Transaction costs in an electronic call auction in the presence of insider information*

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Abstract

This study presents a simple model of price formation with insider information in an electronic call auction. Based on our model we derive a measure of transaction costs in electronic call auctions. We decompose transaction costs in a difference in valuation and an asymmetric information part. These components are similar to the components of the bid-ask spread in an order-driven continuous market and therefore allow for a direct comparison of the composition of trading costs in continuous and periodic auctions. Empirical results for twenty stocks from Euronext Paris are provided. We find strong evidence for the asymmetric information component of transaction costs but in contrast to continuous markets there is no negative relationship between liquidity and asymmetric information problems. Thus, we conclude that for illiquid stocks call auction trading leads to lower transactions costs than continuous trading.

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1 Introduction

The last decade has seen a sharp increase in the use of call auctions in stock markets all over the world. The London Stock Exchange introduced opening and closing auctions in 1997 and 2000, respectively. The Australian Stock Exchange (1997) and the Toronto Stock Exchange (2004) both introduced closing auctions. In 2004 NASDAQ created NASDAQ CROSS, an order facility to obtain single opening and closing prices. On a practical level this renaissance has been made possible by progress in information technology which enables to gather huge amounts of orders and process them into a transaction price at a great speed. On a theoretical level the most prominent advantage is the common belief that periodic call auctions are better suited to aggregate asymmetric information than continuous markets. As a result, call auctions are thought to be most useful in times of market stress, such as the beginning or end of a trading day or the reopening of trade after a trading halt during a continuous trading session.

Yet, we know little about the impact of asymmetric information on transaction costs in an electronic call auction.[1] In fact, there is no generally accepted notion of transaction costs in call markets. In continuous markets, order- or quote-driven, the transaction price at a specific point in time differs whether the incoming order that triggers the transaction is a buy or a sell order. Other things being equal a buy order typically executes at a higher price than an incoming sell order. The difference between these two transaction prices, the bid-ask spread, is used to measure transaction costs. In a periodic call market, however, since all traders, buyers and sellers, trade at the same price there is no such bid-ask spread [cp. Economides and Schwartz (1995)]. As an alternative the bid-ask spread in a call auction is defined as the difference of the prices corresponding to the lowest limit sell and highest limit buy orders that have not been executed. Since usually no trade takes place at these prices this concept of the bid-ask spread is not appropriate to measure actual transaction costs. Therefore some studies use the measure proposed by Roll (1984) to

[1]According to Pagano and Schwartz (2003) "the call auction is the least understood of the three major trading regimes" (p. 440).

estimate transaction costs in call markets [e.g. Haller and Stoll (1989) and Stoll and Whaley (1990)]. Madhavan (1996) and Kehr, Krahnen and Theissen (2001) define transaction costs as the difference of the prices resulting from an additional buy order and an additional sell order of equal size. But a theoretical understanding of the determinants of these measures of transaction costs in an electronic call auction is still lacking.

A second difficulty that arises when studying transaction costs in call auctions is that some call auctions operate with active market makers (NYSE) while others do not (Euronext and Xetra). Most of the existing studies on call auctions assume a market maker who sets the transaction price according to the information she infers from the incoming orders and other factors such as her inventory or price continuity guidelines. The nature of transaction costs in a call auction operating without a market maker, however, is not well understood.

To overcome these problems we present a simple model of price formation in an electronic call auction. Based on this model we derive a new measure to assess trading costs in call auctions which can be directly compared to the bid-ask spread in continuous markets. For certain order sizes this measure coincides with the one proposed by Madhavan (1996) and Kehr, Krahnen and Theissen (2001). The theoretical model enables us to decompose transaction costs in a difference in valuation 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 an order-driven continuous market. This facilitates a direct comparison of the composition of trading costs in continuous and periodic auctions.

Another important feature of the call auction is that it consolidates order flow over time. This is the reason why many stock exchanges, e.g. Xetra and Euronext, organise trade in the least liquid stocks via call auctions only. 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 wait for continuous trading to start. To abstract from this decision between different trading mechanisms we focus on pure call auction trading only. For this reason we estimate our 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. This trading category has received little attention in the literature, probably because it is negligible in terms of market capitalization. Considering the number of firms whose shares are traded in this trading category, however, it is not negligible.[2] A notable exception is Venkataraman and Waisburd (2007) which shows that the introduction of a designated market maker increases market quality in this trading category.

Studying transaction costs in this trading category is also important from a policy perspective. Euronext Paris introduced this trading segment for less active stocks that can only be traded in call auctions in response to high bid-ask spreads for these stocks. Easley, Kiefer, O'Hara and Paperman (1996) report that infrequently traded stocks have substantially higher bid-ask spreads than more frequently traded stocks and they show that at least one reason for this is the fact that the probability of informed trading is decreasing in trading volume. Whether the introduction of a pure call auction trading segment helped to overcome this problem has not been studied so far.

In order to estimate our theoretical model we adopt the Bayesian approach. The Bayesian approach has the advantage that it is easy to obtain finite-sample marginal posterior distributions for parameters of interest that are functions of the estimated model parameters.[3]

The main result of our model is that in electronic call auctions the asymmetric information impact is reflected in the liquidity traders' limit prices and thus translates into the transaction price. Further, our model implies that transaction costs, defined as twice the deviation of the transaction price from the average trader's unconditional expectation, are a decreasing function of liquidity and increasing with information asymmetries. We estimate our model for twenty stocks that are only traded in electronic call auctions on Euronext Paris and decompose transaction costs

[2] In 2005 roughly one third of all stocks traded at Euronext Paris were traded in call auctions only.

[3] Hasbrouck (2009) also proposes a Bayesian approach to estimate trading costs.

in a difference in valuation and an asymmetric information component. Considering that the stocks in our sample are in the least liquid trading category estimated transaction costs are remarkably low. We find that insider trading accounts for an important part of transaction costs. The proportion of transaction costs attributable to asymmetric information in the call auction market is only insignificantly lower than the results of Jong, Nijman and Röell (1996) for the continuous market on the Paris Bourse.

In comparison to continuous markets there have been relatively few attempts to model call auctions. Mendelson (1982) shows that the transaction price in a periodic call auction fluctuates around the asset's true value. The variance of the transaction price decreases as the market becomes more liquid. Ho, Schwartz and Whitcomb (1985) show that the transaction price of a call auction might deviate from its Pareto efficient value if i) the propensities to trade are asymmetric across traders or ii) traders have biased beliefs about the market clearing price. Introducing asymmetric information Madhavan (1992) shows that in the absence of a strategic market maker the call auction price is an unbiased estimator of the asset's true value.[4]

There are several empirical studies that analyse the impact of call auctions on market quality. Pagano and Schwartz (2003) and Pagano, Peng and Schwartz (2008) 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. Amihud, Mendelson and Lauterbach (1997), Lauterbach (2001) and Muscarella and Piwowar (2001) analyse how moving a stock from call auction trading to continuous trading or vice versa affects its price and trading volume. Amihud, Mendelson and Lauterbach (1997) show for the Tel Aviv Stock Exchange that transferring stocks from call auction trading

[4]In addition, there is a branch of the auction theory literature devoted to call auctions. These studies focus primarily on private information about reservation values [see e.g. Satterthwhaite and Williams (1993), Rustichini, Satterthwhaite and Williams (1994) and Cason and Friedman (1997)]. By assuming a continuum of liquidity traders we abstract from incentives to misreport private valuation.

to continuous trading leads to an increase in the stocks value and liquidity. They attribute this value improvement to a reduction in transaction costs. Supplementing Amihud, Mendelson and Lauterbach's study Lauterbach (2001) finds that moving stocks from continuous trading back to call auction trading is on average associated with a decline in liquidity and value. However, Lauterbach (2001) also reports that low volume stocks fared better under call auction trading. For the Paris Bourse Muscarella and Piwowar (2001) also demonstrate a positive liquidity and value effect of transferring stocks to continuous trading, but contrary to Lauterbach (2001) they do not find that call auctions are better suited for infrequently traded stocks. Ellul, Shin and Tonks (2005) study the traders' choice between a dealership market and a call auction on the London Stock Exchange. The present paper is also related to Easley, Kiefer and O'Hara (1993) who estimate the probability of information-based trading in continuous trading on the NYSE.

