *shows that the insider chooses a limit price of* b^*_t *or above and is therefore indifferent between a limit and a market order whenever* $\alpha \leq \frac{(1-\lambda)\sqrt{2/\pi}\,\sigma - \underline{k}}{2\,(\bar{k} - \underline{k})}$.

If the potential insider does not receive a signal but adds a premium k^i *to the value of the stock her utility from a market buy order is* $U^m_{i,t} = \alpha\,[E(\nu_t) + k^i - b^*_t] = \alpha[k^i - \lambda\sqrt{2/\pi}\,\sigma - \underline{k} - (\bar{k} - \underline{k})\alpha]\,.$ *The utility from a limit buy order with limit buy price* b^i *is*

$$U^l_{i,t} = \begin{cases} \alpha(k^i - \lambda\sqrt{2/\pi}\,\sigma - \underline{k} - (\bar{k} - \underline{k})\alpha)\,, & b^i \geq b^*_t, \\ \frac{b^i - \nu_{t-1} - \mu - \lambda\sqrt{2/\pi}\,\sigma - \underline{k}}{\bar{k} - \underline{k}}(E(\nu_t) + k^i - b^i)\,, & b^{\underline{k}}_t \leq b^i < b^*_t, \\ 0\,, & b^i < b^{\underline{k}}_t\,. \end{cases} \tag{13}$$

Maximizing equation (13) with respect to b^i *shows that the insider chooses a limit price of* b^* *or above and is therefore indifferent between a limit and a market order whenever* $\alpha < \frac{k^i - \underline{k} - \lambda\,\sqrt{2/\pi}\,\sigma}{2\,(\bar{k} - \underline{k})}$.

Thus, the condition $\alpha \leq min\{\frac{(1-\lambda)\sqrt{2/\pi}\,\sigma - \underline{k}}{2\,(\bar{k} - \underline{k})}, \frac{k^i - \underline{k} - \lambda\,\sqrt{2/\pi}\,\sigma}{2\,(\bar{k} - \underline{k})}\}$ *ensures that the insider chooses a market buy order when i) she observes a good signal and ii) she receives no signal and adds a premium to the value of the stock. Due to the symmetry of the situation the same condition applies for a market sell order.*

Proof 2 *Plugging equation (5) into the definition of transaction costs, yields*

$$\begin{aligned} S &= \nu_{t-1} + \mu + \underline{k} + (\bar{k} - \underline{k})\alpha + \lambda\sqrt{2/\pi}\,\sigma - (\nu_{t-1} + \mu - (\underline{k} + (\bar{k} - \underline{k})\alpha) - \lambda\sqrt{2/\pi}\,\sigma) \\ &= 2(\underline{k} + (\bar{k} - \underline{k})\alpha) + 2\lambda\sqrt{2/\pi}\,\sigma. \end{aligned}$$

Proof 3 *Straightforward differentiation yields:*

$$\begin{aligned} \frac{\partial 2(\underline{k} + (\bar{k} - \underline{k})\alpha)}{\partial \alpha} &= 2(\bar{k} - \underline{k}) > 0 \\ \frac{\partial 2\lambda\sqrt{2/\pi}\,\sigma}{\partial \lambda} &= 2\sqrt{2/\pi}\,\sigma > 0 \\ \frac{\partial 2\lambda\sqrt{2/\pi}\,\sigma}{\partial \sigma} &= 2\lambda\sqrt{2/\pi} > 0\,. \end{aligned}$$

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Figure 1: *The graphical representation of the order book and the transaction price. In Panel (a) the potential insider places a market buy order of size α resulting in transaction price $p_t^+ = \nu_{t-1} + \mu + \underline{k} + (\bar{k} - \underline{k})\alpha + \lambda\sqrt{2/\pi}\,\sigma$. Panel (b) corresponds to a market sell order and transaction price $p_t^- = \nu_{t-1} + \mu - \underline{k} - (\bar{k} - \underline{k})\alpha - \lambda\sqrt{2/\pi}\,\sigma$.*

