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 di®erent 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 di®erence 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 o±cial 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 `¯nd 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 ¯rst 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 di±culty 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 ¯nal one, or because problems in communication may prevent the trader from cancelling the order. The approach has ¯rst 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 e®ect 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 ¯nal 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 pro¯ts if trade does not occur in the current period.

In this paper we propose a di®erent approach, not relying on a random opening time. Our basic intuition is that in a market in which both informed and noise traders 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

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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

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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 propening 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 π_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[1]. We will

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[1] For the sake of simplicity we assume that the informed trader cancels the order placed

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 multiple of a given minimum quantity, and there is a bound on the total amount that can be ordered. We also assume $0 \in X$ and $x_1 < 0 < x_n$. We denote by $\mathbb{C}^n$ the $n-1$ 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 $Z = \{\ldots, -1, 0, 1, \ldots\}$ and probability distribution $q = \{\ldots, q_{-1}, q_0, q_1, \ldots\}$, with $q_i > 0$ for each $i \in Z$ and $\sum_{-\infty}^{+\infty} q_i = 1$.

Similarly, the order placed by noise traders at the opening is represented by a random variable u_F, with support on Z and probability distribution $w = \{\ldots, w_{-1}, w_0, w_1, \ldots\}$, with $w_i > 0$ for each $i \in Z$ and $\sum_{-\infty}^{+\infty} w_i = 1$. We will assume that noise traders who place an order at the preopening period always confirm the order at the opening period[2]. 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 Z.

A rational expectation equilibrium of this game is given by:

- a price function $p : Z \times Z \to [v_1, v_K]$, 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;

- a function $\gg : Z \times Z \times V \to \mathbb{C}^n$, where $\gg(u_T, z_T, v_i)$ denotes the probability distribution on X adopted by the informed trader who has

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at the preopening period and places a new order. Therefore, when the market is open the contribution of the informed trader is simply x_F. Equivalently, we could assume that the preopening order is confirmed and the agent modifies it with an additional order $\mathbb{C}x_F$. In this case the contribution to the order flow in the open market is $x_T + \mathbb{C}x_F$. The first formulation saves notation.

[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[3];

- a function $\sigma : V \to \mathbb{C}^n$, where $\sigma(v_i)$ denotes the probability distribution on X adopted by the informed trader upon observing v_i;

satisfying the following properties:

- The price function $p(z_T; z_F)$ is given by:

$$p(z_T; z_F) = E[\tilde{v} \mid x_T + u_T = z_T; \ x_F + u_T + u_F = z_F]$$

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 σ and π;

- for each triplet $(u_T; z_T; v_i)$ the probability distribution $\pi(u_T; z_T; v_i) = (\pi_1; \ldots; \pi_n)$ is such that $\pi_i > 0$ only if:

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

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 $(u_T; z_T; v_i)$;

- for each v_i, the probability distribution $\sigma(v_i) = (\sigma_1; \ldots; \sigma_n)$ is such that $\sigma_i > 0$ only if:

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

where $x_F(x_T + u_T; u_T; v_i) \in \text{supp}\,\pi(u_T; x_T + u_T; v_i)$ 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:

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[3] The informed trader observe the preopening order flow z_T and knows the part of the flow 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 $(\pm(v_1);\ldots;\pm(v_K))$, where for each v_i, we have $\pm(v_i) \in \mathbb{C}^n$. It can therefore be described as an element of the set $\mathbb{C}^{n \cdot K}$. We will adopt the notation $\Gamma = \mathbb{C}^{n \cdot K}$, and we let $^\circ$ denote a generic element of Γ.

- The strategy at the opening can be described as a collection

$$f \gg (u_T;z_T;v_i)g_{(u_T;z_T)\in Z \cdot Z, \, v_i \in V}$$

where for each triplet $(u_T;z_T;v_i)$ we have $\gg(u_T;z_T;v_i) \in \mathbb{C}^n$. Call $\copyright$ the set of all possible collections, that is each element $\acute{A} \in \copyright$ is a (countable) list of probability distributions over X, one for each possible triplet $(u_T;z_T;v_i) \in Z \cdot Z \cdot V$. The set $\copyright$ represents the set of all possible strategies at the opening period. It is a convex and compact set[4].