This paper is organised as follows. In section 2 we present our stylised model of an electronic call auction. In section 3 we describe the equilibrium order strategies and derive implications for the transaction price and the proposed measure of transaction costs. Section 4 outlines the estimation procedure. (The details of the estimation algorithm are provided in the Appendix.) In Section 5 we present the data and the empirical results. Section 6 discusses the determinants of the estimated components of transaction costs and section 7 concludes.

2 A stylised 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 and market orders during the order accumulation phase. While market orders are executed with certainty, 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 auction t.[5] After auction t the realisation of ε_t becomes common knowledge.

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 [cp. Foucault (1999) and Handa, Schwartz and Tiwari (2003)]. More specifically, buyer k is characterised 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. Her decision problem is to set an upper limit price b_t^k for the buy order to maximise her pay-off

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

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

Similarly, there is a continuum of sellers characterised 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

[5]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.

[6]The assumption that there is a continuum of liquidity buyers and sellers is not crucial for our

potential seller places one limit sell order for one unit of the stock with limit sell price s_t^k in order to maximise her pay-off

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

In addition, there is a potential insider who values the stock at a premium or a discount of size k^i with equal probabilities. With probabilities λ this trader learns the sign of the realisation 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. The potential insider is assumed to be risk-neutral and trades an amount of $\alpha \in (0, a]$ assets via market sell or market buy orders.[7] Assuming a premium of k^i her pay-off is

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

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. While on average the number of buy and sell orders are the same, in each auction there is a positive or negative order imbalance of size α relative to the maximum trading volume. 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.

main result, namely that liquidity traders adjust their limit prices according to the presence of an insider. But it greatly simplifies the analysis because we do not have to work with step functions.

[7] We will later see that for some boundary on a the assumption that the potential insider trades only via market orders is not necessary. However, it might be in her interest to use market orders, since specifying a limit price could unveil information to other market participants.

3 Equilibrium order strategies and implications

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

Proposition 1 *If* $a = min\{\frac{(1-\lambda)\sqrt{2/\pi}\,\sigma - k^i - \underline{k}}{2\,(\bar{k}-\underline{k})}, \frac{k^i - \underline{k} - \lambda\,\sqrt{2/\pi}\,\sigma}{2\,(\bar{k}-\underline{k})}\}$ *the following strategies constitute an equilibrium:*

- $b_t^k = \nu_{t-1} + \mu + k + \lambda\sqrt{2/\pi}\,\sigma \quad , \forall k \in [\underline{k}, \overline{k}]$
- $s_t^k = \nu_{t-1} + \mu - k - \lambda\sqrt{2/\pi}\,\sigma \quad , \forall k \in [\underline{k}, \overline{k}]$
- *the insider places a market buy (sell) order when she observes a positive (negative) realisation of the noise component or when she receives no information and has a higher (lower) personal valuation of the stock than the average trader.*

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* $E(\varepsilon_t|\, q_t = 1) = \lambda\, E(\varepsilon_t|\, \varepsilon_t > 0) = \lambda\sqrt{2/\pi}\,\sigma$*.*[8] *Therefore the maximum price buyer* k^* *is willing to pay is* $\nu_{t-1} + \mu + k^* + \lambda\sqrt{2/\pi}\,\sigma$*. If the buyer would set a higher limit price, she might incur an expected loss, with a lower price she might forgo expected profits. Of course a symmetric argument applies for a seller.*

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* $k = \underline{k} + (\bar{k} - \underline{k})\alpha$*, i.e.* $b_t^* = \nu_{t-1} + \mu + \underline{k} + (\bar{k} - \underline{k})\alpha + \lambda\sqrt{2/\pi}\,\sigma$*. (See also*

[8] 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, $E(\varepsilon_t|\varepsilon_t > 0) = 2\int_0^\infty \varepsilon_t f(\varepsilon_t)\, d\varepsilon_t = \sqrt{2/\pi}\,[-\sigma\,\exp\{-\varepsilon_t^2/(2\sigma^2)\}]_0^\infty = \sqrt{2/\pi}\,[0-(-\sigma)] = \sqrt{2/\pi}\,\sigma$.

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

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* $b_t^{\underline{k}} = \nu_{t-1} + \mu + \underline{k} + \lambda\sqrt{2/\pi}\,\sigma$ *, because these orders will not execute. If the insider chooses a limit price in-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*

$$U_{i,t}^l = \begin{cases} \alpha(\pm k^i + (1-\lambda)\sqrt{2/\pi}\,\sigma - \underline{k} - (\bar{k} - \underline{k})\alpha), & b^i \geq b_t^*, \\ \frac{b^i - \nu_{t-1} - \mu - \lambda\sqrt{2/\pi}\,\sigma - \underline{k}}{\bar{k} - \underline{k}}(E(\nu_t|\varepsilon_t > 0)\ \pm k^i - b^i), & b_t^{\underline{k}} \leq b^i < b_t^*, \\ 0, & b^i < b_t^{\underline{k}}\,. \end{cases} \tag{5}$$

Maximizing equation (5) with respect to b^i *shows that the insider chooses a limit price above* b_t^* *and is therefore indifferent between a limit and a market order whenever* $\alpha < \frac{(1-\lambda)\sqrt{2/\pi}\,\sigma - k^i - \underline{k}}{2\,(\bar{k} - \underline{k})}$.

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* $U_{i,t}^m = \alpha\,[E(\nu_t) + k^i - b_t^*] = \alpha[k^i - \lambda\sqrt{2/\pi}\,\sigma - \underline{k} - (\bar{k} - \underline{k})\alpha]$ *. The utility from a limit buy order with limit buy price* b^i *is*

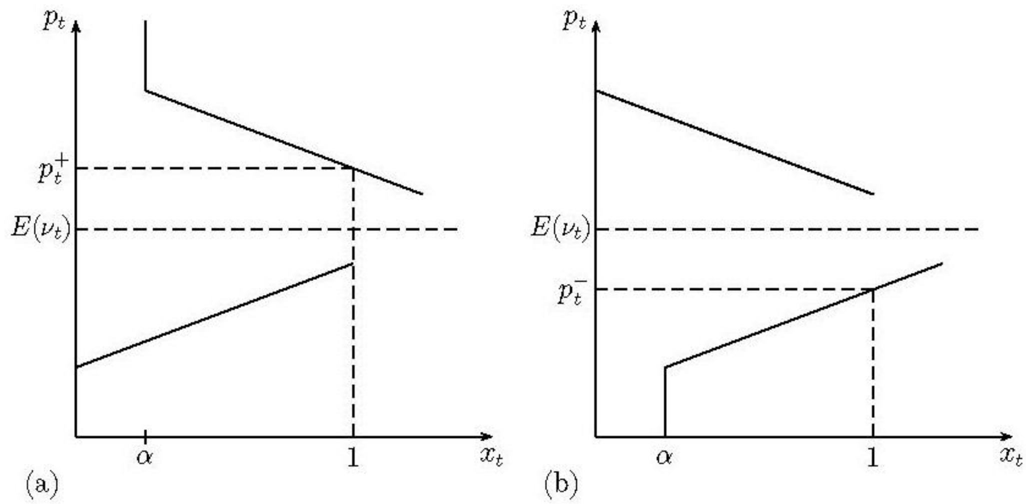
$$U_{i,t}^l = \begin{cases} \alpha(k^i - \lambda\sqrt{2/\pi}\,\sigma - \underline{k} - (\bar{k} - \underline{k})\alpha)\,, & b^i \geq b_t^*, \\ \frac{b^i - \nu_{t-1} - \mu - \lambda\sqrt{2/\pi}\,\sigma - \underline{k}}{\bar{k} - \underline{k}}(E(\nu_t)\ + k^i - b^i)\,, & b_t^{\underline{k}} \leq b^i < b_t^*, \\ 0\,, & b^i < b_t^{\underline{k}}\,. \end{cases} \tag{6}$$

