Price Discovery in the Pre-Opening Period. Theory and Evidence from the Madrid Stock Exchange

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Abstract

Some stock exchanges, such as the Spanish Stock Exchange and Euronext (Paris), allow traders to place orders in a 'pre-opening' period. Orders placed in this period are used to determine the opening price, and can be cancelled at any moment and at no cost by the traders. We consider a model in which noise traders can appear in the market before or after the opening, and a strategic informed trader decides her order strategy at the preopening and at the opening period. We characterize the equilibrium of such a model, showing that at the pre-opening there is a non-monotonic relation between the aggregate quantity ordered and prices. Thus, the equilibrium at the preopening stage is determined in a way which is fundamentally different from the equilibrium in the open market. We proceed to study the implications of the existence of a pre-opening period on information revelation and on the determination of the opening price. We present evidence from the Spanish Stock Exchange that seem to support the theoretical predictions, showing a clear difference in behavior between the market behavior before and after the opening of the market.

1 Introduction

Various stock exchanges (e.g. Madrid and Paris) have a phase of 'price discovery' in which agents place tentative orders and tentative prices are

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quoted. The orders placed in this phase are not binding, since they can be cancelled at no cost at any point before the official opening. The preopening phase is usually quite active and many of the orders placed turn out to be serious orders (see Biais, Hillion and Spatt (1999) for evidence from the Paris Bourse). It is usually thought that the preopening phase helps markets to ‘find the right price’ at the opening, making public the information accumulated during the no-trade period. Yet, from the theoretical point of view it is not clear why this should be the case. In particular, since orders placed in the pre-opening phase are non-binding, the first question one has to answer is: Why do agents bother to place orders at all? In particular, it appears that informed agents should be reluctant to place any order that could reveal their information.

One way to overcome the difficulty is to assume that an order placed during the pre-opening period has a strictly positive probability, although possibly very low, of being executed. This may occur either because the opening time of the market is stochastic, so that there is always a positive probability that an order will be the final one, or because problems in communication may prevent the trader from cancelling the order. The approach has first been proposed by Vives (1995a, 1995b), who considers competitive models in which a continuum of traders place limit orders. Biais, Hillion and Spatt (1999) and Medrano and Vives (2001) have introduced the presence of a strategic informed trader, who takes into account the effect of her orders on information disclosure. In this class of models, agents place orders in the preopening phase because there is a positive probability that the order will be the final one. Thus, in order to exploit their superior information, informed traders place meaningful orders. However, their orders will be more ‘restrained’ than in the case in which trade occurs with probability 1. The reason is that by placing orders an informed trader reveals information, and this reduces future profits if trade does not occur in the current period.

In this paper we propose a different approach, not relying on a random opening time. Our basic intuition is that in a market in which both informed and noisetraders are present, the preopening period provides, as a minimum, a signal on the extent of noise trading.

Consider a simple two period model, in which agents place orders at the preopening period and at the ‘open market’ period. Orders at the preopening period are essentially cheap talk, since they can be cancelled at no cost; if not cancelled, they are executed when the market opens. Orders placed when the market is open are executed immediately. Suppose now that noise traders arrive randomly at the market, and that noise traders who place an
order at the preopening period do not cancel it. Can there be an equilibrium in which the informed trader is not active at the preopening period? The answer is no. If only noise traders appear at the preopening, then the order flow of the preopening provides a signal of the extent of noise trading, and this signal is taken into account when setting the price at the opening. For example, if a market maker observes a large demand at the preopening, then she will be inclined to believe that a large demand in the open market is mostly the result of noise, rather than the consequence of strategic behavior on the part of the noise trader. This in turn makes the price less sensitive to the order flow. But this situation cannot be an equilibrium. An informed trader who receives good news on the asset, so that she is likely to buy the asset when the market opens, will want to increase the estimate of noise trading made by the market maker. Thus, she places orders at the preopening. But this contradicts the original assumption that only noise trading is active at the preopening.

The previous argument implies that any equilibrium must see the active participation of the informed trader at the preopening period, even if there is no positive probability that the market will execute the orders. This in turn implies that the order flow at the preopening provides a signal both about the extent of noise trading and the value of the asset. It turns out however that, differently from what happens when the market is open, the relation between the order flow at the preopening period and the value of the asset is not monotonic. This is a consequence of the fact that at the preopening period the informed trader has no incentive to reveal its information. The only reason why she is in the market is to garble the message about liquidity trading, revealing as little as possible of her information. We will show that a monotonic strategy (that is, a strategy in which the informed agent places higher orders when the value of the signal is higher) cannot be part of an equilibrium, which in turn implies that the relation between the value of the asset and the order flow cannot be monotonic. To sum up, our theoretical model predicts a quite different behavior at the preopening phase and at the open market, and a non-monotonic relation between the value of the asset and the order flow at the preopening.

We test the predictions of the theoretical model using data from the electronic continuous market used in Spain for equity trading, known by the Spanish acronym SIBE (Sistema de Interconexión Bursatil Español). We have limit order book data over a month for the 35 most actively traded stocks in the market, both in the pre-opening phase and in the first 15 minutes of the open market. For each stock we can observe at each moment
the equilibrium price and quantity as well as part of the demand and supply curve. This data can be used to check whether market behavior is different before and after the preopening of the market. We also have closing prices for stocks, that we can use to proxy for the value of the asset and check for the relation between asset value and prices and volume at the preopening phase. Results seem to support the theoretical predictions, showing a clear difference in market behavior depending on the timing of preopening and after the opening of the market.

2 The Model

There is a risky asset which can take a finite number of values:

\[ V = v_1; \ldots; v_k \]

with \( v_i < v_{i+1} \) for \( i = 1; \ldots; K - 1 \). The prior probability distribution of the value of the asset is given by \( \pi = \pi_1; \ldots; \pi_K \), with \( \pi_i \) being the probability that the asset will take value \( v_i \) and \( \pi_i > 0 \) each \( i \).

We will assume that trading activity takes place over two periods, structured as follows:

Preopening period During this period agents place market orders. The total orders are collected by a market maker, and the net amount is made public. No trading takes place at this point. We will use the subscript \( T \) (temporary) to refer to the preopening period.

Opening period During this period agents again place market orders. Orders placed at the preopening period are considered valid orders, unless explicitly cancelled. A market maker observes the total order flow and determines the price, setting it equal to the expected value of the asset. Orders are executed, and each agent pays (receives) the price multiplied by the order placed. We will use the subscript \( F \) (final) to refer to the opening period.

There are two types of traders in the market. The first is an informed speculator. This speculator observes the value of the asset before the preopening period. We denote by \( x_T \) the order placed by the informed trader at the preopening period, and by \( x_F \) the order placed at the opening period\footnote{For the sake of simplicity we assume that the informed trader cancels the order placed...}. We will
assume that orders have to belong to a finite set \( X = \{x_1, \ldots, x_n\} \), where each \( x_i \) is an integer number. This is equivalent to assume that orders have to be a multiple of a given minimum quantity, and there is a bound on the total amount that can be ordered. We also assume \( 0 \leq X \leq x_n \). We denote by \( \mathcal{X} \) the \( n \)-dimensional simplex, that is the space of all probability distribution on \( X \).

Beside the informed trader we have noise traders, who can place their orders both at the preopening and at the opening period. The number of noise traders is random, and each noise trader places a order of size 1 or \(-1\). The total amount ordered by noise traders at the preopening period can be represented as a random variable \( u_T \), with support on the set of integers \( \mathbb{Z} = \{-1, 0, 1, \ldots\} \) and probability distribution \( q = \{q_{-1}, q_0, q_1, \ldots\} \), with \( q_i > 0 \) for each \( i \in \mathbb{Z} \) and \( \sum_{i=-1}^{\infty} q_i = 1 \).