Let $- = \Gamma \cdot \copyright$ the strategy space of the informed trader, a compact and convex set. Define next the space P of all possible price functions, that is P is the set of all sequences $fp(z_T;z_F)g_{(z_T;z_F)\in Z \cdot Z}$ such that $p(z_T;z_F) \in [v_1;v_K]$ for each pair $(z_T;z_F)$, and again observe that this is a compact and convex set.

Define now the correspondence:

$$p : - \to P$$

as:

$$p^! (z_T;z_F) = E^! [v \mid \tilde{x}_T + \theta_T = z_T; \tilde{x}_F + \theta_T + \theta_F = z_F]$$

that is, for each element $! = (^\circ;\acute{A})$ 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 $^\circ$ at the pre-opening period and the strategy described by $\acute{A}$ at the opening period. Notice that since both θ_T and θ_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 $!$, 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:

$$\Pi(x_F;p \mid (u_T;z_T;v_i)) = \sum_{j \in Z} w_j (v_i - p(z_T;u_T + j + x_F)) x_F$$

[4] See e.g. Royden (1988), chapter 7, exercise 30.

where $w_j = \Pr(u_F = j)$. Let $\varpi \in \mathbb{C}^n$ be a probability distribution over X, with $\varpi(x_F)$ denoting the probability of choosing x_F. De¯ne:

$$\pi(\varpi; p_j(u_T; z_T; v_i)) = \sum_{x_F \in X_F} \varpi(x_F)\, \pi(x_F; p_j(u_T; z_T; v_i)).$$

Let $\acute{A} = f\varpi(u_T; z_T; v_i)g_{(u_T; z_T) \in Z \pounds Z; v_i \in V} \in \copyright$ represent a policy followed by the informed trader at the opening period. For a given policy $\acute{A}$ we set

$$\pi(\acute{A}; p_j(u_T; z_T; v_i)) = \pi(\varpi(u_T; z_T; v_i); p_j(u_T; z_T; v_i))$$

Next, de¯ne the function $\pi^{\tt x}(x_T; \acute{A}; p_j v_i)$ as:

$$\pi^{\tt x}(x_T; \acute{A}; p_j v_i) = \sum_{j \in Z} q_j\, \pi(\acute{A}; p_j(j; x_T + j; v_i))$$

where $q_j = \Pr(u_T = j)$. For a probability distribution $\pm = (\pm_1; :::; \pm_n)$ over X we de¯ne:

$$\pi^{\tt x}(\pm; \acute{A}; p_j v_i) = \sum_{k=1}^{n} \pm_k\, \pi(x_k; \acute{A}; p_j v_i)$$

where $\pm_k$ is the probability of choosing x_k. De¯ne the collection $° = (\pm^{v_1}; :::; \pm^{v_K})$, where $\pm^{v_i}$ denotes the probability distribution over X chosen at the preopening when the observed value of the asset is v_i. We de¯ne:

$$\pi(°; \acute{A}; p) = \sum_{i=1}^{K} \Pr(v_i)\, \pi(\pm^{v_i}; \acute{A}; p_j v_i)$$

and setting $! = (°; \acute{A})$ we are going to use the more compact notation $\pi(!; p)$. We now de¯ne the correspondence:

$$\mu : P \; ! \; -$$

as:

$$\mu(p) = \arg\max_{! \in -} \pi(!; p)$$

For each price function p the correspondence μ selects the set of pro¯t-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 $\mid (p;!)$ is continuous in $(p;!)$, the theorem of the maximum ensures that the correspondence μ is u.h.c. and compact-valued. Linearity in $!$ ensures that the correspondence is convex-valued. Similarly, the mapping p is continuous, convex and compact valued. Therefore, by Kakutani's theorem, the mapping:

$$\mu \pounds p : - \pounds P ! - \pounds P$$

has a ¯xed point. Given the de¯nitions of μ and p, the ¯xed 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 $f(x;t)$ satis¯es increasing di®erences if whenever $t^0 > t$, the di®erence $f(x;t^0)$ ¡ $f(x;t)$ increases in x. Consider now the function $\mid (»;pj(u_T;z_T;v_i))$. For a given price function p and observation $(u_T;z_T)$ this can be seen as a function of $»$ and v_i. The variable $»$ belongs to $\mathbb{C}^n$, the space of probability distributions over X. We order $\mathbb{C}^n$ using the criterion of ¯rst order stochastic dominance (FOSD), that is $» \circ »^0$ if $\sum_{i=1}^r »(x_i)$ $\sum_{i=1}^r »^0(x_F)$ 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 $»^{v_i}$ 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 ¯rst order stochastic dominance.

Proof. Take as given p and $(u_T;z_T)$, and de¯ne $f(»;v_i) = \mid (»;pj(u_T;z_T;v_i))$. The objective function of the informed trader is given by:

$$f(»;v_i) = \sum_{j=1}^n »_j [v_i ¡ E(p(z_T;u_T + u_F + x_j))]x_j$$

where the expectation is taken over u_F. Therefore, if we take $v_k > v_i$ we have:

$$f(»;v_k) ¡ f(»;v_i) = (v_k ¡ v_i)\sum_{j=1}^n »_j x_j$$

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Since v_k ¡ $v_i > 0$, this di®erence is increasing in ». Since the objective function satis¯es increasing di®erences, the optimal action $»(v_i)$ is non-decreasing in v_i. ∎

We can use lemma 1 to provide a ¯rst 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 $E[v j z_T; z_F^0; u_T] \geq E[v j z_T; z_F; u_T]$ whenever $z_F^0 > z_F$. This in turn implies:

$$p\left(z_T; z_F^0\right) = E^{u_T}\left[E\left[v j z_T; z_F^0; u_T\right]\right] \geq E^{u_T}[E[v j z_T; z_F; u_T]] = p(z_T; z_F)$$

∎

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 °ow 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 di®erent strategies in dependence of di®erent 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 ¯rst 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 °ow z_T at the preopening period the market maker is able to infer exactly he 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 $p(z_T; z_F) \geq v_1$ 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^α to x_1, the lowest possible order.

If $x^\alpha = x_1$ 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 profitable deviate to x_1, while the informed agent who has observed v_K can profitable 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 $\pm^{v_i}$ dominates $\pm^{v_j}$ in the sense of first order stochastic dominance whenever $v_i > v_j$. We first observe that in this case, given two order flows $z_T^0 > z_T$, the conditional probability distribution of v given z_T^0 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_F. 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 preopening 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 modi¯cations, 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 ¯rst 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 ¯ts it, or the order is cancelled. In this period prices of the stocks are changing in real time depending on the °ow 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 Råell (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 show how information °ow 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 di®erence that during the pre-opening period there is no

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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 here

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

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[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^{π} and volume Q^{π} at the same moment.

Table 2 here

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

Insert Figure 1

Additionally, we su®er a transparency problem because we only observe best ¯ve levels of LOB instead of complete LOB. Given this degree of transparency we observe:

Bid		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}

Slopes A and B are given by:

$$A_k = \frac{P^{\pi} \text{ i } P_{k1}}{Q^{\pi} \text{ i } Q_{k1}} \qquad 8j > 1$$

If $P^{\pi} > P_{kj}$!

$$B_k = \frac{P^{\pi} \text{ i } P_{k5}}{Q^{\pi} \text{ i } \sum_{j=1}^{5} Q_{kj}}$$

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 $P^{\pi} = 15{:}65$, and an equilibrium quantity of $Q^{\pi} = 35634$.