Maximizing equation (6) with respect to b^i *shows that the insider chooses a limit price above* b^* *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 $\alpha < a = min\{\frac{(1-\lambda)\sqrt{2/\pi}\,\sigma - k^i - \underline{k}}{2\,(\bar{k} - \underline{k})}, \frac{k^i - \underline{k} - \lambda\,\sqrt{2/\pi}\,\sigma}{2\,(\bar{k} - \underline{k})}\}$ *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.*

Of course 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

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



order will always be executed and her limit price will never be binding. However, if we assume some uncertainty over α on the part of the liquidity traders, every liquidity trader will set her limit price such that she will break even if her limit price is binding. Hence, they will behave according to Proposition 1. Moreover, 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.

Proposition 1 shows that the liquidity traders' limit prices consist of three parts: the asset's unconditional expectation, the personal premium or discount and the informational impact of the potential insider trading in the same direction. Note that it is not important that a liquidity trader observes the order of the potential insider since her limit price can only be binding when the potential insider trades in the same direction. This implies that transparency of the order book is not an issue here.

3.1 The transaction price

Given these strategies 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 by 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

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

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 us to our definition of transaction costs.

3.2 Measures of transaction costs

We define the theoretical measure of transaction costs as the difference of 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 observable.

Definition 1 *Transaction costs in an electronic call auction are defined as the difference of the two transaction prices that would result from a positive order imbalance and a positive order imbalance, 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 (7)) in our definition of transaction costs we obtain

$$\begin{aligned} S &= p_t(q_t = 1) - p_t(q_t = -1) \\ &= 2(\underline{k} + (\bar{k} - \underline{k})\alpha) + 2\lambda\sqrt{2/\pi}\,\sigma\,. \end{aligned} \quad (8)$$

Corollary 1 *Transaction costs in an electronic call auction consist of two components: 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 this model transaction costs consist of two components. The first component is the difference in valuation of the buyer with the lowest limit buy price and the seller with the highest limit sell price whose orders are being executed. The second component is the familiar 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)). Hence, the two components of transaction costs in a call auction have similar interpretations as those Handa, Schwartz and Tiwari (2003) find for the bid-ask spread in an order-driven market. Note, however, that transaction costs in a call auction are minimised for $\alpha = 0$ whereas Handa, Schwartz and Tiwari (2003) show that the bid-ask spread in a continuous call market is *largest* for a zero order imbalance.

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. Using equation (7) and assuming $\alpha \leq 1/2$ this

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

measure of transaction costs can be written as

$$\tilde{S}(\Delta) = \begin{cases} 2\Delta(\bar{k} - \underline{k}) & \text{if } \Delta < \alpha\,, \\ 2(\underline{k} + (\bar{k} - \underline{k})\Delta) + 2\lambda\sqrt{2/\pi}\,\sigma & \text{if } \alpha \leq \Delta < 1 - \alpha\,, \\ 2\underline{k} + (\bar{k} - \underline{k})(1 - \alpha + \Delta) + 2\lambda\sqrt{2/\pi}\,\sigma & \text{if } \Delta \geq 1 - \alpha\,. \end{cases} \tag{9}$$

For an order size equal to the average order imbalance α this definition is equal to equation (8). Using order book information Kehr, Krahnen and Theissen (2001) calculate $\tilde{S}$ for large and small Δ for the opening, noon and closing auction at the Frankfurt Stock Exchange. They find that the increase in trading costs associated with a change from a small order size to a large order size is surprisingly large. Equation (9) shows that this is in line with our model. For low order sizes, i.e. $\Delta < \alpha$, the investor faces no asymmetric information effect and if traders within both of the two groups, buyers and sellers, are homogeneous, i.e. $\bar{k} - \underline{k} \to 0$, trading costs go to zero. For heterogeneous traders $\tilde{S}$ increases linearly with order size until $\Delta = \alpha$ where transaction costs jump to a new level. This level coincides with our proposed measure and therefore contains the full difference in valuation component as well as the asymmetric information component. For higher order sizes transaction costs increase again linearly until they jump again at $\Delta = 1 - \alpha$. From that point on the relation between order size and transaction costs is flatter.

3.3 The transactions return process

Taking the first difference of equation (7) and substituting equation (1) yields

$$p_t - p_{t-1} = \mu + (\underline{k} + (\bar{k} - \underline{k})\,\alpha)(q_t - q_{t-1}) + \lambda\sqrt{2/\pi}\,\sigma\,(q_t - q_{t-1}) + \varepsilon_{t-1}\,. \tag{10}$$

Although there is no explicit bid-ask spread in a call market equation (10) implies negative serial correlation between successive returns just as Roll (1984) finds for continuous markets.[10] The result that asymmetry in the order flow leads transaction

[10] Equation (10) implies that the measure proposed by Roll (1984) is as applicable to call auctions as it is to continuous markets, i.e. it is downward biased in the presence of positive correlation in q_t and does not fully account for the asymmetric information component as pointed out by Choi, Salandro and Shastri (1988) and George, Kaul and Nimalendran (1991), respectively.

returns to be negatively correlated has been previously noted by Ho, Schwartz and Whitcomb (1985), in the present model, however, the correlation is further increased by asymmetric information problems.

4 Estimation

When estimating equation (10) ex post it should be noted that conditional on q_t, ε_t is not normally distributed anymore. The distribution of ε_t given q_t is normal with probability $(1-\lambda)$ and truncated normal with probability λ, i.e.

$$\varepsilon_t|\, q_t = \begin{cases} q_t \cdot \varepsilon_t|(\varepsilon_t > 0) & \text{with prob. } \lambda\,, \\ \varepsilon_t & \text{with prob. } (1-\lambda)\,. \end{cases} \tag{11}$$

Therefore we estimate equation (10) using the following mixture model

$$p_t - p_{t-1} = \mu + S/2 \cdot (q_t - q_{t-1}) + \zeta_{t-1} \cdot q_{t-1} \cdot \varepsilon_{t-1}|(\varepsilon_{t-1} > 0) + (1-\zeta_{t-1}) \cdot \varepsilon_{t-1}\,, \tag{12}$$

where for each t the latent variable ζ_t equals 1 if the insider has 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 one can split the measure of transaction costs, S, in its two components.

The generalisation 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 (7) does still hold if we assume that i) limit buy and sell prices of the last orders that are being executed will be symmetric around the unconditional expectation of the asset's true value and ii) in the case of a zero order imbalance the transaction price is at 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 (12) with this extension. Of course, ζ_t cannot equal 1 when $q_t = 0$ and thus λ is the proportion of informed trade relative to the total number of participations 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.[11]

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 $K = S/2 - \Lambda$. The mean and standard deviation of the marginal distributions of these parameters are presented in Table 2.

5 Empirical analysis

5.1 Data

In order to estimate the model we use data from a trading category at Euronext Paris that consists of stocks that trade in two call auctions per day only. At the end of 2005 this trading category comprised 250 stocks which make up approximately 30% of all firms traded at Euronext. For the analysis we randomly chose twenty companies. Data on transaction prices as well as best bid and ask prices and trading volume are provided by Euronext. Table 1 presents summary statistics for these stocks for the period between 1/01/2006 and 31/12/2006.