Similarly, the order placed by noise traders at the opening is represented by a random variable \( u_F \), with support on \( \mathbb{Z} \) and probability distribution \( w = \{w_{-1}, w_0, w_1, \ldots\} \), with \( w_i > 0 \) for each \( i \in \mathbb{Z} \) and \( \sum_{i=-1}^{\infty} w_i = 1 \).

We will assume that noise traders who place an order at the preopening period always confirm the order at the opening period. The total noise order placed at the opening period is therefore \( u_T + u_F \). We will denote by \( z_T = x_T + u_T \) the order flow observed at the preopening period and by \( z_F = x_F + u_T + u_F \) the order flow observed at the opening period.

Notice that the variable \( z_T \) is publicly observed before the beginning of the opening period, and the set of all possible orders observable at the preopening period and at the opening period is the set of integers \( \mathbb{Z} \).

A rational expectation equilibrium of this game is given by:

\[ p : \mathbb{Z} \to [v_1, v_K], \]
\[ \pi : \mathbb{Z} \to \mathcal{X}, \]

where \( p(z_T; z_F) \) is the price set when the order flow \( z_T \) is observed at the preopening period and the order flow \( z_F \) is observed at the opening period;

\[ \pi(u_T; z_T; v_i) \]

denotes the probability distribution on \( \mathcal{X} \) adopted by the informed trader who has

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2 This assumption is not essential. All we need is that there is a noise component in the preopening period, and that this noise is not independent of noise trading at the opening period.
observed \( v_i \), an order \( z_T \) at the preopening and a noise order \( u_T \) at the preopening period\(^2\);

\(^2\) a function \( \pm: V \rightarrow \mathbb{R}^n \), where \( \pm(v_i) \) denotes the probability distribution on \( X \) adopted by the informed trader upon observing \( v_i \);

satisfying the following properties:

\(^2\) The price function \( p(z_T;z_F) \) is given by:

\[
p(z_T;z_F) = \mathbb{E}[e^{v_T x_T + u_T + u_F}] = \mathbb{E}[e^{v_T x_T + u_T + u_F}] = \mathbb{E}[e^{v_T x_T + u_T + u_F}]
\]

that is \( p(z_T;z_F) \) is the conditional expected value of the asset given the observed order flows, where the expectation is taken making use of the probability distributions \( \pm \) and \( \ » \);

\(^2\) for each triplet \((u_T;z_T;v_i)\) the probability distribution \( »(u_T;z_T;v_i) = (»_1;\ldots;»_n) \) is such that \( »_i > 0 \) only if:

\[
x_i \in \arg\max_{x_F \in X} \mathbb{E}[(v_i \cdot p(z_T;x_F + u_T + u_F)) x_F]
\]

that is an order is placed with positive probability only if it maximizes the expected profit of the informed trader, where the expectation is conditional on the informed trader’s information \((u_T;z_T;v_i)\);

\(^2\) for each \( v_i \), the probability distribution \( \pm(v_i) = (\pm_1;\ldots;\pm_n) \) is such that \( \pm > 0 \) only if:

\[
x_T \in \arg\max_{x_F \in X} \mathbb{E}[(v_i \cdot p(x_T + u_T;x_F (\mathbb{E}_T;x_T + u_T;v_i) + u_T + u_F)) x_F (\mathbb{E}_T;x_T + u_T;v_i)]
\]

where \( x_F (x_T + u_T;u_T;v_i) \) \( \supp(»(u_T;x_T + u_T;v_i)) \) for each triplet \((u_T;x_T + u_T;v_i)\), that is an order \( x_i \) is placed with positive probability only if it maximizes the expected profit, taking into account the optimal policy of the informed trader at the opening period and conditioning on the known value \( v_i \).

We first show that a rational expectation equilibrium exists. The strategy of the informed trader can be described as follows:

\(^2\) The informed trader observes the preopening order flow \( z_T \) and knows the part of the order due to its own order \( x_T \). She can therefore compute the demand coming from noise traders as \( u_T = z_T - x_T \).
The strategy at the preopening period is a collection $(±(v_i); \ldots; ±(v_K))$, where for each $v_i$, we have $±(v_i) \in \mathbb{R}$. It can therefore be described as an element of the set $\mathbb{R}^K$. We will adopt the notation $i = ±(v_i)$, and we let $i$ denote a generic element of $i$.

The strategy at the opening can be described as a collection

\[ f = (u_T; z_T; v_i)g(u_T; z_T) \in \mathbb{R}^* \]

where for each triplet $(u_T; z_T; v_i)$ we have $f = (u_T; z_T; v_i) \in \mathbb{R}$. Call $\mathcal{E}$ the set of all possible collections, that is each element $A \in \mathcal{E}$ is a (countable) list of probability distributions over $X$, one for each possible triplet $(u_T; z_T; v_i)$ $\in \mathbb{R}^*$. The set $\mathcal{E}$ represents the set of all possible strategies at the opening period. It is a convex and compact set.

Let $\mathcal{S} = \mathcal{E} \cap \mathcal{E}$ the strategy space of the informed trader, a compact and convex set. Define next the space $\mathcal{P}$ of all possible price functions, that is $\mathcal{P}$ is the set of all sequences $p(u_T; z_T; v_F) \in \mathbb{R}^*$ such that $p(u_T; z_T; v_F) \in [v_1; v_K]$ for each pair $(u_T; z_T)$, and again observe that this is a compact and convex set.

Define now the correspondence:

\[ p: \mathcal{S} \to \mathcal{P} \]

as:

\[ p' = E^i [w_j (v_i + u_T + u_T + u_T + u_F = z_T)] \]

that is, for each element $i = (\theta; \tilde{A})$ the function $p$ selects, for each pair $(z_T; z_F)$ the expected value of $v$ given that the informed agent uses the strategy described by $\theta$ at the pre-opening period and the strategy described by $\tilde{A}$ at the opening period. Notice that since both $u_T$ and $u_F$ have support on $Z$ and the set $X$ of orders by the informed trader is finite, every pair $(z_T; z_F)$ has positive probability under any strategy $i$, so that the conditional expectation is always well defined.

Given a price function $p$, the expected profit for the informed trader who has observed $(u_T; z_T; v_i)$ and chosen $x_F$ is given by:

\[ \mathbb{E} (x_F; p' (u_T; z_T; v_i)) = \sum_{j \in Z} w_j (v_i \cdot p(z_T; u_T + j + x_F)) x_F \]

\[ ^{4}\text{See e.g. Royden (1988), chapter 7, exercise 30.} \]
where \( w_j = \Pr(u_F = j) \). Let \( \pi \in \pi^n \) be a probability distribution over \( X \), with \( \pi(x_F) \) denoting the probability of choosing \( x_F \). Define:

\[
\rho \left( \pi; p_j \left( u_T, z_T; v_i \right) \right) = \max_{x_F \in X_F} \pi(x_F) \max_{x_F \in X_F} \left( x_F ; p_j \left( u_T, z_T; v_i \right) \right).
\]

Let \( \hat{A} = \left( u_T, z_T; v_i \right) q_{u_T} z_T 2 Z E z_T 2 V 2 \) represent a policy followed by the informed trader at the opening period. For a given policy \( \hat{A} \) we set

\[
\rho \left( \hat{A}; p_j \left( u_T, z_T; v_i \right) \right) = \rho \left( \pi \left( u_T, z_T; v_i \right) ; p_j \left( u_T, z_T; v_i \right) \right)
\]