	Bid		Ask
14094	17:99	13:31	19235
77	17:90	14:00	2260
700	17:50	15:00	1120
12695	17:00	15:40	3000
5000	16:75	15:44	350

Then bid side slopes are given by:

$$A_{bid} = \frac{P^{\alpha} - P_{bid1}}{Q^{\alpha} - Q_{bid1}} = \frac{15:65 - 17:99}{35634 - 14094} = -0:01086351$$

$$B_{bid} = \frac{P^{\alpha} - P_{bid5}}{Q^{\alpha} - \sum_{j=1}^{5} Q_{bidj}} = \frac{15:65 - 16:75}{35634 - 32566} = -0:03585398$$

And ask side slopes by:

$$A_{ask} = \frac{P^{\alpha} - P_{ask1}}{Q^{\alpha} - Q_{ask1}} = \frac{15:65 - 13:31}{35634 - 19235} = 0:01426916$$

$$B_{ask} = \frac{P^{\alpha} - P_{ask5}}{Q^{\alpha} - \sum_{j=1}^{5} Q_{askj}} = \frac{15:65 - 15:44}{35634 - 25965} = 0:00217189$$

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 di®erent from the B slopes, so that we calculate one additional measures: $Log(\frac{A}{B})$

This measure will capture di®erences 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 ¯rst and ¯fth 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 di®erent e®ects, we will use two di®erent variables. First is time to preopening to end. To capture seasonality e®ects we divide our sample in three di®erent 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 di®erent in preopening depending on the time before the end. Both e®ects should be present in the level and changes of slopes.

Second e®ect is cross section e®ect. Although, we only consider 34 assets, Spanish stock exchange is a concentrated market. Over 132 ¯rms, selected 34 ¯rms represent more that 90% of e®ective volume of the whole sample. Additionally, we divide our 34 sample into 5 activity groups. Next table show group e®ective volume a month before the study. We can observe that subsamples are so di®erent.

Group	Group EV/Total Sample EV	Group EV/Market EV
BB	82.1%	74.8%
BM	10.6%	9.6%
MM	4.1%	3.8%
MS	2.0%	1.8%
SS	1.4%	1.3%

Table 3 shows some descriptive statistics about the sample

Insert Table 3

There is no clear relationship between number of observations and group classi¯cation. 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 di®erences in Log(A/B) variable.

Contrary to previous result, we ¯nd 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 di®er in their behavior. On one hand, Ask side show a median rising value at least if we compare ¯rst 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 cero. As in the Ask side, A is greater than B but contrary to Ask result di®erences 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 ¯rms have a greater number of slope observations than the any other activity classi¯cation 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 E®ects

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

$$y_{it} = \text{®} + \bar{}_2 D_2 + \bar{}_3 D_3 + "_{it}$$

Insert table 3

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

We can observe some important di®erences 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 °ow. This increase in liquidity is higher in A slopes so higher improvement of liquidity is

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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

$$y_{it} = \alpha + \beta_{BM}D_{BM} + \beta_{MM}D_{MM} + \beta_{MS}D_{MS} + \beta_{SS}D_{SS} + \varepsilon_{it}$$

Insert table 5

where y_{it} refers to either slope A, B or Log($\frac{A}{B}$) 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 specialy important for B slopes. Although Log($\frac{A}{B}$) 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 volatilty influences the preopening slopes of Demand and Supply curves.

We calculate volatility from fteen minutes returns:

Daily volatility proxy is a mean average of absolute value of returns.

Given that we try to detect di®erences 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 di®erent.

Firs we sholud construct a volatiliyt measure. Based solely on Anderse et al (199,****) we construct daily volatility measure. we rst de ne returns as:

$$r(j;t) = Log(S(j;t)) \text{ ¡ } Log(S(j \text{ ¡ } 1;t))$$

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.

$$\text{¾}_S^2 = \frac{1}{N} \sum^{h} abs(r(j;t))^i$$

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

$$R^i \text{¾}_S^{2\, \text{¢}} = \frac{\text{¾}^2}{\frac{1}{N}[\text{¾}_S^2]}$$

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 $R^i \text{¾}_S^{2\,\text{¢}}$ 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.

$$y_{it} = \text{®} + \text{¯} D_{90} + \text{"}$$
Insert table 6

Results can be summarize indicating that arrival information days exhibit di®erent 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 di®erent. 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 signi¯cantly change.

