An Analysis of Cancellations in the Spanish Stock Exchange

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Abstract

The Spanish Stock Exchange is a trasparent market where traders have access to the limit order book and have the option to cancel limit orders not yet fulfilled. The option may be used if market conditions move adversely but also as a way to discover more about the market in a period of uncertainty.

We study the empirical determinants of cancellations in the Spanish stock market. In general, orders which are cancelled very quickly after placement are probably aimed at collecting information, while cancellations of orders occurring after longer periods are probably inspired by changing market conditions.

We are interested in finding out the factors affecting the decision of cancelling in both cases. In the first case we use a multinomial logit model in order to test the order submission strategy. We find that the likelihood of placing an exploratory order is positively related to the spread, the volatility, the trading activity and the previous submission of a market order.

In the case of the cancellation determined by the market changing conditions we use a logistic probability model. In this case we find that the decision of cancelling is related to the spread and the volatility computed at the moment of the cancellation, the change in the number of traders in the market, the movement of the orders along the levels of the book and the level at which the order is introduced.

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1 Introduction

Many security markets allow traders to place both limit and market orders. Limit orders are collected in the Limit Order Book (LOB), and the information about the state of the book is often made available in real time to market participants. The choice between market and limit orders is influenced by the conditions of the market, such as the volatility of the price and the level of trading activity, and the rules of trade. A potentially important rule is given by the existence of an option to cancel a limit order when it is not executed. This option is allowed in various stock exchanges, including the Spanish one.

In principle, there are two distinct reasons for cancelling an order. First, the trader may have placed an order only to acquire information about the state of the market, i.e. to see how equilibrium prices and quantities change when the new order is introduced. These 'exploratory' or 'fleeting' orders are cancelled soon after the information is obtained, so we should expect a very short period of time between order placement and order cancellation. Second, cancellations may occur because changing market conditions convince a trader to modify the order. In these cases the order initially placed is 'serious', i.e. the trader expects to trade at the stated price, but new information eventually convinces the trader that the initial order is not the best option. In such circumstances cancellations should take more time, and should occur only when market conditions change.

This paper analyzes empirically the determinants of the cancellation decision in the Spanish stock market. Our database provides information about the five best bids and offers on the book for each stock at each moment, and the transactions occurred. The dataset includes all the assets belonging to the IBEX 35, the index of the most traded Spanish stocks, for the period between July and September 2000.

We approach the problem first by estimating multinomial logit models for the each stock. The possible alternatives are not participating in the market, placing a market order, placing a 'serious' limit order and placing a 'fleeting' order. Following Hasbrouck and Saar [17], we identify empirically an order as 'fleeting' if it is cancelled before a certain cutoff period, and as 'serious' if it is cancelled after the cutoff period. Through this analysis, we want to uncover the conditions under which a trader is more likely to choose a certain type of order (or no order at all) than another. Thus, the relevant explanatory variables have to be taken at the moment at which the order is placed.

The results obtained for the market, limit orders and the case of no activity confirm the ones provided by the theorethical and empirical literature summarized in Ellul et al. [11]. As for fleeting orders, we find that their placement is positively related with volatility, spread, trading activity and the previous submission of market orders. On the other hand depth does not seem to be important, probably because fleeting orders are not supposed to be actually executed.

We next explore the changes in market conditions that may cause the cancellation of 'serious' orders, i.e. orders that are cancelled after the cutoff period. In this case, we have to look at the history of the explanatory variables between the moment in which the order is placed and the moment in which the order is cancelled. We use a logistic probability model in which the dependent variable is the cancellation indicator. The explanatory variables take into account the evolution of market conditions since the placement of the order and include, among others, the level of the book at which the order is placed, the movement of the orders along the levels, the change in the number of traders outstanding in the market. We show that the decision of cancellation is positively related to the spread and the volatility at the moment of the cancellation, the change in the number of traders, the movement of the orders along the levels of the book and the level at which the order is introduced.

The rest of the paper is organized as follow. The next section contains a brief review of the literature. Section 3 describes the institutional characteristic of SIBE and the database we use, and provides a descriptive analysis of the order flow in the Spanish Stock Exchange. We estimate the models in section 4, and section 5 contains the conclusions.