Next, define the function \( \bar{\rho} \left( x_T; \hat{A}; p_j v_i \right) \) as:

\[
\bar{\rho} \left( x_T; \hat{A}; p_j v_i \right) = \max_{j \in Z} q_j \rho \left( \hat{A}; p_j \left( j; x_T + j; v_i \right) \right)
\]

where \( q_j = \Pr \left( u_T = j \right) \). For a probability distribution \( \pi = (\pi_1; \cdots; \pi_n) \) over \( X \) we define:

\[
\bar{\rho} \left( \pi \hat{A}; p_j v_i \right) = \max_{k=1}^{X_0} \pi_k \rho \left( \hat{A}; p_j \left( x_k; \hat{A}; p_j v_i \right) \right)
\]

where \( \pi_k \) is the probability of choosing \( x_k \). Define the collection \( \otimes = (\otimes_1; \cdots; \otimes_k) \), where \( \otimes_k \) denotes the probability distribution over \( X \) chosen at the preopening when the observed value of the asset is \( v_i \). We define:

\[
\rho \left( \otimes; \hat{A}; p \right) = \max_{i=1}^{X_0} \Pr \left( v_i \right) \rho \left( \otimes_i; \hat{A}; p_j v_i \right)
\]

and setting \( \pi = \left( \otimes; \hat{A} \right) \) we are going to use the more compact notation \( \rho \left( \pi; p \right) \). We now define the correspondence:

\[
\mu: \Pi \rightarrow \Pi
\]

as:

\[
\mu(p) = \arg \max_{\pi} \rho \left( \pi; p \right)
\]

For each price function \( p \) the correspondence \( \mu \) selects the set of profit-maximizing trading strategies for the informed trader.

We can now prove the existence of a rational expectations equilibrium.

**Proposition 1** A rational expectation equilibrium exists.
Proof. Since \( \mu(p;\sigma) \) is continuous in \((p;\sigma)\), the theorem of the maximum ensures that the correspondence \( \mu \) is u.h.c. and compact-valued. Linearity in \( \sigma \) ensures that the correspondence is convex-valued. Similarly, the mapping \( p \) is continuous, convex and compact valued. Therefore, by Kakutani’s theorem, the mapping:

\[ \mu \mathbb{E} p : \mathbb{E} P ! - \mathbb{E} P \]

has a fixed point. Given the definitions of \( \mu \) and \( p \), the fixed point is a rational expectations equilibrium.

2.1 Characterization of the equilibrium

Once the existence of the equilibrium has been established, we can proceed to characterize its properties. We remind the reader that a function \( f(x;t) \) satisfies increasing differences if whenever \( t_0 > t \), the difference \( f(x;t) \) increases in \( x \). Consider now the function \( \mu(p;\sigma(u_T;z_T;v_i)) \). For a given price function \( p \) and observation \((u_T;z_T)\) this can be seen as a function of \( \sigma \) and \( v_i \). The variable \( \sigma \) belongs to \( \mathcal{C}^\mathbb{E} \), the space of probability distributions over \( X \). We order \( \mathcal{C}^\mathbb{E} \) using the criterion of first order stochastic dominance (FOSD), that is \( \sigma \sigma' \) if \( \sum_{i=1}^{r_n} \mathbb{E}(x_i) \) for each \( r_n \). We have the following result about the strategy of the informed trader at the opening.

Lemma 1 For a given price function \( p \) and observation \((u_T;z_T)\) let \( \sigma^\mathbb{E} \) be an optimal strategy chosen when the observed value of the asset is \( v_i \). Then the strategy of the informed trader at the opening is increasing in \( v_i \) in the sense of first order stochastic dominance.

Proof. Take as given \( p \) and \((u_T;z_T)\), and define \( \sigma(p;\sigma(u_T;z_T;v_i)) \). The objective function of the informed trader is given by:

\[
    f(\sigma;v_i) = \sum_{j=1}^{\mathbb{X}^n} \mathbb{E}_j (p(z_t;u_T+\mathbb{B}_F + x_j)) x_j
\]

where the expectation is taken over \( \mathbb{B}_F \). Therefore, if we take \( v_k > v_i \) we have:

\[
    f(\sigma;v_k) - f(\sigma;v_i) = (v_k - v_i) \sum_{j=1}^{\mathbb{X}^n} x_j
\]
Since $v_k > v_i > 0$, this difference is increasing in $v$. Since the objective function satisfies increasing differences, the optimal action $>(v_i)$ is non-decreasing in $v_i$.

We can use lemma 1 to provide a first characterization of the price function.

**Lemma 2** In each rational expectations equilibrium the price function $p(z_T; z_F)$ is non-decreasing in $z_F$ for each given $z_T$.

**Proof.** For each given $u_T$, lemma 1 implies $E_v [v_j z_T; z_0 F; u_T]$, $E_v [v_j z_T; z_F; u_T]$ whenever $z_0 F > z_F$. This in turn implies:

$$p(z_T; z_0 F) = E_{u_T} E_v [v_j z_T; z_0 F; u_T] = E_{u_T} E_v [v_j z_T; z_F; u_T] = p(z_T; z_F)$$

The properties of the price function described in lemma 2 are standard. The informed trader wants to increase the size of its order when she obtains better information, so that the market maker interprets an increase in the order flow as a noisy signal of the value of the assets. This leads to a function $p$ increasing in $z_F$.

The more interesting part however is the characterization of the equilibrium at the preopening stage. We start observing that in general at the preopening stage the informed trading must be active, meaning that she chooses different strategies in dependence of different observed values of the asset.

**Lemma 3** There is no equilibrium in which the informed agent follows a constant policy at the preopening period.

**Proof.** Suppose first that the informed agent always selects the same quantity $x^*$ for each value $v_i$, and assume that $x^* > x_1$, where $x_1$ is the lowest possible order. This implies that for every order flow $z_T$ at the preopening period the market maker is able to infer exactly the amount of noise trading as $u_T = z_T - x^*$.

Consider now the informed agent who has observed $v_1$, the lowest possible value of the asset. This trader will only post negative orders at the opening period, since $p(z_T; z_F) > v_1$ for each realization $(z_T; z_F)$. This implies that in this case the informed agent wants to obtain a price at the opening which is as high as possible. This in turn implies that she wants to convince the market maker that the demand at the opening comes mostly
from the informed trader, and liquidity demand is low. Finally, this implies that upon observing \( v_1 \) the informed agent can profitably deviate from \( x^a \) to \( x_1 \), the lowest possible order.

If \( x^a = x_1 \) then we can apply a similar argument to show that the informed trader has a profitable deviation when the highest possible value \( v_K \) for the asset is observed.

The argument can be directly extended to mixed strategies. If the same mixed strategy is being used by the informed trader for each \( v_i \) then the order flow \( z_T \) is considered by the market maker as a noisy signal of \( u_T \), with no information about the value of the asset. Then the informed agent who has observed \( v_1 \) can profitably deviate to \( x_1 \), while the informed agent who has observed \( v_K \) can profitably deviate to \( x_n \).

The lemma implies that in every equilibrium there is non-trivial action at the preopening stage by the informed trader. By this we mean that the informed trader intervenes at the pre-opening stage selecting different strategies depending on the information possessed.

The next observation is that in a rational expectations equilibrium the informed trader does not select a monotonic strategy at the preopening period.

**Lemma 4** There is no equilibrium in which the informed agent adopts a monotonically increasing policy at the preopening period.