At the end of 2005 these twenty firms have an average market capitalization of €407 million, ranging from 157 million to 962 million. The number of trades in the year 2005 varies considerably across the twenty stocks; from 160 to 6,266 trades. Turnover ranges from €264,000 to €39 million with an average of approximately €5.9 million.

The year 2006 had 255 trading days. Thus, with two call auctions a day there were 510 possible observations per stock. However, not all auctions had sufficiently demand and supply to facilitate trade. If the limit buy and limit sell orders of a

[11] The details of the estimation procedure are given in the Appendix.

particular auction could not be matched, i.e. if no transaction price exists which generates positive trading volume, this observation is discarded. Therefore only auctions that resulted in a transaction price are considered. The resulting number of auctions varies across stocks between 45 and 488 (see the seventh column of Table 1).

The indicator variable q_t is set to 1 if the transaction price of auction t is closer to the ask price and it is set to -1 if the transaction price is closer to the bid price.[12] In some instances these three prices coincide. This can be interpreted as the potential insider not participating in this day's auction and thus all orders being executed. In these cases the indicator variable is set to zero.

Column 8 of Table 1 shows the volatility of the transaction returns, $r_t = p_t - p_{t-1}$. Volatility varies between 0.68 and 9.46 with an average of 2.4. Average prices vary from €1.55 to €6118.35. The last column provides average bid-ask spread in 2006, where the bid-ask spread is defined as the difference of the lowest limit sell and the highest limit buy price that remain in the order book after the auction has cleared. Average bid-ask spreads range from 0.53% to 15.81% with an cross-section average of 3.25%.

5.2 Results

Table 2 shows the results of the estimation for each of the twenty assets. Average transaction costs are 1.85. They vary between 0.40 and 5.45. 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 *Crcam oise*. This provides additional evidence for the claim that bid-ask spreads are not a good measure of trading costs on call auctions since they overestimate actual costs.

Kehr, Krahnen and Theissen (2001) apply their measure of transaction costs to the opening auction of fifteen stocks on the Frankfurt Stock Exchange in 1996

[12] This procedure is analogous to trade indicator classification in continuous markets (see, e.g., Finucane (2000) for a discussion). It is based on the assumption that the bid-ask spread is symmetric around the unconditional or conditional expectation of the true value of the asset.

Name	Market capitalization in €1,000	Number of trading days (in 2005)	Number of trades	Number of shares traded (in 1,000)	Turnover in €1,000	Number of auctions	Std. dev. of returns	Avg. price	Avg. bid-ask spread
AES CHEMUNEX	266,300	186	2,205	4,323	2,249	406	5.52	1.55	3.26
ALTAREA	743,405	255	954	63	5,534	275	1.05	125.12	1.34
ARTOIS NOM.	362,831	132	389	2	2,087	251	2.47	2107.54	3.56
BANQUE TARNEAUD	243,753	249	1,720	33	4,699	422	1.14	160.30	0.90
BQUE DE LA REUNION	364,198	244	1,505	17	5,247	366	0.68	275.77	0.74
CAMBODGE NOM.	845,200	77	211	1	1,515	139	4.40	2572.18	9.38
CFCAL BANQUE	202,708	230	1,367	33	4,006	432	1.55	78.30	1.60
CHAUF.URB.	157,004	72	166	3	264	55	5.20	100.18	15.81
COFITEM	318,086	257	758	47	3,935	378	1.21	99.93	1.88
CRCAM CEN. LOIRE	195,915	255	3,083	122	7,838	468	0.70	72.11	0.53
CRCAM OISE	236,320	256	6,266	152	14,014	488	1.05	80.91	0.65
DISTRIBORG	305,826	72	160	3	432	45	9.46	190.27	8.90
EXACOMPTA CLAIREF	183,073	189	778	22	3,506	270	1.82	160.32	2.13
FINATIS	639,225	170	595	56	8,079	241	2.88	116.11	2.84
FONCIERE DES MURS	541,081	165	1,015	65	4,700	425	1.81	86.79	1.70
FROMAGERIES BEL	962,127	203	1,064	31	4,319	375	1.60	152.60	1.69
GRAND MARNIER	512,125	127	272	0	2,360	234	1.45	6118.35	2.70
HOT.CAS.DEAUVILLE	515,523	68	274	88	39,021	62	2.47	2.90	2.90
ICADEFONCPIMONTS	321,380	115	360	9	882	331	1.11	105.29	1.43
IPO	228,614	232	1,377	37	3,186	342	1.26	86.87	1.06
Average	407,234	178	1,226	255	5,894	300	2.44	634.67	3.25

Table 1: *Stock characteristics*

Name	S	K	Λ	$\Lambda/(\Lambda+K)$	λ	σ	st. dev. R	μ	obs.	zeros	B	$P(\lambda > 0)$
AES CHEMUNEX	3.0364	1.1395	0.3787	0.2501	0.1291	3.6761	5.5187	0.3067	406	1	613.89	1.00
	(0.2529)	(0.1792)	(0.1450)	(0.0956)	(0.0493)			(0.1457)				
ALTAREA	1.0922	0.5114	0.0347	0.0636	0.0844	0.5155	0.9248	0.1034	375	4	66.04	0.99
	(0.0481)	(0.0301)	(0.0196)	(0.0359)	(0.0476)			(0.0201)				
ARTOIS NOM.	2.2172	1.0536	0.0550	0.0496	0.0498	1.3829	2.4674	0.3058	251	4	17.81	0.95
	(0.1260)	(0.0739)	(0.0425)	(0.0384)	(0.0384)			(0.0819)				
BANQUE TARNEAUD	0.8374	0.3596	0.0591	0.1416	0.1041	0.7112	1.1351	0.0595	422	3	340.74	1.00
	(0.0514)	(0.0370)	(0.0275)	(0.0665)	(0.0483)			(0.0302)				
BQUE DE LA REUNION	1.0763	0.3168	0.2213	0.4112	0.6393	0.4339	0.6833	0.0251	366	0	> 1000	1.00
	(0.0200)	(0.0162)	(0.0172)	(0.0298)	(0.0457)			(0.0184)				
CAMBODGE NOM.	3.2408	1.5028	0.1175	0.0731	0.0534	2.7578	4.3971	0.6515	139	1	10.41	0.91
	(0.3578)	(0.1984)	(0.0948)	(0.0593)	(0.0430)			(0.2240)				
CFCAL BANQUE	1.0518	0.4943	0.0315	0.0594	0.0407	0.9718	1.5465	0.0126	432	0	23.02	0.96
	(0.0678)	(0.0394)	(0.0296)	(0.0547)	(0.0383)			(0.0447)				
CHAUF.URB.	5.4468	2.5652	0.1582	0.0591	0.0684	2.8976	5.2030	0.0795	55	0	5.50	0.85
	(0.6706)	(0.3651)	(0.1426)	(0.0546)	(0.0613)			(0.3779)				
COFITEM	0.9937	0.4050	0.0918	0.1845	0.1492	0.7718	1.2114	0.0417	378	7	464.99	1.00
	(0.0621)	(0.0400)	(0.0339)	(0.0669)	(0.0549)			(0.0298)				
CRCAM CEN. LOIRE	0.4025	0.1637	0.0376	0.1874	0.1014	0.4643	0.6953	-0.0350	468	7	485.45	1.00
	(0.0348)	(0.0236)	(0.0175)	(0.0878)	(0.0473)			(0.0188)				
CRCAM OISE	0.9304	0.2378	0.2274	0.4892	0.4464	0.6382	1.0520	-0.0393	488	0	> 1000	1.00
	(0.0351)	(0.0258)	(0.0212)	(0.0469)	(0.0398)			(0.0230)				
DISTRIBORG	4.7028	1.4207	0.9307	0.4300	0.1823	6.4024	9.4569	0.9384	45	0	14.71	0.94
	(1.4565)	(0.8647)	(0.6095)	(0.3577)	(0.1181)			(0.7847)				
EXACOMPTA CLAIREF	1.8161	0.7911	0.1169	0.1286	0.1438	1.0191	1.8172	0.0520	270	0	93.03	0.99
	(0.0993)	(0.0671)	(0.0544)	(0.0593)	(0.0666)			(0.0411)				
FINATIS	2.1328	0.9354	0.1311	0.1237	0.0918	1.7898	2.8769	0.1292	241	0	35.78	0.97
	(0.1715)	(0.1188)	(0.0815)	(0.0776)	(0.0569)			(0.0895)				
FONCIERE DES MURS	1.1822	0.4667	0.1244	0.2109	0.1302	1.1967	1.8126	-0.0462	425	2	65.71	0.99
	(0.0905)	(0.0620)	(0.0476)	(0.0809)	(0.0497)			(0.0325)				
FROMAGERIES BEL	1.4436	0.5773	0.1445	0.2001	0.1977	0.9158	1.6042	0.0660	375	1	> 1000	1.00
	(0.0622)	(0.0436)	(0.0373)	(0.0508)	(0.0506)			(0.0407)				
GRAND MARNIER	1.1548	0.5149	0.0625	0.1093	0.0838	0.9353	1.4482	0.0748	234	3	27.95	0.97
	(0.1179)	(0.0705)	(0.0394)	(0.0699)	(0.0528)			(0.0416)				
HOT.CAS.DEAUVILLE	2.5190	0.7344	0.5251	0.4116	0.4342	1.5149	2.4723	0.1806	62	0	154.50	0.99
	(0.3177)	(0.1712)	(0.1989)	(0.1418)	(0.1613)			(0.1305)				
ICADEFONCPIMONTS	0.7606	0.3345	0.0458	0.1214	0.0788	0.7282	1.1132	0.0904	331	19	52.59	0.98
	(0.0719)	(0.0487)	(0.0332)	(0.0893)	(0.0571)			(0.0393)				
IPO	0.9769	0.3643	0.1242	0.2520	0.1996	0.7793	1.2633	0.0288	342	1	429.05	1.00
	(0.0686)	(0.0344)	(0.0413)	(0.0745)	(0.0657)			(0.0186)				
Average	1.8507	0.7444	0.1809	0.1978	0.1704	1.5251	2.4350	0.1513	305	3		