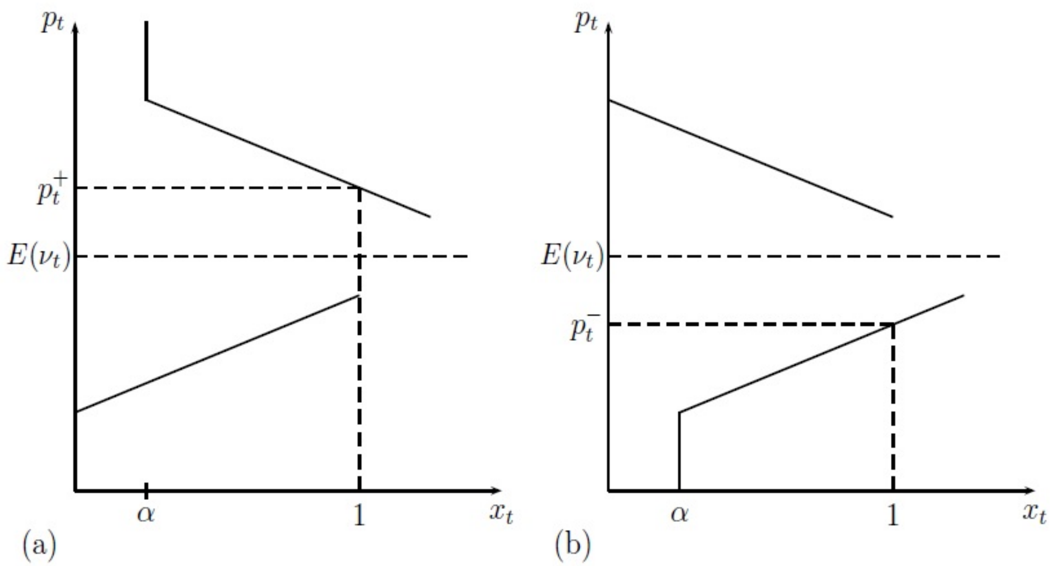

Table 1: Stock characteristics. *The first four columns -Number of auctions, Standard deviation of returns, Average price and Average bid-ask spread- all refer to the trading year 2006. The remaining four columns -Number of trading days, Trading volume, Amihud illiquidity measure and Roll measure- describe trading activity and liquidity during the year 2005. The bid-ask spread is defined as the difference of the lowest limit sell and the highest limit buy price that remained in the order book after the auction had cleared divided by their mid-point.*

	2006				2005			
	Number of auctions	Std. dev. of returns	Avg. price in €	Avg. bid-ask spread in %	Number of trading days	Trading volume in 1,000 of shares	Amihud illiquidity measure	Roll measure
AES Chemunex	406	5.52	1.55	3.26	186	4,323	26.41	47.21
Altarea	275	1.05	125.12	1.34	255	63	3641.71	0
Artois Nom.	251	2.47	2107.54	3.56	132	2	8357.56	2.71
Banque Tarneaud	422	1.14	160.30	0.90	249	33	2.37	0.87
Banque de la Reunion	366	0.68	275.77	0.74	244	17	13.93	2.46
Cambodge Nom.	139	4.40	2572.18	9.38	77	1	18522.82	2.05
Credit Foncier Communal d'Alsace	432	1.55	78.30	1.60	230	33	7.92	3.31
Chauffage Urbain	55	5.20	100.18	15.81	72	3	10541.95	6.13
Cofitem	378	1.21	99.93	1.88	257	47	3448.58	2.44
Credit Agricole Centre Loire	468	0.70	72.11	0.53	255	122	2.31	0.85
Credit Agricole Oise	488	1.05	80.91	0.65	256	152	1.64	0.49
Distriborg	45	9.46	190.27	8.90	72	3	31.74	26.52
Exacompta Clairefontaine	270	1.82	160.32	2.13	189	22	10685.45	2.66
Finatis	241	2.88	116.11	2.84	170	56	9918.47	1.90
Fonciere des Murs	425	1.81	86.79	1.70	165	65	24837.96	7.99
Fromageries Bel	375	1.60	152.60	1.69	203	31	6325.08	2.16
Grand Marnier	234	1.45	6118.35	2.70	127	0	11.52	2.93
Hotels et Casino de Deauville	62	2.47	2.90	2.90	68	88	2.72	3.93
Icade Fonciere des Pimonts	331	1.11	105.29	1.43	115	9	20.97	6.24
Institut de Participations de l'Ouest	342	1.26	86.87	1.06	232	37	2.61	2.92
Average	300	2.44	634.67	3.25	178	255	4820.19	6.29

Table 2: Estimation results. (Standard deviations in parentheses.) *Transaction costs, S, the probability of insider information, λ, volatility of the asset's true value, σ and the drift term, μ, are the estimated parameters of the mixture model. The asymmetric information component is $\Lambda = \lambda\sqrt{2/\pi}\,\sigma$. The difference in valuation component is computed by subtracting the asymmetric information component from half of the transaction costs, i.e., $K = \frac{S}{2} - \lambda\sqrt{2/\pi}\,\sigma$.*