**Proof.** (Sketch) Suppose that the informed agent selects a monotonically increasing strategy, so that \( \pm \) dominates \( \pm' \) in the sense of first order stochastic dominance whenever \( v_i > v_j \). We first observe that in this case, given two order flows \( z_0^T > z_T \), the conditional probability distribution of \( v \) given \( z_0^T \) first-order stochastically dominates the conditional probability distribution of \( v \) given \( z_T \). This follows from the fact that \( z_T \) is a noisy signal of \( x_T \), which in turn is a noisy signal of \( v \).

Next we observe that the informed trader who has observed \( v_K \), the highest possible value, prefers that the conditional distribution of the market maker be as low as possible in a FOSD sense, while the informed trader who has observed \( v_1 \) has preferences which are exactly the opposite. The reason is that the only way in which it can be worse for type \( v_K \) that the market maker has a lower estimate of \( v \) is that in this case the market maker forecasts a more aggressive bidding by the informed trader, so that the price function is more sensitive to \( z_T \). This would prevent the informed trader from placing larger orders at the opening. But a more aggressive belief
cannot be self-confirming, because in this case the informed trader would be less aggressive.

This implies that type \( v_k \) will want to deviate and adopt at the pre-opening stage a strategy adopted by lower types, in order to induce a lower price at the opening. An analogous deviation is available for type \( v_1 \).

What are the empirical predictions of the model presented in this section? The existence of the preopening period provides information which is valuable for the determination of the price at the opening, since it provides a signal on the extent of liquidity demand. The informed trader tries to manipulate this signal, taking advantage of the fact that the orders placed in this phase are basically `cheap talk' and can be cancelled at no cost.

In equilibrium however the relation between the total order flow and the extent of liquidity trading cannot be monotonic. If this were the case, an informed trader who has a high probability of being on the buying side at the opening (which happens when a high value of \( v \) is observed) would place a high order, so to convince the market maker that most of the demand comes from liquidity traders. However, in a rational expectation equilibrium this maneuvering cannot occur, since the market maker would consider a high level of demand at the preopening as a signal of a high value of the asset.

If a price is computed at the pre-opening stage, and the price is set equal to expected value of the asset, then the preopening price will not have a monotonic relation with the asset's value. The monotonic relation is restored when the market opens, since in this case orders are executed and the only way in which an informed trader can take advantage of her information is by following an order strategy monotonically related to the asset value.

3 Empirical Analysis

In this section we provide a description of the institutional features of the Spanish stock market and of the data we plan to use for the empirical analysis.

3.1 Institutional Organization of the Spanish Stock Market

The market for equities in Spain (SIBE) is organized as an electronic continuous market. It is a nationally unified market, in which a single order book
exists for each stock. During the period object of the analysis (November 1999) a day of trade was divided into three parts:

1. **Preopening period**, from 9:00 am to 10:00 am. In this period modifications, cancellations and introduction of limit orders are allowed. Depending on demand and supply on every stock the system calculates in real time a preopening price; when there are multiple equilibrium prices, the one that maximizes the volume traded is chosen.

   At 10:00 am the system determines the opening price. Orders entered previously and not cancelled are now executed. Priority is first by price and then by time of introduction.

2. **Open Market period**, from 10:00 am to 17:00 pm. In this period limit and market orders are introduced and if a counterpart is found they are automatically executed. If not, the order remains in the book until an incoming order fits it, or the order is cancelled. In this period prices of the stocks are changing in real time depending on the flow of buy and sell orders.

3. **Special Operations period**, from 17:30 pm to 20:00 pm. During this period pre-agreed block trades are reported.

The market is still organized in this way, but now the preopening period runs from 8:30 am to 9:00 am and the open market period runs from 9:00 am to 17:30 pm.

The open market is an order driven market. De Jong, Nijman and Röell (1996), among others, point out that trading mechanism operating in markets driven by orders can be formally described by the ideal electronic open limit order book framework proposed by Glosten (1994). Glosten (1994) theoretical model shows how information flow cause price revisions by trading throughout the limit order book mechanism. Glosten develops both average and marginal price functions from the point of view of the agent providing liquidity. These functions are supply and demand functions. From the empirical point of view Martinez, Rubio and Tapia (2000) and Blanco (1999) discusses similar functions, and construct supply and demand functions. These analysis are developed in an open market situation but give us insights about the information that should be present in supply and demand functions.

The pre-opening period is similar to the open market trading mechanism, with the important difference that during the pre-opening period there is no
transaction and orders are left unmatched. However, during the preopening period the Exchange uses the order to determine in real time the equilibrium price and the quantity traded at that price. So, whenever an order is cancelled, modified or a new order arrives the equilibrium price and quantity are changed. The opening price is set at 10:00, and the transactions are actually carried on.

3.2 Data and Methodology

The open limit order book contains information about the five best prices on the selling and buying side for all assets.

Table 1 shows the situation for one asset at two successive moments right before the opening of the market and right after the opening of the market on November 1, 1999. The book (including prices, volume of shares outstanding at that price and number of orders which supports such volume) was observable by market participants at every moment during the preopening and the open market period. Investors were also able to observe the equilibrium price. Furthermore, whenever a new order is entered the limit order book shows the new values of the variables, while the time stamp indicates exactly the time of this change (approximated by tenths of a second).

In November 1999 the SIBE included approximately 150 assets. We analyze the behavior of the 35 most actively traded stocks\(^5\). Our sample period covers all trading days of November 1999. For each trading day we consider the time period between 9:30 AM and 10:00 AM, comprising the last half hour of the preopening period.

The empirical analysis is intended to answer two questions.

1. Are the supply and demand functions observed at the preopening period different at the end of preopening period?

2. Does same day volatility affect this behavior?

The predictions of the model spelled out in section 2 are that the relation between the prices observed at the preopening and the value of the asset should be non-monotonic, and that we should observe structurally different behavior for the supply and demand functions before and after the opening

\(^5\)Activity is measured by mean effective volume six months before the sample period.
of the market, especially for stocks exhibiting a high degree of asymmetric information.

In order to answer these questions and test empirical implications of the model, we use the limit order book (LOB) and we calculate two slopes for demand and two slopes for supply. As we mentioned, we consider time period between 9:30 AM and 10:00 AM (preopening period).

3.3 Slopes in the Preopening Period

During the preopening period, additionally to demand and supply LOB provides equilibrium price and quantities. The market calculates these equilibrium variables. Suppose that you observe the complete LOB at a given moment, and the equilibrium price \( P^\ast \) and volume \( Q^\ast \) at the same moment.

With this LOB we can build a complete Demand and Supply functions.

Additionally, we suffer a transparency problem because we only observe best five levels of LOB instead of complete LOB. Given this degree of transparency we observe:

\[
\begin{array}{llllll}
\text{Bid} & \text{Ask} \\
Q_{bid1} & P_{bid1} & Q_{ask1} & P_{ask1} \\
Q_{bid2} & P_{bid2} & Q_{ask2} & P_{ask2} \\
Q_{bid3} & P_{bid3} & Q_{ask3} & P_{ask3} \\
Q_{bid4} & P_{bid4} & Q_{ask4} & P_{ask4} \\
Q_{bid5} & P_{bid5} & Q_{ask5} & P_{ask5} \\
\end{array}
\]

Slopes \( A \) and \( B \) are given by:

\[
A_k = \frac{P^\ast_i - P_{kj}}{Q^\ast_i - Q_{kj}} \quad 8j > 1
\]

\[
B_k = \frac{P^\ast_i - P_{kj}}{Q^\ast_i - j=1 Q_{kj}}
\]

where \( k \) represent ask or bid prices and \( j \) represent level of prices of the limit order book. See an example: suppose that you observe the LOB of Table 1, an equilibrium price of \( P^\ast = 15.65 \), and an equilibrium quantity of \( Q^\ast = 35634 \).