Table 2: *Estimation results. Standard deviations in parentheses.*

and find average transaction costs of 0.33 and 2.37 for small and large order sizes, respectively.[13] Thus, our estimated transaction costs are roughly comparable with the previously documented transaction costs in auction markets for large orders. Kasch-Haroutounian and Theissen (2009) report effective half spreads for continuously traded stocks on Euronext Paris from May to July 2002. From the 40 French stocks in their sample the two lowest quartiles together have approximately the same market capitalization as the stocks in our sample. Kasch-Haroutounian and Theissen (2009) find an average effective half spread of 0.793% for these stocks. Given that the average *daily* turnover of these continuously traded stocks is larger than the average *annual* turnover in our sample transaction costs for the stocks traded in call auctions only are remarkably low.

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 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 auction. 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 order-driven market on Euronext Paris but the difference is not statistically significant.[14]

The proposed decomposition of transaction costs by subtracting $\lambda\sqrt{2/\pi}\,\sigma$ from $S/2$ is only correct if the liquidity traders assess the asymmetric information com-

[13] Kehr, Krahnen and Theissen (2001) also calculate transaction costs for the noon and closing auction but the opening auction is the most appropriate auction to compare with daily auctions since it is preceded by the longest interval where no trading takes place.

[14] 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% .

ponent correctly. If the liquidity traders underestimate the informational impact of the potential insider, by underestimating λ or σ, the decomposition attributes too large a part 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 information in their limit prices.

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% of the stock price. 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 0.17 across the twenty stocks. For *Cfcal Banque* 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. The estimated probabilities of inside information in a transaction are lower than the results of Handa, Schwartz and Tiwari (2003). They estimate the probability of trading with an informed investor to be 0.34 on average ranging from 0.10 to 0.57.

λ is continuously distributed between 0 and 1. Hence, $P(\lambda = 0)$ is zero. We can, however, assess the significance of λ by evaluating the Bayes Factor for the mixture model versus the restricted model with $\lambda = 0$.[15] If we ascribe equal prior probabilities to the competing models the Bayes Factor, $B_{M,R}$, is the posterior odds ratio. $B_{M,R}/(1 + B_{M,R})$ is the implied posterior probability that the mixture model is the correct model, i.e. $\lambda > 0$. This probability is reported in the last

[15] 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.

column of Table 2.[16] The probability that λ is positive exceeds 85% for all stocks in the sample. For nineteen stocks λ is significantly positive on a 10%-level and seventeen stocks show significant insider trading on 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 in call auctions.

Both the differences in valuation and the asymmetric information component seem to be smaller in a call auction than in an order-driven market. Thus, one might ask what the relative importance of asymmetric information on transaction costs are in the two trading mechanism. Comparing column 4 of Table 2 with the results of Jong, Nijman and Röell (1996) for the continuous market on the Paris Bourse we see that the asymmetric information component constitutes a smaller part of transaction costs in electronic call auctions. The average proportion of the asymmetric information component of total trading costs for the call auction is 20% while the asymmetric information component in continuous trading amounts to 45% of the bid-ask spread.

Column 6 and 7 of Table 2 document the familiar insight that transaction costs induce additional volatility to the trading process. For each individual stock the standard deviation of the return on the true value σ is lower than the standard deviation of the transaction return. The trend in the true value process μ is positive for most the stocks in our sample although it is only significant for six stocks.

6 Determinants of transaction costs

In the preceding section we estimated transaction costs and their components in electronic call auctions. In the following we want to study whether the two components conform to the predictions of our theoretical model.

The model predicts that the difference in valuation component is an increasing

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

	K	BAS	TRADES	TO	N	STDEV	P
K	1						
	—						
BAS	0.96	1					
	(14.35)	—					
TRADES	-0.43	-0.41	1				
	(-2.01)	(-1.89)	—				
TO	-0.20	-0.22	0.16	1			
	(-0.88)	(-0.95)	(0.69)	—			
N	-0.74	-0.75	0.66	-0.17	1		
	(-4.61)	(-4.79)	(3.76)	(-0.72)	—		
STDEV	0.76	0.74	-0.31	-0.18	-0.64	1	
	(4.93)	(4.63)	(-1.36)	(-0.77)	(-3.53)	—	
P	0.07	0.12	-0.26	-0.19	-0.23	-0.02	1
	(0.28)	(0.50)	(-1.14)	(-0.81)	(-1.03)	(-0.08)	—

Table 3: *Correlations of the difference in valuation component K with stock characteristics. t-statistics are given in parentheses.*

function of illiquidity measured by the relative order imbalance, α. If the potential insider's order absorbs a large amount of the liquidity traders' orders the limit price that will determine the transaction price will stem from a trader with a high premium or discount.

Since we do not have data of the order imbalances we use the following proxies for liquidity: average bid-ask spread in 2006 (BAS), number of trades in 2005 (Trades), turnover in 2005 (TO) and the number of auctions in 2006 (N). Table 3 presents the correlations of the difference in valuation component K with these proxies. The average bid-ask spread is strongly correlated with the difference in valuation component; the correlation coefficient is 0.96. But also other proxies for liquidity are significantly correlated with K. This is especially true for the number of trades which is measured for 2005. This shows that the causality is in deed from liquidity to difference in valuation component and not the other way around. In addition, the difference in valuation component is positively correlated with the volatility of the returns, although the causality is less clear.