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

$$y_{it} = \text{®} + \bar{}_2 D_2 + \bar{}_3 D_3 + \bar{}_{90} D_{90} + \text{°}^2_{90} (D_2 \text{¤} D_{90}) + \text{°}^3_{90} (D_3 \text{¤} D_{90}) + \text{"}_{it}$$

Insert table 7

Looking at results interaction have a di®erent sign that direct e®ects. This e®ect is specially important in Ask Log(A/B) variable. Although volatile days exhibit higher liquidity this e®ect 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 coe±cients are not so much di®erent 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 di®erent 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 de¯ne

$$y_{S;MaxMin} = Max(y_{S;j}) \text{¡} Min(y_{S;j})$$

To carry out this analysis we will use daily observations and exogeneous variables are dispersion variables of each of the slopes, volatility and three di®erent activity variables. These are natular log of volume in shares ($V_{S;j\text{¡}1}$), e®ective volume in euros ($EffV_{S;j\text{¡}1}$) and number of trades for each day and each asset. We include these four variables with a lag. We run two di®erent regressions to capture exogeneous lagged e®ects and contemporary dispersion measures e®ec. The regressions we run are given by:

$$\bar{y}_{it} = \text{®} + \text{°}_1 R \text{¾}^2_{S;j\text{¡}1} + \text{°}_2 Log (V_{S;j\text{¡}1}) + \text{°}_3 Log(EffV_{S;j\text{¡}1}) + \text{°}_4 Log(NTran_{S;j\text{¡}1}) + \text{"}_{it}$$

$$\bar{y}_{it} = \text{®} + \text{°}_1 R \text{¾}^2_{S;j\text{¡}1} + \text{°}_2 Log (V_{S;j\text{¡}1}) + \text{°}_3 Log(EffV_{S;j\text{¡}1}) + \text{°}_4 Log(NTran_{S;j\text{¡}1})$$
$$+ \text{°}_A A_{MaxMin} + \text{°}_B B_{MaxMin} + \text{°}_{Log} Log(A=B)_{MaxMin} + \text{"}_{it}$$

Insert table 8

Results show that greater volatility ¯gures becomes in no change except if we look at Log(A=B) variable. Additionally, the efects of volatility are di®erent if we see the ¯gures of ask and bid side. Reason behind this result is November bull market. Looking at activity e®ects, higher shares volume implies higher liquidity on the preopening. contrary to this result, higher e®ective volume implies lower liquidity. This result is natural given that higher price implies lower liquidity. Number of transactions is representing similar intuition that e®ective volume. If we use average transaction size in shares and average transaction size in euros we obtain similar results in terms of signs and signi¯cance.

As we mention, a complementary analysis is given by analyzing if contemporary volatility measure with $y_{S;MaxMin}$ a®ect slope behavior. Results are included in table 9.

Insert table 9

Looking at results we observe that contemporary dispersion measures a®ect mean slopes. Both measures of slope dispersion do less liquid the market. This e®ect 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 signi¯cance. Log(A/B) con¯rm these e®ects.

5   Conclusions

We can consider at least three reason why preopening is an important period. Protocol procedure is di®erent 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 e®ective 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 di®erent 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 di®erent 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 a®ect slopes.

Information arrival days exhibit di®erent 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 e®ective volume implies lower liquidity. This result is natural given that higher price implies lower liquidity. Number of transactions is representing similar intuition that e®ective volume. If we use average transaction size in shares and average transaction size in euros we obtain similar results in terms of signs and signi¯cance.These results are consistent with our model.

References

[1] Admati, A. and P. P°eiderer (1989) `Divide and Conquer: A Theory of Intraday and Day-of-the-Week Mean E®ects', Review of Financial Studies; 2: 189-223.