Name	S	K	Λ	λ	σ	μ	$q_t = 0$	B	$P(\lambda > 0)$
AES Chemunex	3.036	1.140	0.379	0.129	3.676	0.307	1	613.89	1.00
	(0.253)	(0.179)	(0.145)	(0.049)		(0.146)			
Altarea	1.092	0.511	0.035	0.084	0.516	0.103	4	66.04	0.99
	(0.048)	(0.030)	(0.02)	(0.048)		(0.0201)			
Artois Nom.	2.217	1.054	0.055	0.05	1.383	0.306	4	17.81	0.95
	(0.126)	(0.074)	(0.043)	(0.038)		(0.082)			
Banque Tarneaud	0.837	0.36	0.059	0.104	0.711	0.06	3	340.74	1.00
	(0.051)	(0.037)	(0.028)	(0.048)		(0.030)			
Banque de la Reunion	1.076	0.317	0.221	0.639	0.434	0.025	0	> 1000	1.00
	(0.020)	(0.016)	(0.017)	(0.046)		(0.018)			
Cambodge Nom.	3.241	1.503	0.118	0.053	2.758	0.652	1	10.41	0.91
	(0.358)	(0.198)	(0.095)	(0.043)		(0.224)			
Credit Foncier Communal d'Alsace	1.052	0.494	0.032	0.041	0.972	0.013	0	23.02	0.96
	(0.068)	(0.039)	(0.03)	(0.038)		(0.045)			
Chauffage Urbain	5.447	2.565	0.158	0.068	2.898	0.08	0	5.50	0.85
	(0.671)	(0.365)	(0.143)	(0.061)		(0.378)			
Cofitem	0.994	0.405	0.092	0.149	0.772	0.042	7	464.99	1.00
	(0.062)	(0.04)	(0.034)	(0.055)		(0.03)			
Credit Agricole Centre Loire	0.403	0.164	0.038	0.101	0.464	-0.035	7	485.45	1.00
	(0.035)	(0.024)	(0.018)	(0.047)		(0.019)			
Credit Agricole Oise	0.93	0.238	0.227	0.446	0.638	-0.039	0	> 1000	1.00
	(0.035)	(0.026)	(0.021)	(0.04)		(0.023)			
Distriborg	4.703	1.421	0.931	0.182	6.402	0.938	0	14.71	0.94
	(1.457)	(0.865)	(0.61)	(0.118)		(0.785)			
Exacompta Clairefontaine	1.816	0.791	0.117	0.144	1.019	0.052	0	93.03	0.99
	(0.099)	(0.067)	(0.054)	(0.067)		(0.041)			
Finatis	2.133	0.935	0.131	0.092	1.79	0.129	0	35.78	0.97
	(0.172)	(0.119)	(0.082)	(0.057)		(0.09)			
Fonciere des Murs	1.182	0.467	0.124	0.13	1.197	-0.046	2	65.71	0.99
	(0.091)	(0.062)	(0.048)	(0.05)		(0.033)			
Fromageries Bel	1.444	0.577	0.145	0.198	0.916	0.066	1	> 1000	1.00
	(0.062)	(0.044)	(0.037)	(0.051)		(0.041)			
Grand Marnier	1.155	0.515	0.063	0.084	0.935	0.075	3	27.95	0.97
	(0.118)	(0.071)	(0.039)	(0.053)		(0.042)			
Hotels et Casino de Deauville	2.519	0.734	0.525	0.434	1.515	0.181	0	154.50	0.99
	(0.318)	(0.171)	(0.199)	(0.161)		(0.131)			
Icade Fonciere des Pimonts	0.761	0.335	0.046	0.079	0.728	0.09	19	52.59	0.98
	(0.072)	(0.049)	(0.033)	(0.057)		(0.039)			
Institut de Participations de l'Ouest	0.977	0.364	0.124	0.2	0.779	0.029	1	429.05	1.00
	(0.069)	(0.034)	(0.041)	(0.066)		(0.019)			
Average	1.8507	0.7444	0.1809	0.1704	1.5251	0.1513	3		

Table 3: Correlation between the components of transaction costs and liquidity measures. *This table reports the Spearman correlation coefficients. p-values are given in parentheses.*

	Difference in valuation component	Asymmetric information component
Roll	0.382	0.340
	(0.097)	(0.143)
Amihud	0.657	0.063
	(0.002)	(0.792)
Volume	-0.349	0.092
	(0.132)	(0.700)
Zeros	0.753	0.246
	(0.000)	(0.296)