15
Then bid side slopes are given by:

$$A_{bd} = \frac{P^b_i - P^b_{bid}}{Q^b_i - Q^b_{bid}} = \frac{15.65 - 17.99}{35634 - 14094} = 0.01086351$$

$$B_{bd} = \frac{P^b_i - P^b_{bidd}}{Q^b_i - Q^b_{bidd}} = \frac{15.65 - 16.75}{35634 - 32566} = 0.03585398$$

And ask side slopes by:

$$A_{ask} = \frac{P^a_i - P^a_{ask1}}{Q^a_i - Q^a_{ask1}} = \frac{15.65 - 13.31}{35634 - 19235} = 0.01426916$$

$$B_{ask} = \frac{P^a_i - P^a_{ask5}}{Q^a_i - Q^a_{ask5}} = \frac{15.65 - 15.44}{35634 - 25965} = 0.00217189$$

These slopes give us information about sensitivities of demand and supply and information asymmetries. Not surprisingly, in order to calculate A and B slopes, we need two Demand (Supply) prices higher (lower) than the equilibrium price.

4 Results

We calculate slopes in the preopening when it is possible, that is when there is an equilibrium and we observe at least two prices in order to be able to compute the slopes. We are interested in the question of whether the A slopes are different from the B slopes, so that we calculate one additional measures: \( \log(\frac{A}{B}) \)

This measure will capture differences between slopes. When \( \log(\frac{A}{B}) \) is greater (lower) than 0 A is greater (lower) than B. this variable will permit to observe changes in both slopes. Given degree of transparency, it could
be the case that observed quotes are not closest prices from equilibrium price (like the example). In order to match theory, and avoid this problem, we select from the whole sample observations where equilibrium price is between best first and fifth level of LOB. Additionally, we eliminate extrem observations of our sample. So, results are derived from the restricted simple without extrem values. An observation is considered an extreme one if it exceeds three times standard deviation.

In order to separate different effects, we will use two different variables. First is time to preopening to end. To capture seasonality effects we divide our sample in three different periods, one for each ten minutes interval. It is well known the last minutes of the preopening period tend to be more active (see Biais et al (1999) for evidence on Paris and Sola (2000) for Madrid). Additionally, one consequence of the model is that the behavior of investors is different in preopening depending on the time before the end. Both effects should be present in the level and changes of slopes.

Second effect is cross section effect. Although, we only consider 34 assets, Spanish stock exchange is a concentrated market. Over 132 firms, selected 34 firms represent more than 90% of effective volume of the whole sample. Additionally, we divide our 34 sample into 5 activity groups. Next table show group effective volume a month before the study. We can observe that subsamples are so different.

<table>
<thead>
<tr>
<th>Group</th>
<th>Group EV/Total Sample EV</th>
<th>Group EV/Market EV</th>
</tr>
</thead>
<tbody>
<tr>
<td>BB</td>
<td>82.1%</td>
<td>74.8%</td>
</tr>
<tr>
<td>BM</td>
<td>10.6%</td>
<td>9.6%</td>
</tr>
<tr>
<td>MM</td>
<td>4.1%</td>
<td>3.8%</td>
</tr>
<tr>
<td>MS</td>
<td>2.0%</td>
<td>1.8%</td>
</tr>
<tr>
<td>SS</td>
<td>1.4%</td>
<td>1.3%</td>
</tr>
</tbody>
</table>

Table 3 shows some descriptive statistics about the sample

Insert Table 3

There is no clear relationship between number of observations and group classification. as expected given the way we used to select the sample most actively traded stocks have less number of observations than other groups. Looking at median measures, we observe that BM and MM groups have
higher values of slopes both on Ask and Bid. As a consequence we do not observe important differences in Log(A/B) variable.

Contrary to previous result, we find greater number of observations as the end of preopening period comes closer. In general, looking at Log(A/B) results it seems that ask and bid side differ in their behavior. On one hand, Ask side show a median rising value at least if we compare first ten minutes with the rest of the sample. This results implies that A slope on the ask side becomes greater (between 2 and 3 times) than B or B is more elastic. This implies that prices close to equilibrium are more liquid.

On the other hand, Bid side median log(A/B) variable becomes closer to zero. As in the Ask side, A is greater than B but contrary to Ask result differences between both slopes are decreasing and both slopes are becoming more inelastic.

If we take into account the whole sample, assets with the larger level of activity (BB) are the ones with most observations. However, if we only look at restricted sample, then the group with more observations is SS. Additionally, the number of observations is not monotonic in the capitalization. In fact, MM firms have a greater number of slope observations than the any other activity classification except SS.

As expected, the number of observations computed in a given time interval during the preopening period increases as the time approaches the opening period.

4.1 Seasonality and Cross-sectional Effects

The first analysis we carry out is about seasonality. In order to capture seasonality effects we construct 3 dummy variables in the preopening period, one for ten minutes interval. We run one regression. Results are in table 3.

\[ y_{it} = \beta_0 + \beta_2 D_2 + \beta_3 D_3 + \epsilon_{it} \]

where \( y_{it} \) refers to either slope A, B or Log(A/B) and to either bid or ask.

We can observe some important differences between slopes and between ask and bid side. Looking at ask results, table shows that preopening ending implies that market ask side becomes more elastic and as a consequence more liquid, that is equilibrium price is less sensitive to changes in order flow. This increase in liquidity is higher in A slopes so higher improvement of liquidity is
far away from equilibrium price. This result implies lower insider camouflage opportunities near equilibrium price. However, this result is not confirmed by Log(A/B).

When we look at bid results A slope does not significantly change. We observe the opposite result in B slope. B slope changes are significant and negative. This implies more liquidity around equilibrium price. Given the value of Log(A/B) for the bid side, A slope is greater than bid slope close to equilibrium price.

Comparing ask with bid slopes, bid slopes show higher degree of seasonality. One possible explanation of this results is that November 1999 was a period of bull market, and as a consequence, activity should be reflected mostly on ask side.

We calculate cross-sectional effects in the same way, we construct 5 different dummy variables, one for each group considered. Given the differences among groups, we should expect different degree of asymmetric information and as a consequence different slope behaviour. We run one regression. Results are in table 5

\[ y_{it} = \alpha + \beta_{BM} D_{BM} + \beta_{MM} D_{MM} + \beta_{MS} D_{MS} + \beta_{SS} D_{SS} + \epsilon_{it} \]

where \( y_{it} \) refers to either slope A, B or Log(A/B) and to either bid or ask.

Ask side show significant differences among different activity groups. Groups of lowest activity show more elastic A and B slopes. This result is similar on the bid side. So, highest and lowest levels of activity are more liquid than the rest of groups. This effect is especially important for B slopes. Although Log(A/B) variable present similar idea, we observe that on ask side constant is not statistically different from zero and yes it is on bid side. Both sides, ask and bid, present greater differences between SS and BB activity groups. This result is especially important in the ask side.

4.2 Volatility effect

The volatility of asset prices is influenced by the rate at which new information arrives and by the rate at which private information is disclosed. Since the predictions of our model depend on the presence of informed traders, it is useful to see how volatility influences the preopening slopes of Demand and Supply curves.
We calculate volatility from fifteen minutes returns: Daily volatility proxy is a mean average of absolute value of returns. Given that we try to detect differences in asymmetric information level we divide each volatility variable by mean sample volatility. In addition we detect two most volatile days and build a dummy variable for those volatile days. First analysis we carry out is a regression analysis with these dummy variable. We regress each variable on this dummy in order to detect if slopes calculated this volatile days are different.