[2] Biais, B., P. Hillion and Chester Spatt (1999) `Price Discovery and Learning During the Pre-Opening Period in the Paris Bourse', Journal of Political Economy, 107: 1218-1248.

[3] De Jong, F., Nijman, T. and A. Räell (1996). "Price E®ects of Trading and Components of the Bid-Ask Spread on the Paris Bourse", Journal of Empirical Finance 3: 193-213.

[4] Glosten L. (1994). "Is the Electronic Open Limit Order Book Inevitable?", Journal of Finance, 49: 1127-1161.

[5] Medrano, L. A. and X. Vives (2001) `Strategic Behavior and Price Discovery', Rand Journal of Economics, 32:221-248.

[6] Madhavan, A. and V.Panchapagesan (2000) `Price Discovery in Auction Markets: A Look Inside the Black Box', Review of Financial Studies; 13: 627-58.

[7] Martínez, M.A., G. Rubio and M. Tapia (2000): `Understanding Liquidity: A Closer Look at the Limit Order Book', Universidad Carlos III Working Papers 00-52.

[8] H.L. Royden (1988) Real Analysis, 3rd edition, Macmillan, New York.

[9] Rubio, G. and M. Tapia (1998) `The Liquidity Premium in Equity Pricing under a Continuous Auction System', European Journal of Finance, 4:1-28.

[10] Sola, P. (2000) `E¯ciencia Informativa de Precios Indicativos en el Periodo de Ajuste de la Bolsa de Madrid', mimeo, CEMFI, Madrid.

[11] Vives, X. (1995a) `Short Term Investment and the Informational E±ciency of the Market', Review of Financial Studies, 8:125-160.

[12] Vives, X. (1995b) `The Speed of Information Revelation in a Financial Market Mechanism', Journal of Economic Theory, 67: 178-204.

Figure 1

Demand and Supply functions
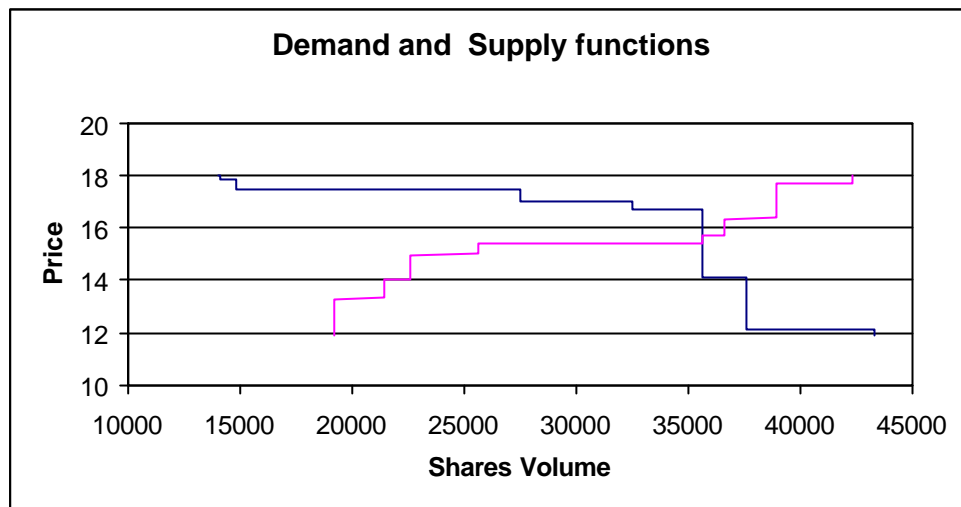
Table 1

LOB at 9:59:59			
Bid		**Ask**	
14094	17.99	13.31	19235
77	17.90	14.00	2260
700	17.50	15.00	1120
12695	17.00	15.40	3000
5000	16.75	15.44	350

LOB at 10:00:10			
Bid		**Ask**	
151	15.54	15.70	2534
1537	15.53	15.71	1336
835	15.50	15.72	1200
1300	15.48	15.73	504
3000	15.47	15.74	3307