	Λ	BAS	TRADES	TO	N	STDEV	P
Λ	1						
	—						
BAS	0.33	1					
	(1.50)	—					
TRADES	-0.08	-0.41	1				
	(-0.34)	(-1.89)	—				
TO	0.28	-0.22	0.16	1			
	(1.24)	(-0.95)	(0.69)	—			
N	-0.51	-0.75	0.66	-0.17	1		
	(-2.49)	(-4.79)	(3.76)	(-0.72)	—		
STDEV	0.77	0.74	-0.31	-0.18	-0.64	1	
	(5.15)	(4.63)	(-1.36)	(-0.77)	(-3.53)	—	
P	-0.19	0.12	-0.26	-0.19	-0.23	-0.02	1
	(-0.80)	(0.50)	(-1.14)	(-0.81)	(-1.03)	(-0.08)	—

Table 4: *Correlations of the asymmetric information component Λ with stock characteristics. t-statistics are given in parentheses.*

In contrast, the asymmetric information component should not be directly affected by liquidity. The determinants of the asymmetric information component are the probability of insider participation, λ, and the volatility of the true value, σ. These two variables have been used to decompose the spread, thus, the positive relationship between these two variables and the asymmetric information component is present by construction.

Table 4 confirms that the asymmetric information component (Λ) is not very closely related to the proxies for liquidity. The only liquidity proxy that has a significant impact is the number of auctions (N) and this effect is due to the close correlation between the number of auctions and volatility σ. As predicted by our model this implies that the relation between liquidity and transaction costs is largely attributable to the difference in valuation component. Moreover, Table 4 shows that using the bid-ask spread to measure transaction costs in call markets is problematic, because the bid-ask spread reflects only the difference in valuation component and is not informative about the asymmetric information component. Finally, Λ is strongly

	λ	1/BAS	TRADES	TO	N	STDEV	P
λ	1						
	—						
1/BAS	0.41	1					
	(1.93)	—					
TRADES	0.39	0.74	1				
	(1.79)	(4.7)	—				
TO	0.53	0.13	0.16	1			
	(2.62)	(0.54)	(0.69)	—			
N	0.08	0.72	0.66	-0.17	1		
	(0.34)	(4.39)	(3.76)	(-0.72)	—		
STDEV	-0.18	-0.63	-0.31	-0.18	-0.64	1	
	(-0.75)	(-3.42)	(-1.36)	(-0.77)	(-3.53)	—	
P	-0.23	-0.27	-0.26	-0.19	-0.23	-0.02	1
	(-1.00)	(-1.18)	(-1.14)	(-0.81)	(-1.03)	(-0.08)	—

Table 5: *Correlations of probability of insider information λ with stock characteristics. t-statistics are given in parentheses.*

correlated with the volatility of returns.

The probability that an order of the potential insider is triggered by inside information is an exogenous parameter in our model. One could ask, however, whether there are certain stock characteristics that make informed trade more likely. Table 5 shows the relationship between λ and the inverse of the bid-ask spread and other stock characteristics. The probability of informed trade is higher when the bid-ask spread is low. Turnover in 2005 is also positively correlated with λ. Although this relationship is not explicitly formalized in our model, it is quite intuitive: Suppose, e.g., that obtaining a signal about the future realisation of the stock's value requires some small cost. Then it might not be worthwhile for the potential insider to invest in the signal if she expects that there will be few liquidity traders and she will only be able to trade one or two shares. If, however, the market is very liquid she can easily recoup her costs by trading a large quantity of shares.

Interestingly, the correlation between the probability that the insider receives a signal and other measures of trading activity like the number of trades in 2005 and number of auctions is positive but insignificant. In contrast, Easley, Kiefer, O'Hara and Paperman (1996) find that on the NYSE the probability of informed trade was decreasing in trading activity. Thus, Euronext Paris' decision to introduce a pure call auction trading segment for less actively traded stocks was a successful policy measure since it not only helped to keep transaction costs low in general but also eliminated the negative relationship between trading activity and probability of informed trading.

7 Conclusions

We have presented a model of price formation in an electronic call auction. In our model asymmetric information is reflected in the liquidity traders' limit prices and therefore affects the transaction price. Our model implies that transaction costs, defined as twice the deviation of the transaction price from the average trader's unconditional expectation, are a decreasing function of liquidity and increasing with information asymmetries. We estimate our model for twenty stocks on Euronext Paris and decompose transaction costs in a difference in valuation and an asymmetric information component. Considering that the stocks in our sample are in the least liquid trading category estimated transaction costs are remarkably low. Moreover, in contrast to continuous markets for infrequently traded stocks information asymmetries do not lead to excessive transaction costs.

However, our results do not preclude that it can be desirable for *liquid* stocks to switch from one or two call auctions a day to a continuous trading mechanism as shown by Amihud, Mendelson and Lauterbach (1997). We show that call auction trading breaks the negative relation between liquidity and the asymmetric information component of transaction costs that is present in continuous markets and thus prevents excessive transaction costs for illiquid assets. This is in line with Lauterbach's (2001) finding that illiquid stocks fared better under the call auction trading regime than under a continuous trading. Our findings are also in accordance with Venkataraman and Waisburd (2007) who show that for very illiquid stocks the introduction of a designated market maker can improve market quality. By reducing the order imbalance the designated market maker lowers the difference in valuation component of transaction costs.

Appendix

This appendix provides the details of our estimation procedure. In Section A we derive the posterior distribution. Section B describes the MCMC algorithm used to obtain draws from the posterior distribution and in Section C we present the method for our model check.

A Derivation of posterior distribution

A.1 Likelihood

The likelihood of observing return r_t given the parameters $\mu, S, \sigma, \{\zeta_{t-1}\}, \lambda$ is

$$\begin{aligned} p(r_t|\mu, S, \sigma, \{\zeta_{t-1}\}, \lambda) &= (\frac{2}{\sqrt{2\pi}\,\sigma} \exp\{-\frac{(q_{t-1}(r_t - \mu - S/2(q_t - q_{t-1})))^2}{2\,\sigma^2}\})^{\zeta_{t-1}} \\ &\quad \times(\frac{1}{\sqrt{2\pi}\,\sigma} \exp\{-\frac{(r_t - \mu - S/2(q_t - q_{t-1}))^2}{2\,\sigma^2}\})^{(1-\zeta_{t-1})} \\ &= 2^{\zeta_{t-1}} \frac{1}{\sqrt{2\pi}\,\sigma} \exp\{-\frac{(r_t - \mu - S/2(q_t - q_{t-1}))^2}{2\,\sigma^2}\}\,. \end{aligned}$$

The joint likelihood of the return vector $r = (r_2, r_3, ..., r_T)$ is given by

$$p(r|\mu, S, \sigma, \{\zeta_{t-1}\}, \lambda) = \prod_{t=2}^{T} 2^{\zeta_{t-1}} \frac{1}{\sqrt{2\pi}\,\sigma} \exp\{-\frac{(r_t - \mu - S/2(q_t - q_{t-1}))^2}{2\,\sigma^2}\}\,.$$

A.2 Priors

We assume an uninformative (and improper) joint prior for μ, S and σ :

$$p(\mu, S, \sigma) \propto \sigma^{-2}\,.$$

We further assume that *a priori* λ follows a beta distribution. The density of the beta distribution is given by

$$p(x; \alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\,\Gamma(\beta)} x^{\alpha-1}\,(1 - x)^{\beta-1}.$$

For the prior of λ we choose $\alpha = \beta = 1$ such that the beta distribution equals a uniform distribution on $[0, 1]$. Given λ the prior for $\{\zeta_{t-1}\}_{t=2}^{T}$ is

$$p(\{\zeta_{t-1}\}|\lambda) = \prod_{t=2}^{T} \lambda^{\zeta_{t-1}}(1-\lambda)^{1-\zeta_{t-1}} = \lambda^{h}(1-\lambda)^{T-1-g-h},$$

where $h = \sum_{t=2}^{T} \zeta_{t-1}$ and $g = \sum_{t=2}^{T} q_{t-1}^2$.