First we should construct a volatility measure. Based solely on Andersen et al. (199,***) we construct daily volatility measure. We first define returns as:

\[
r(j; t) = \log(S(j; t)) - \log(S(j - 1; t))
\]

where \(S\) is the price of asset on day \(t\) between \(j\) and \(j-1\) time interval. Second, daily volatility proxy is a mean average of absolute value of returns.

\[
\frac{\sigma^2}{S} = \frac{1}{N} \sum_{i} \text{abs}(r(j; t))
\]

Third, given that we try to detect differences in asymmetric information level we calculate a ratio between each volatility variable by mean sample volatility of the sample included.

\[
R = \frac{\sigma^2}{\frac{1}{N} \sum_{i} \text{abs}(r(j; t))}
\]

In addition we detect two most volatile days and build a dummy variable for those volatile days. First analysis we carry out is a regression analysis with these dummy variable (\(D_{90}\)) which takes value 1 if \(R\) belongs to the top decile and 0 otherwise. These observations in which \(D_{90} = 1\) correspond to days and assets in which important movements occur from preopening to closing price, presumably because of information disclosure. We run the next regression for each side and each variable.

\[
y_t = \beta_0 + \beta D_{90} + \epsilon
\]

Results can be summarize indicating that arrival information days exhibit different behavior in preopening slopes. Slopes are greater or equal than days of lower volatility that is more inelastic. This result implicates that before higher volatility days we can detect higher asymmetric information level and as a consequence more inelastic demand and supply curves.
Looking at Ask slopes, A slope is more inelastic and B is not different. Contrary to this result Log(A/B) is lower on volatility days. When we observe Bid side, slopes become greater in absolute value. This change is greater in B slope. Log(A/B) does not significantly change.

Given the important role of Dummy variable we look at interactions between time dummy and volatility dummy in order to capture different behavior those volatile days. We run the next regression.

\[ y_{it} = \beta_0 + \beta_2 D_2 + \beta_3 D_3 + \beta_{90} D_{90} + \beta_2 D_2 \times D_{90} + \beta_3 D_3 \times D_{90} + \epsilon_{it} \]

Looking at results interaction have a different sign that direct effects. This effect is specially important in Ask Log(A/B) variable. Although volatile days exhibit higher liquidity this effect is more than compensated with interaction variables. Similar can be found in B slope on the Bid side but not on Log(A/B) variable. Additionally, dummy coefficients are not so much different than previous estimated ones.

The second analysis related with information arrival use some information variables in order to explain the behavior of slopes. Now instead of preopening observations we summarize slopes information in two different measures. First measure is a mean of slopes values for each asset each day. Second measure is a dispersion ones. Also, it is well known that We define

\[ y_{S;j}^{\text{MaxMin}} = \max(y_{S;j}) - \min(y_{S;j}) \]

To carry out this analysis we will use daily observations and exogenous variables are dispersion variables of each of the slopes, volatility and three different activity variables. These are natural log of volume in shares \((V_{S;j})\), effective volume in euros \((\text{Eff}V_{S;j})\) and number of trades for each day and each asset. We include these four variables with a lag. We run two different regressions to capture exogenous lagged effects and contemporaneous dispersion measures effects. The regressions we run are given by:

\[ y_{it} = \beta_0 + \beta_1 R_{S;j} + \beta_2 \log(V_{S;j}) + \beta_3 \log(\text{Eff}V_{S;j}) + \beta_4 \log(\text{NTran}_{S;j}) + \epsilon_{it} \]

\[ y_{it} = \beta_0 + \beta_1 R_{S;j} + \beta_2 \log(V_{S;j}) + \beta_3 \log(\text{Eff}V_{S;j}) + \beta_4 \log(\text{NTran}_{S;j}) + \beta_{A} \text{MaxMin}_{A} + \beta_{B} \text{MaxMin}_{B} + \beta_{\log(A/B)} \text{MaxMin} + \epsilon_{it} \]
Results show that greater volatility figures becomes in no change except if we look at \( \log(A/B) \) variable. Additionally, the effects of volatility are different if we see the figures of ask and bid side. Reason behind this result is November bull market. Looking at activity effects, higher shares volume implies higher liquidity on the preopening. Contrary to this result, higher effective volume implies lower liquidity. This result is natural given that higher price implies lower liquidity. Number of transactions is representing similar intuition that effective volume. If we use average transaction size in shares and average transaction size in euros we obtain similar results in terms of signs and significance.

As we mention, a complementary analysis is given by analyzing if contemporary volatility measure with \( y_{S; \text{MaxMin}} \) affect slope behavior. Results are included in table 9.

Looking at results we observe that contemporary dispersion measures affect mean slopes. Both measures of slope dispersion do less liquid the market. This effect is specially important in B slopes. That is B slopes are more sensitive to contemporaneous volatility. Another important aspect is that ask and bid side results are quite similar in signs and significance. \( \log(A/B) \) confirm these effects.

5 Conclusions

We can consider at least three reason why preopening is an important period. Protocol procedure is different from open market period, it provides price discovery, and investors use it as an important part of the market. In SSE preopening can cross between 20 and 30% of daily effective volume.

Our model implies that a rational expectation equilibrium exists with the active participation of the informed trader and uninformed traders. An important theoretical result is that informed trader selects different strategies depending on the information possessed.

The empirical part is based on the study of behavior of LOB slopes. Main results indicate behavior of investors is different depending where they put the orders, close or not to the equilibrium price, the way they introduce.
Additionally, some variables as time to preopening to expire or activity affect slopes.

Information arrival days exhibit different behavior in preopening slopes but if we look at activity measures instead of volatility. Higher shares volume implies higher liquidity on the preopening. Contrary to this result, higher effective volume implies lower liquidity. This result is natural given that higher price implies lower liquidity. Number of transactions is representing similar intuition that effective volume. If we use average transaction size in shares and average transaction size in euros we obtain similar results in terms of signs and significance. These results are consistent with our model.

References


Figure 1

Demand and Supply functions

Table 1
LOB at 9:59:59

<table>
<thead>
<tr>
<th>Bid</th>
<th>Ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>14094</td>
<td>17.99</td>
</tr>
<tr>
<td>77</td>
<td>17.90</td>
</tr>
<tr>
<td>700</td>
<td>17.50</td>
</tr>
<tr>
<td>12695</td>
<td>17.00</td>
</tr>
<tr>
<td>5000</td>
<td>16.75</td>
</tr>
</tbody>
</table>

LOB at 10:00:10

<table>
<thead>
<tr>
<th>Bid</th>
<th>Ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>151</td>
<td>15.54</td>
</tr>
<tr>
<td>1537</td>
<td>15.53</td>
</tr>
<tr>
<td>835</td>
<td>15.50</td>
</tr>
<tr>
<td>1300</td>
<td>15.48</td>
</tr>
<tr>
<td>3000</td>
<td>15.47</td>
</tr>
</tbody>
</table>

Table 2
LOB at 9:59:59

<table>
<thead>
<tr>
<th>Bid</th>
<th>Ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>14094</td>
<td>17.99</td>
</tr>
<tr>
<td>77</td>
<td>17.90</td>
</tr>
<tr>
<td>700</td>
<td>17.50</td>
</tr>
<tr>
<td>12695</td>
<td>17.00</td>
</tr>
<tr>
<td>5000</td>
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<td>3068</td>
<td>16.50</td>
</tr>
<tr>
<td>2000</td>
<td>14.00</td>
</tr>
<tr>
<td>5673</td>
<td>12.00</td>
</tr>
</tbody>
</table>

P*=15.65  
Q* =35634
### Table 3

**Descriptive Statistics**

This table contains Descriptive Statistics of slopes in preopening. \((A_{ASK}, B_{ASK}, \log(A/B)_{ASK}, A_{BID}, B_{BID}, \log(A/B)_{BID})\).