Table 2

LOB at 9:59:59			
Bid		**Ask**	
14094	17.99	13.31	19235
77	17.90	14.00	2260
700	17.50	15.00	1120
12695	17.00	15.40	3000
5000	16.75	15.44	350
3068	16.50	15.60	9669
2000	14.00	15.70	1000
5673	12.00	17.00	3345

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

Ask

	Obs.	A Mean	A Median	A Std. Dev.	B Mean	B Median	B Std. Dev.	Log(A/B) Mean	Log(A/B) Median	Log(A/B) Std. Dev.
BB	634	0.239	0.098	0.412	0.768	0.118	2.544	-0.126	0.017	1.985
BM	866	1.263	0.197	4.997	1.724	0.061	13.646	1.121	0.967	1.847
MM	1037	0.485	0.205	0.743	0.867	0.050	3.036	1.127	1.226	2.270
MS	620	0.186	0.070	0.305	0.212	0.019	0.744	1.135	1.145	1.938
SS	1184	0.229	0.088	0.437	0.224	0.024	1.039	1.109	1.021	1.607

Bid

	Obs.	A Mean	A Median	A Std. Dev.	B Mean	B Median	B Std. Dev.	Log(A/B) Mean	Log(A/B) Median	Log(A/B) Std. Dev.
BB	512	-0.152	-0.074	0.300	-0.425	-0.030	4.054	0.416	0.575	2.444
BM	795	-1.263	-0.178	3.741	-3.139	-0.185	11.265	0.186	0.083	2.219
MM	1039	-0.438	-0.217	0.594	-0.766	-0.174	2.168	0.366	0.222	1.778
MS	675	-0.250	-0.095	0.658	-0.289	-0.052	0.942	0.642	0.553	1.812
SS	1228	-0.203	-0.078	0.344	-0.420	-0.031	1.737	0.848	0.651	1.662

Panel B: Slope Classification by Minute

Ask

Min.	Obs.	A Mean	A Median	A Std. Dev.	B Mean	B Median	B Std. Dev.	LOG(A/B) Mean	LOG(A/B) Median	LOG(A/B) Std. Dev.
0-9	932	0.866	0.141	4.618	1.820	0.061	13.277	0.769	0.675	2.138
10-19	1544	0.549	0.160	1.281	0.586	0.050	2.331	1.058	0.942	1.903
20-29	1865	0.257	0.084	0.581	0.362	0.034	1.429	0.926	0.859	1.953

Bid

Min.	Obs.	A Mean	A Median	A Std. Dev.	B Mean	B Median	B Std. Dev.	LOG(A/B) Mean	LOG(A/B) Median	LOG(A/B) Std. Dev.
0-9	768	-0.389	-0.144	0.789	-0.419	-0.035	1.118	0.942	0.889	2.018
10-19	1592	-0.526	-0.120	1.747	-0.935	-0.067	4.147	0.487	0.447	1.896
20-29	2014	-0.513	-0.118	1.979	-1.308	-0.101	6.890	0.414	0.320	1.935

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

$$y_j = a + b_2 D_2 + b_3 D_3 + e_j$$

	Ask			Bid		
	A	B	Log(A/B)	A	B	Log(A/B)
a	0.454 *	0.457 *	0.868 *	-0.370 *	-0.395 *	0.905 *
b_2	-0.039	0.040	0.172 *	-0.019	-0.273 *	-0.441 *
b_3	-0.218 *	-0.110*	0.051	0.003	-0.191 *	-0.426 *

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

$$y_j = a + b_{BM} D_{BM} + b_{MM} D_{MM} + b_{MS} D_{MS} + b_{SS} D_{SS} + e_j$$

	ASK			BID		
	A	B	Log(A/B)	A	B	Log(A/B)
a	0.239 *	0.552 *	-0.096	-0.403*	-0.553 *	0.522 *
b_{BM}	0.344 *	-0.081	1.210 *	-0.263*	-0.521 *	-0.240 *
b_{MM}	0.246 *	0.129	1.258 *	-0.035	-0.134**	-0.138
b_{MS}	-0.053*	-0.339*	1.231 *	0.166 *	0.289 *	0.126
b_{SS}	-0.010*	-0.328*	1.205 *	0.200 *	0.191 *	0.335 *