2 Related Literature

The role played by cancellations as part of a optimal dynamic trading strategy has been analyzed only recently. From the theoretical point of view, Harris [15] has proposed a dynamic model in which a trader tries to minimize the purchase price of a fixed quantity subject to a deadline. The optimal strategy consists of initially placing a limit order, then cancelling and repricing the order more aggressively as the deadline approaches and finally, if necessary, using a market order.

Large [19] considers a model in which traders are uncertain about the underlying distribution in the asset's value. Limit orders are riskier than market orders, since they may not be executed or their execution may be delayed. Risk neutral market participants trade off the cost of immediate execution against the cost of delayed execution. Immediate execution is performed at a disadvantageous price and delayed execution is costly because traders are impatient. Traders choose strategically between limit and market orders, but price limit orders competitively at the best price in the book. Traders arrive at the market uncertain of its state but quickly learn its true state simply by placing a limit order and watching the evolution of the market. If the uncertainty is quickly resolved, limit orders are submitted and quickly cancelled. Thus, fleeting orders are observed as part of an optimal strategy. Uncertainty can encourage the placement of limit orders, since the option to cancel reduces downside risk, while the upside potential remains. The paper shows that even in the absence of informational asymmetries, the option to cancel an order can narrow the bid–ask spread. Thus, the possibility of cancellation encourages the provision of liquidity.

From the empirical point of view, various papers have analyzed cancellations in the French, US and Spanish markets. Biais et al. [5], in their analysis of the Paris Bourse, consider order strategies of varying aggressiveness, with cancellation being the less aggressive one. Hasbrouck and Saar [16] introduce the concept of fleeting limit orders as orders that are canceled almost immediately after submission. They find that over one quarter of the limit order submitted to the Island ECN are cancelled unexecuted within two seconds or less. This is a substantial portion of the order flow, and it questions the usual characterization of limit order traders as patient suppliers of liquidity.

The authors provide some explanations for the existence of fleeting limit orders. One possibility is that Island receives orders from automated order routing systems, which act as intelligent agents for customer orders. The strategies used by these systems frequently involve successive attempts to achieve execution at different market centers. Another possible reason is that submitters want to find out hidden orders that improve the opposing quotes. Here a fleeting orders represents a liquidity demander, rather than a supplier. Finally, another potential explanation for fleeting limit orders is a manipulative tactic known as 'spoofing'. The idea is to place a visible order in the opposite direction of the trade that is genuinely desired in order to move favorably the price. For example, a seller might post a small buy order priced above the current bid, in order to convince other buyers to match or outbid. If this occurs, the trader can sell to the higher price. This practice is seen with suspect by the regulatory authorities because it disseminates misleading price information (see Connor [7]). In recent work Hasbrouck and Saar [17] have shown that the main motive for placing fleeting orders is to 'fish' for hidden orders placed inside the quotes.

Ellul et al. [11] analyze the determinants of electronic order submission strategy by using the New York Stock Exchange system order data. They use a multinomial logit specification in order to test order submission theory. They find that wider (narrower) quoted spreads increase the probability of limit (market) orders, more depth elicits net demand for liquidity and positive own (market) return leads to the placement of more sell (buy) orders. Favorable (unfavorable) private information increases the likelihood of buy (sell) orders.

For the Spanish market, Abad and Tapia [2] analyze the consequences of the existence of minimum price variation (ticks) for different market variables. They focus on the behavior of the bid-ask spread, market depth, trading activity and volatility on investor order submission strategies. They use the change which occurred in the tick in preparation for the introduction of the euro in 1999. This event allows them to obtain a stock sample with a reduced tick size and another whose tick increased slightly. They observe that stock experiencing an increase in the tick also have a higher number of cancellations.