**Panel A: Slope Classification by Activity**

<table>
<thead>
<tr>
<th></th>
<th>(A)</th>
<th>(B)</th>
<th>(\log(A/B))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>BB</td>
<td>634</td>
<td>0.239</td>
<td>0.098</td>
</tr>
<tr>
<td>BM</td>
<td>866</td>
<td>1.263</td>
<td>0.197</td>
</tr>
<tr>
<td>MM</td>
<td>1037</td>
<td>0.485</td>
<td>0.205</td>
</tr>
<tr>
<td>MS</td>
<td>620</td>
<td>0.186</td>
<td>0.070</td>
</tr>
<tr>
<td>SS</td>
<td>1184</td>
<td>0.229</td>
<td>0.088</td>
</tr>
</tbody>
</table>

**Bid**

<table>
<thead>
<tr>
<th></th>
<th>(A)</th>
<th>(B)</th>
<th>(\log(A/B))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>BB</td>
<td>512</td>
<td>-0.152</td>
<td>-0.074</td>
</tr>
<tr>
<td>BM</td>
<td>795</td>
<td>-1.263</td>
<td>-0.178</td>
</tr>
<tr>
<td>MM</td>
<td>1039</td>
<td>-0.438</td>
<td>-0.217</td>
</tr>
<tr>
<td>MS</td>
<td>675</td>
<td>-0.250</td>
<td>-0.095</td>
</tr>
<tr>
<td>SS</td>
<td>1228</td>
<td>-0.203</td>
<td>-0.078</td>
</tr>
</tbody>
</table>

**Panel B: Slope Classification by Minute**

### Ask

<table>
<thead>
<tr>
<th>Min.</th>
<th>Obs.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-9</td>
<td>932</td>
<td>0.866</td>
<td>0.141</td>
<td>4.618</td>
<td>1.820</td>
<td>0.061</td>
<td>13.277</td>
<td>0.769</td>
<td>0.675</td>
<td>2.138</td>
</tr>
<tr>
<td>10-19</td>
<td>1544</td>
<td>0.549</td>
<td>0.160</td>
<td>1.281</td>
<td>0.586</td>
<td>0.050</td>
<td>2.331</td>
<td>1.058</td>
<td>0.942</td>
<td>1.903</td>
</tr>
<tr>
<td>20-29</td>
<td>1865</td>
<td>0.257</td>
<td>0.084</td>
<td>0.581</td>
<td>0.362</td>
<td>0.034</td>
<td>1.429</td>
<td>0.926</td>
<td>0.859</td>
<td>1.953</td>
</tr>
</tbody>
</table>

### Bid

<table>
<thead>
<tr>
<th>Min.</th>
<th>Obs.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-9</td>
<td>768</td>
<td>-0.389</td>
<td>-0.144</td>
<td>0.789</td>
<td>-0.419</td>
<td>-0.035</td>
<td>1.118</td>
<td>0.942</td>
<td>0.889</td>
<td>2.018</td>
</tr>
<tr>
<td>10-19</td>
<td>1592</td>
<td>-0.526</td>
<td>-0.120</td>
<td>1.747</td>
<td>-0.935</td>
<td>-0.067</td>
<td>4.147</td>
<td>0.487</td>
<td>0.447</td>
<td>1.896</td>
</tr>
<tr>
<td>20-29</td>
<td>2014</td>
<td>-0.513</td>
<td>-0.118</td>
<td>1.979</td>
<td>-1.308</td>
<td>-0.101</td>
<td>6.890</td>
<td>0.414</td>
<td>0.320</td>
<td>1.935</td>
</tr>
</tbody>
</table>
### Table 4
**Dummy Time Regression**

This table contains the time series coefficients of slopes in preopening. The dependent variable is one of the slope variable (A\_ASK, B\_ASK, Log(A/B)\_ASK, A\_BID, B\_BID, Log(A/B)\_BID). The explanatory variables are two dummy variables that capture time till the end of the preopening period effect. *(***) indicates significance at 5%(10%). White standard errors are used

\[ y_j = \alpha + \beta_2 D_2 + \beta_3 D_3 + \varepsilon_j \]

<table>
<thead>
<tr>
<th></th>
<th>Ask</th>
<th></th>
<th>Bid</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>0.454 * 0.457 * 0.868</td>
<td></td>
<td>-0.370 * -0.395 * 0.905 *</td>
<td></td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>-0.039 0.040 0.172</td>
<td></td>
<td>-0.019 -0.273 * -0.441 *</td>
<td></td>
</tr>
<tr>
<td>(\beta_3)</td>
<td>-0.218 * -0.110 * 0.051</td>
<td></td>
<td>0.003 -0.191 * -0.426 *</td>
<td></td>
</tr>
</tbody>
</table>

### Table 5
**Activity Effect Regression**

This table contains the Activity influence on slopes in preopening. The dependent variable is one of the slope variable (A\_ASK, B\_ASK, Log(A/B)\_ASK, A\_BID, B\_BID, Log(A/B)\_BID). The explanatory variables are four dummy variables that capture Activity or Size effect. *(***) indicates significance at 5%(10%). White standard errors are used

\[ y_j = \alpha + \beta_{BM} D_{BM} + \beta_{MM} D_{MM} + \beta_{MS} D_{MS} + \beta_{SS} D_{SS} + \varepsilon_j \]

<table>
<thead>
<tr>
<th></th>
<th>ASK</th>
<th></th>
<th>BID</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>0.239 * 0.552 * -0.096</td>
<td></td>
<td>-0.403 * -0.553 * 0.522 *</td>
<td></td>
</tr>
<tr>
<td>(\beta_{BM})</td>
<td>0.344 * -0.081 1.210</td>
<td></td>
<td>-0.263 * -0.521 * -0.240 *</td>
<td></td>
</tr>
<tr>
<td>(\beta_{MM})</td>
<td>0.246 * 0.129 1.258</td>
<td></td>
<td>-0.035 -0.134 ** -0.138</td>
<td></td>
</tr>
<tr>
<td>(\beta_{MS})</td>
<td>-0.053 * -0.339 * 1.231</td>
<td></td>
<td>0.166 * 0.289 * 0.126</td>
<td></td>
</tr>
<tr>
<td>(\beta_{SS})</td>
<td>-0.010 * -0.328 * 1.205</td>
<td></td>
<td>0.200 * 0.191 * 0.335 *</td>
<td></td>
</tr>
</tbody>
</table>

### Table 6
**Volatility Dummy Regression**

This table contains volatility influence on slopes in preopening. The dependent variable is one of the slope variable (A\_ASK, B\_ASK, Log(A/B)\_ASK, A\_BID, B\_BID, Log(A/B)\_BID). The explanatory variable is a Dummy variable that reflect higher volatility day. *(***) indicates significance at 5%(10%). White standard errors are used

\[ y_j = \alpha + \beta_{90} D_{90} + \varepsilon_j \]