A.3 Posterior

Multiplying the likelihood of the return vector with the prior densities we get the posterior density up to normalizing constant:

$$\begin{aligned} p(\mu, S, \sigma, \{\zeta_{t-1}\}, \lambda|r) &\propto \sigma^{-2}\lambda^{h}(1-\lambda)^{T-1-g-h} \prod_{t=2}^{T} 2^{\zeta_{t-1}} \frac{1}{\sqrt{2\pi}\,\sigma} \exp\{-\frac{(r_t - \mu - S/2(q_t - q_{t-1}))^2}{2\,\sigma^2}\} \\ &\propto \sigma^{-(T+1)}\lambda^{h}(1-\lambda)^{T-1-g-h} 2^{h} \exp\{-\frac{\sum_{t=2}^{T}(r_t - \mu - S/2(q_t - q_{t-1}))^2}{2\,\sigma^2}\}\,. \end{aligned}$$

This posterior density is not analytically tractable and therefore we have to use numerical tools to draw inference about the parameters of interest.

B Obtaining draws from the posterior distribution

Gibbs sampler with three blocks:

1. Draw $\mu, S, \{\zeta_{t-1}\}|\lambda, \sigma, r$ with a Metropolis-Hastings algorithm. The proposal density of $\tilde{\mu}, \tilde{S}$ at the j-th step of the Metropolis-Hastings algorithm is $N((\mu^{j-1}, S^{j-1}), V)$, where V is the inverse of the negative of the Hessian. The conditional posterior probability of $\zeta_{t-1} = 1$ given λ is

$$P(\zeta_{t-1} = 1|\lambda, r) = \frac{p(\zeta_{t-1} = 1|\lambda, r)}{p(\zeta_{t-1} = 1|\lambda, r) + p(\zeta_{t-1} = 0|\lambda, r)} = \frac{2\lambda}{2\lambda + (1-\lambda)}\,.$$

   The joint proposal density for a move from $\{\mu, S, \{\zeta_{t-1}\}\}$ to $\{\tilde{\mu}, \tilde{S}, \{\tilde{\zeta}_{t-1}\}\}$ is

$$\begin{aligned} q(\{\mu, S, \{\zeta_{t-1}\}\}, \{\tilde{\mu}, \tilde{S}, \{\tilde{\zeta}_{t-1}\}\}|\lambda, \sigma, r) &= (2\pi)^{-1}|V|^{-1/2} \\ &\times \exp\{\frac{-1}{2}((\tilde{\mu}, \tilde{S}) - (\mu, S))V^{-1}((\tilde{\mu}, \tilde{S}) - (\mu, S))'\} \\ &\times (\frac{2\lambda}{2\lambda + (1-\lambda)})^{\tilde{h}}(\frac{1-\lambda}{2\lambda + (1-\lambda)})^{T-1-g-\tilde{h}}\,. \end{aligned}$$

The proposal is accepted with probability $\min\{\alpha(\{\mu, S, \{\zeta_{t-1}\}\}, \{\tilde{\mu}, \tilde{S}, \{\tilde{\zeta}_{t-1}\}\}), 1\}$, where

$$\begin{aligned}
\alpha(\{\mu, S, \{\zeta_{t-1}\}\}, \{\tilde{\mu}, \tilde{S}, \{\tilde{\zeta}_{t-1}\}\}) &= \frac{\lambda^{\tilde{h}}(1-\lambda)^{T-1-g-\tilde{h}}2^{\tilde{h}} \exp\{-\frac{\sum_{t=2}^{T}(r_t-\tilde{\mu}-\tilde{S}/2(q_t-q_{t-1}))^2}{2\,\sigma^2}\}}{\lambda^{h}(1-\lambda)^{T-1-g-h}2^{h} \exp\{-\frac{\sum_{t=2}^{T}(r_t-\mu-S/2(q_t-q_{t-1}))^2}{2\,\sigma^2}\}} \\
&\times \frac{\exp\{-1/2((\mu,S)-(\tilde{\mu},\tilde{S}))V^{-1}((\mu,S)-(\tilde{\mu},\tilde{S}))'\}}{\exp\{-1/2((\tilde{\mu},\tilde{S})-(\mu,S))V^{-1}((\tilde{\mu},\tilde{S})-(\mu,S))'\}} \\
&\times \frac{(\frac{2\lambda}{2\lambda+(1-\lambda)})^{h}(\frac{1-\lambda}{2\lambda+(1-\lambda)})^{T-1-g-h}}{(\frac{2\lambda}{2\lambda+(1-\lambda)})^{\tilde{h}}(\frac{1-\lambda}{2\lambda+(1-\lambda)})^{T-1-g-\tilde{h}}} \\
&= \frac{\exp\{-\frac{\sum_{t=2}^{T}(r_t-\tilde{\mu}-\tilde{S}/2(q_t-q_{t-1}))^2}{2\,\sigma^2}\}}{\exp\{-\frac{\sum_{t=2}^{T}(r_t-\mu-S/2(q_t-q_{t-1}))^2}{2\,\sigma^2}\}}.
\end{aligned}$$

2. Draw $\lambda|\mu, S, \{\zeta_{t-1}\}, \sigma, r$ from a beta$(h+1, T-1-g-h+1)$ distribution.

3. Draw $\sigma|\mu, S, \{\zeta_{t-1}\}, \lambda, r$ with a M-H algorithm. The proposal density of a move from σ to $\tilde{\sigma}$ is the scaled inverse χ^2-distribution:

$$q(\sigma, \tilde{\sigma}) = \frac{((T-1)/2)^{(T-1)/2}}{\Gamma((T-1)/2)}\sigma^{T-1}\tilde{\sigma}^{-(T+1)}\exp\{\frac{-(T-1)\sigma^2}{2\tilde{\sigma}^2}\}.$$

The probability that proposal $\tilde{\sigma}$ is accepted is then given by $\min\{\alpha(\sigma, \tilde{\sigma}), 1\}$, where

$$\begin{aligned}
\alpha(\sigma, \tilde{\sigma}) &= \frac{\tilde{\sigma}^{-(T+1)}\exp\{-\frac{\sum_{t=2}^{T}(r_t-\mu-S/2(q_t-q_{t-1}))^2}{2\,\tilde{\sigma}^2}\}}{\sigma^{-(T+1)}\exp\{-\frac{\sum_{t=2}^{T}(r_t-\mu-S/2(q_t-q_{t-1}))^2}{2\,\sigma^2}\}} \\
&\times \frac{\tilde{\sigma}^{T-1}\sigma^{-(T+1)}\exp\{\frac{-(T-1)\tilde{\sigma}^2}{2\sigma^2}\}}{\sigma^{T-1}\tilde{\sigma}^{-(T+1)}\exp\{\frac{-(T-1)\sigma^2}{2\tilde{\sigma}^2}\}} \\
&= \frac{\exp\{-\frac{\sum_{t=2}^{T}(r_t-\mu-S/2(q_t-q_{t-1}))^2}{2\,\tilde{\sigma}^2}\}\tilde{\sigma}^{T-1}\exp\{\frac{-(T-1)\tilde{\sigma}^2}{2\sigma^2}\}}{\exp\{-\frac{\sum_{t=2}^{T}(r_t-\mu-S/2(q_t-q_{t-1}))^2}{2\,\sigma^2}\}\sigma^{T-1}\exp\{\frac{-(T-1)\sigma^2}{2\tilde{\sigma}^2}\}}.
\end{aligned}$$

C Model choice

We test our model against the alternative where $\lambda = 0$ and consequently all ζ_{t-1}, for $t = 2, ..., T$ are zero. Model 1 is the unrestricted model ($\lambda > 0$) and model 2 is the restricted ($\lambda = 0$) model. All parameters of model $i \in \{1, 2\}$ are grouped into the set θ_i. The posterior odds ratio of the two models is

$$\frac{Pr(M_1|y)}{Pr(M_2|y)} = \frac{Pr(M_1)}{Pr(M_2)}\frac{\int p(r|\theta_1, M_1)\,p(\theta_1|M_1)\,d\theta_1}{\int p(r|\theta_2, M_2)\,p(\theta_2|M_2)\,d\theta_2}.$$

We assume equal prior probabilities for the two models and, thus, the posterior odds ratio is the ratio of the marginal likelihoods of the two models, also called the Bayes factor. Note that the marginal likelihood is the (inverse of) the normalising constant and therefore in order to find the model that better explains the data we have to calculate the ratio of two normalising constants. From the many methods available to tackle this problem, we choose iterative bridge sampling proposed by Meng and Wong (1996).