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

$$y_j = a + b_{90} D_{90} + e_j$$

	Ask			Bid		
	A	B	Log(A/B)	A	B	Log(A/B)
a	0.349 *	0.429 *	0.969 *	-0.367 *	-0.557*	0.560 *
b_{90}	0.062**	-0.009	-0.212 *	-0.068**	-0.177*	0.018

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_{ASK}, B_{ASK}, Log(A/B)$_{ASK}$, A_{BID}, B_{BID}, Log(A/B) $_{BID}$). 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

$$y_j = a + b_2 D_2 + b_3 D_3 + b_{90} D_{90} + g_{90}^2 (D_3 * D_{90}) + g_{90}^3 (D_3 * D_{90}) + e_j$$

	Ask						Bid					
	A		B		Log(A/B)		A		B		Log(A/B)	
a	0.458	*	0.435	*	0.949	*	-0.358	*	-0.418	*	0.892	*
b_2	-0.051		0.077		0.098		-0.024		-0.208	*	-0.436	*
b_3	-0.231	*	-0.088		-0.039		-0.003		-0.145	*	-0.401	*
b_{90}	-0.048		0.209		-0.804	*	-0.089		0.164	*	0.092	
g_{90}^2	0.139		-0.400	*	0.726	*	0.037		-0.492	*	-0.033	
g_{90}^3	0.145	*	-0.217		0.920	*	0.019		-0.413	*	-0.219	

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_{ASK}, B_{ASK}, Log(A/B)$_{ASK}$, A_{BID}, B_{BID}, Log(A/B)$_{BID}$). 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. *(**) indicates significance at 5%(10%). White standard errors are used.

$$y_j = a + g_1 s_{jt-1} + g_2 Log(V_{jt-1}) + g_3 Log(EffV_{jt-1}) + g_4 Log(NTran_{jt-1}) + e_j$$

	Ask						Bid					
	A		B		Log(A/B)		A		B		Log(A/B)	
a	0.727	*	0.152		4.943	*	-0.629	*	-0.996	*	1.287	
g_1	-0.018		-0.001		-0.312	*	-0.011		0.070		0.233	**
g_2	-0.355	*	-0.298	*	-0.161		0.220	*	0.417	*	0.296	*
g_3	0.180	*	0.164	*	0.028		-0.162	*	-0.236	*	-0.111	**
g_4	0.062	*	0.125	**	-0.446	*	0.057	*	-0.016		-0.273	*

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_{ASK}, B_{ASK}, Log(A/B)$_{ASK}$, A_{BID}, B_{BID}, Log(A/B) $_{BID}$) 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

$$y_j = a + g_1 R(s_{S,j-1}) + g_2 Log(V_{jt-1}) + g_3 Log(EffV_{jt-1}) + g_4 Log(NTran_{jt-1})$$

$$+ g_A A_{MaxMin} + g_B B_{MaxMin} + g_{Log} Log(A/B)_{MaxMin} + e_j$$

	Ask						Bid					
	A		B		Log(A/B)		A		B		Log(A/B)	
a	0.533	*	0.179		4.775	*	-0.439	*	-0.033		1.876	*
g_1	0.008		-0.068		-0.255	**	0.019		0.057	**	0.205	**
g_2	-0.262	*	-0.139	*	-0.180	**	0.082	*	0.127	*	0.170	**
g_3	0.131	*	0.062	*	0.048		-0.046	*	-0.092	*	-0.076	
g_4	0.053	*	0.090	**	-0.435	*	0.022	*	-0.042		-0.272	*
g_A	0.484	*	-0.027		0.381	*	-0.552	*	0.109		0.395	*
g_B	0.040	*	0.547	*	-0.273	*	-0.043	*	-0.674	*	-0.453	*
g_{Log}	-0.065	*	-0.093	*	0.015		0.023	*	0.075	*	0.035	