<table>
<thead>
<tr>
<th></th>
<th>Ask</th>
<th></th>
<th>Bid</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>0.349 * 0.429 * 0.969</td>
<td></td>
<td>-0.367 * -0.557 * 0.560 *</td>
<td></td>
</tr>
<tr>
<td>(\beta_{90})</td>
<td>0.062 ** -0.009 -0.212</td>
<td></td>
<td>-0.068 ** -0.177 * 0.018</td>
<td></td>
</tr>
</tbody>
</table>
Table 7
Time of Preopening and Volatility Dummy Regression

This table contains Time of Preopening, Activity and Volatility influence on slopes in preopening including interaction effects. The dependent variable is one of the slope variable (A\textsubscript{ASK}, B\textsubscript{ASK}, Log(A/B)\textsubscript{ASK}, A\textsubscript{BID}, B\textsubscript{BID}, Log(A/B)\textsubscript{BID}). The explanatory variables are Dummy variables that reflect Time of Preopening, Activity and higher volatility day and interaction among them. *(**) indicates significance at 5%(10%). White standard errors are used.

\[ y_j = \alpha + \beta_2 D_2 + \beta_3 D_3 + \beta_90 D_{90} + \gamma_90^2 (D_3 * D_{90}) + \gamma_90^3 (D_3 * D_{90}) + \varepsilon_j \]

<table>
<thead>
<tr>
<th>Ask</th>
<th></th>
<th></th>
<th></th>
<th>Bid</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.458</td>
<td>0.435</td>
<td>0.949</td>
<td>-0.358</td>
<td>-0.418</td>
<td>0.892</td>
<td>*</td>
</tr>
<tr>
<td>B</td>
<td>-0.051</td>
<td>0.077</td>
<td>0.098</td>
<td>-0.024</td>
<td>-0.208</td>
<td>* -0.436</td>
<td>*</td>
</tr>
<tr>
<td>\beta_2</td>
<td>-0.231</td>
<td>-0.088</td>
<td>-0.039</td>
<td>-0.003</td>
<td>-0.145</td>
<td>* -0.401</td>
<td>*</td>
</tr>
<tr>
<td>\beta_3</td>
<td>-0.048</td>
<td>0.209</td>
<td>-0.804</td>
<td>-0.089</td>
<td>0.164</td>
<td>* 0.092</td>
<td></td>
</tr>
<tr>
<td>\gamma_90</td>
<td>0.139</td>
<td>-0.400</td>
<td>0.726</td>
<td>0.037</td>
<td>-0.492</td>
<td>* -0.033</td>
<td></td>
</tr>
<tr>
<td>\gamma_90</td>
<td>0.145</td>
<td>-0.217</td>
<td>0.920</td>
<td>0.019</td>
<td>-0.413</td>
<td>* -0.219</td>
<td></td>
</tr>
</tbody>
</table>

Table 8
Volatility Regression.

This table contains volatility influence on slopes in preopening. The dependent variable daily average of one of the slope variable (A\textsubscript{ASK}, B\textsubscript{ASK}, Log(A/B)\textsubscript{ASK}, A\textsubscript{BID}, B\textsubscript{BID}, Log(A/B)\textsubscript{BID}). The lagged explanatory variables are volatility measure as Anders en et al (1998), natural logarithm of volume in shares, effective volume in Euros and Number of transaction. *(**) indicates significance at 5%(10%). White standard errors are used.

\[ y_j = \alpha + \gamma_1 \sigma_{j-1} + \gamma_2 \log(V_{j-1}) + \gamma_3 \log(\text{EffV}_{j-1}) + \gamma_4 \log(N\text{Tran}_{j-1}) + \varepsilon_j \]

<table>
<thead>
<tr>
<th>Ask</th>
<th></th>
<th></th>
<th></th>
<th>Bid</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.727</td>
<td>* 0.152</td>
<td>4.943</td>
<td>-0.629</td>
<td>-0.996</td>
<td>1.287</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>-0.018</td>
<td>-0.001</td>
<td>-0.312</td>
<td>-0.011</td>
<td>0.070</td>
<td>0.233</td>
<td>**</td>
</tr>
<tr>
<td>\gamma_1</td>
<td>-0.355</td>
<td>-0.298</td>
<td>-0.161</td>
<td>0.220</td>
<td>0.417</td>
<td>0.296</td>
<td>*</td>
</tr>
<tr>
<td>\gamma_2</td>
<td>0.180</td>
<td>* 0.164</td>
<td>0.028</td>
<td>-0.162</td>
<td>-0.236</td>
<td>-0.111</td>
<td>**</td>
</tr>
<tr>
<td>\gamma_3</td>
<td>0.062</td>
<td>* 0.125</td>
<td>-0.446</td>
<td>0.057</td>
<td>-0.016</td>
<td>-0.273</td>
<td>*</td>
</tr>
</tbody>
</table>
Table 9
Volatility Regression.

This table contains volatility influence on slopes in preopening and measures of dispersion of each of the variables considered in the analysis. The dependent variable is one of the slope variable (A<sub>ASK</sub>, B<sub>ASK</sub>, Log(A/B)<sub>ASK</sub>, A<sub>BID</sub>, B<sub>BID</sub>, Log(A/B)<sub>BID</sub>) as an average of each variable. The lagged explanatory variables are volatility measure as Andersen et al (1998), natural logarithm of volume in shares, effective volume in Euros and Number of transaction and maximum less minimum of the data estimated for each day and each asset. We estimate Volatility using Andersen et al (1998) approach. *(***) indicates significance at 5%(10%). White standard errors are used.

\[ y_j = \alpha + \gamma_1 R(\sigma_{S,j-1}) + \gamma_2 \log(V_{j-1}) + \gamma_3 \log(EffV_{j-1}) + \gamma_4 \log(NTran_{j-1}) + \gamma_A A_{MaxMin} + \gamma_B B_{MaxMin} + \gamma_{Log} \log(A/B)_{MaxMin} + \epsilon_j \]

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>Log(A/B)</th>
<th>A</th>
<th>B</th>
<th>Log(A/B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.533 *</td>
<td>0.179</td>
<td>4.775 *</td>
<td>-0.439 *</td>
<td>-0.033</td>
<td>1.876 *</td>
</tr>
<tr>
<td>0.008</td>
<td>-0.068</td>
<td>-0.255 **</td>
<td>0.019</td>
<td>0.057 **</td>
<td>0.205 **</td>
</tr>
<tr>
<td>-0.262 *</td>
<td>-0.139 *</td>
<td>-0.180 **</td>
<td>0.082 *</td>
<td>0.127 *</td>
<td>0.170 **</td>
</tr>
<tr>
<td>0.131 *</td>
<td>0.062 *</td>
<td>0.048</td>
<td>-0.046 *</td>
<td>0.092 *</td>
<td>-0.076</td>
</tr>
<tr>
<td>0.053 *</td>
<td>0.090 **</td>
<td>-0.435 *</td>
<td>0.022 *</td>
<td>-0.042</td>
<td>-0.272 *</td>
</tr>
<tr>
<td>0.484 *</td>
<td>-0.027</td>
<td>0.381 *</td>
<td>-0.552 *</td>
<td>0.109</td>
<td>0.395 *</td>
</tr>
<tr>
<td>0.040 *</td>
<td>0.547 *</td>
<td>-0.273 *</td>
<td>-0.043 *</td>
<td>-0.674 *</td>
<td>-0.453 *</td>
</tr>
<tr>
<td>-0.065 *</td>
<td>-0.093 *</td>
<td>0.015</td>
<td>0.023 *</td>
<td>0.075 *</td>
<td>0.035</td>
</tr>
</tbody>
</table>