Let w_{ij} for $j = 1, ..., n_i$ be the generated draws of model i and $s_i = n_i/(n_1 + n_2), i \in \{1, 2\}$. Define $l_{ij} = q_1(w_{ij})/q_2(w_{ij})$, where $q_i(\,)$ is the (unnormalised) posterior density of model i . Meng and Wong (1996) show that the following iterative method converges to the desired ratio of normalising constant, and hence, the posterior odds ratio:

$$\hat{r}_O^{(t+1)} = \frac{\frac{1}{n_2}\sum_{j=1}^{n_2}(\frac{l_{2j}}{s_1 l_{2j} + s_2 \hat{r}_O^{(t)}})}{\frac{1}{n_1}\sum_{j=1}^{n_1}(\frac{1}{s_1 l_{1j} + s_2 \hat{r}_O^{(t)}})} \tag{13}$$

References

Amihud, Y., H. Mendelson and B. Lauterbach (1997): "Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange," *Journal of Financial Economics*, 45, 365–390.

Brooks, R. and T. Su (1997): "A simple cost reduction strategy for small liquidity traders: Trade at the opening," *Journal of Financial and Quantitative Analysis*, 32, 525–540.

Cason, T. N. and D. Friedman (1997): "Price formation in single call markets," *Econometrica*, 65, 311–345.

Choi, J. Y., D. Salandro and K. Shastri (1988): "On the estimation of bid-ask spreads: Theory and evidence," *Journal of Financial and Quantitative Analysis*, 23(2), 219–230.

Easley, D., S. Hvidkjaer and M. O'Hara (2002): "Is information risk a determinant of asset returns?," *Journal of Finance*, 57(5), 2185–2221.

Easley, D., N. M. Kiefer and M. O'Hara (1993): "One day in the life of a very common stock," *working paper, Cornell University.*

Easley, D., N. M. Kiefer, M. O'Hara and J. B. Paperman (1996): "Liquidity, information, and infrequently traded stocks," *Journal of Finance*, 51(4), 1405–1436.

Economides, N. and R. A. Schwartz (1995): "Electronic call market trading," *Journal of Portfolio Management*, 21(3), 10–18.

Ellul, A., H. S. Shin and I. Tonks (2005): "Opening and closing the market: Evidence from the London Stock Exchange," *Journal of Financial and Quantitative Analysis*, 40(4), 779–801.

Finucane, T. J. (2000): "A direct test of methods for inferring trade direction from intra-day data," *Journal of Financial and Quantitative Analysis*, 35, 553–576.

Foucault, T. (1999): "Order flow composition and trading costs in a dynamic limit order market," *Journal of Financial Markets*, 2, 99–134.

George, T. J., G. Kaul and M. Nimalendran (1991): "Estimation of the bid-ask spread and its components: A new approach," *Review of Financial Studies*, 4(4), 623–656.

Glosten, L. R. and P. R. Milgrom (1985): "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders," *Journal of Financial Economics*, 13, 71–100.

Haller, A. and H. R. Stoll (1989): "Market structure and transaction costs: Implied spreads in the German stock market," *Journal of Banking and Finance*, 13, 697–708.

Handa, P., R. A. Schwartz and A. Tiwari (2003): "Quote setting and price formation in an order driven market," *Journal of Financial Markets*, 6(4), 461–489.

Hasbrouck, J. (2009): "Trading costs and returns for U.S. equities: Estimating effective costs from daily data," *Journal of Finance*, 64(3), 1445–1477.

Ho, T. S. Y., R. A. Schwartz and D. K. Whitcomb (1985): "The trading decision and market clearing under transaction price uncertainty," *Journal of*

Finance, 40(1), 21–42.

JONG, F. D., T. NIJMAN AND A. RÖELL (1996): "Price effects of trading and components of the bid-ask spread on the Paris Bourse," *Journal of Empirical Finance*, 3, 193–213.

KASCH-HAROUTOUNIAN, M. AND E. THEISSEN (2009): "Competition between exchanges: Euronext versus Xetra," *European Financial Management*, 15(1), 181–207.

KEHR, C.-H., J. P. KRAHNEN AND E. THEISSEN (2001): "The anatomy of a call market," *Journal of Financial Intermediation*, 10(3), 249–270.

LAUTERBACH, B. (2001): "A note on trading mechanism and securities' value: The analysis of rejects from continuous trade," *Journal of Banking and Finance*, 25, 419–430.

MADHAVAN, A. (1992): "Trading mechanisms in securities markets," *Journal of Finance*, 47(2), 607–641.

——— (1996): "Security prices and market transparency," *Journal of Financial Intermediation*, 5, 255–283.

MADHAVAN, A. AND V. PANCHAPAGESAN (2000): "Price discovery in auction markets: A look inside the black box," *Review of Financial Studies*, 13(3), 627–658.

MENDELSON, H. (1982): "Market behavior in a clearing house," *Econometrica*, 50(6), 1505–1524.

MENG, X.-L. AND W. H. WONG (1996): "Simulating ratios of normalizing constants via a simple identity: A theoretical exploration," *Statistica Sinica*, 6, 831–860.

MUSCARELLA, C. J. AND M. S. PIWOWAR (2001): "Market microstructure and securities values: Evidence from the Paris Bourse," *Journal of Financial Markets*, 4, 209–229.

PAGANO, M. AND A. RÖELL (1996): "Transparency and liquidity: A comparison of auction and dealer markets with informed trading," *Journal of Finance*, 51(2), 579–611.

PAGANO, M. S., L. PENG AND R. A. SCHWARTZ (2008): "The quality of price formation at market openings and closings: Evidence from the Nasdaq Stock Market," Cfs working paper no. 2008/45.

PAGANO, M. S. AND R. A. SCHWARTZ (2003): "A closing call's impact on market quality at Euronext Paris," *Journal of Financial Economics*, 68, 439–484.

ROLL, R. (1984): "A simple implicit measure of the effective bid-ask spread in an efficient market," *Journal of Finance*, 39(4), 1127–1139.

RUSTICHINI, A., M. A. SATTERTHWHAITE AND S. R. WILLIAMS (1994): "Convergence to efficiency in a simple market with incomplete information," *Econometrica*, 62, 1041–1063.

SATTERTHWHAITE, M. A. AND S. R. WILLIAMS (1993): "The bayesian theory of the k-double auction," in *The Double Auction Market. Institutions, Theories, and Evidence*, ed. by D. Friedman, and J. Rust, pp. 99–124, Reading, Massachusetts. Addison-Wesley.

STOLL, H. R. AND R. E. WHALEY (1990): "Stock market structure and volatility," *Review of Financial Studies*, 3(1), 37–71.

THEISSEN, E. (2000): "Market structure, informational efficiency and liquidity: An experimental comparison of auction and dealer markets," *Journal of Financial Markets*, 3, 333–363.

VENKATARAMAN, K. AND A. C. WAISBURD (2007): "The value of the designated market maker," *Journal of Financial and Quantitative Analysis*, 42(3), 735–758.