Pascual and Veredas [22] analyze what pieces of book information are important in explaining the time between two consecutive trades, limit order submission and cancellations on the same side of the market in the Spanish Stock Exchange. Only the bid–ask spread shows a strongly significant effect. As the spread increases the time between consecutive trades increases, and the time between consecutive cancellations and limit order submissions decreases on both sides of the book. Pardo and Pascual [20] provide the first study focused on hidden orders applied to the Spanish Stock Exchange and clarify how hidden orders function in this market. Their goal is to determine whether hidden orders conceal informed traders or liquidity traders. They point out that hidden limit order are usually placed by large liquidity (institutional) investors. They find that there is no relevant impact on either prices or volatility associated with the placement of disclosed orders. Then, they show that hidden limit order detection temporally increases the aggressiveness of other traders but on the opposite side of the market.

Finally, Crowley and Sade [8] have analyzed experimentally whether the ability of traders to cancel orders before their potential execution, in a double auction framework, can affect price variables and the volume of orders and transactions. Their results indicate that the option to cancel affects trading volume more than price-associated variables. The number of submitted orders and the number of transactions is higher when players are allowed to cancel orders.

The paper more related to our work is Ellul et al. [11]. We use a similar econometric model, a multinomial logit in which the traders choose between different submission strategies, but we add as a possible strategic choice the possibility of placing fleeting orders. We show that the probability of placing a fleeting order increases with the volatility, the spread, the trading activity and when the previous order is a market order. Furthermore, for other order types the results that we obtain are similar to the ones obtained by Ellul et al. [11]. This confirms that fleeting order are distinct from other limit orders, and deserve to be treated separately.

3 The Spanish Stock Exchange and the Datasets

In this section we briefly present the institutional characteristics of the Spanish stock market, known as SIBE, and the datasets we use (a more complete description is given in Gava [13]). We also provide a description of the order flow and its composition over the trading day.

3.1 Institutional Characteristics of SIBE

The Spanish market is an order driven market, with liquidity providers for certain shares. The market features real time information on trading activity, so that transparency is fully guaranteed, and it is open from Monday to Friday.

The trading day is divided in different phases. There are two auctions: one at the beginning of the trading session, called **Opening Auction**, and the other at the end, called **Closing Auction**. The first lasts 30 minutes, opening at 8:30 am, with a 30-second random end period to prevent price manipulation. The second lasts between 5:30pm and 5:35pm, with the same characteristics as the opening auction. During the auctions orders are entered, altered and cancelled, but no trade is executed. After the random end, the allocation period begins, during which the shares included in orders subject to execution at the fixed auction price are traded.

Between the two auctions there is the **Open Market** period, running from 9am to 5:30pm. During this period orders can be entered, altered or cancelled, with trading taking place at the price determined according to the open market's matching rules. The order book is open and available to all market members and orders with the best price (highest buy and lowest sell) have priority in the book. When prices are the same, orders entered first have priority. Furthermore, market orders entered in the system are executed at the best opposite side price. Orders may be fully executed (in one or several steps), partially executed, cancelled or not executed, so each order can generate several trades.

Orders may have hidden volumes, so that only part of the trading volume is displayed in the system but (differently from the ECN market analyzed in Hasbrouck and Saar [17]) completely hidden orders are not allowed[1]. Once the displayed volume has been executed, the rest is considered as newly introduced hidden volume (iceberg) order. SIBE orders may be valid for the following periods of time: *for one day*; *until a specific date, until cancelled*. Orders with a validity of more than one day maintain their priority in the system in accordance with their price and time of entry with respect to orders generated during the session. When a modification to an order impacts priority, a new order number is generated and enters the system as a newly entered order.

3.2 Datasets

The dataset of the orders submitted, their outcome and their duration are not immediately available, so it is necessary to construct them using three datasets provided by *Sociedad de Bolsas*, the company running the SIBE. We describe briefly the information available in the three datasets and the algorithms we use; for a more complete description see Gava [13].
Dataset MP contains information about the limit order book as available to market participants. This is given by the five first best orders on the bid and ask side of the book; each level contains the price of the order, the total volume and the number of outstanding limit orders at that price. All events leading to a potential order book modification are time stamped and recorded in real time.
Dataset SM contains information about volume and price of the first best levels on the bid and ask sides. All the modifications occurred in the first best levels are recorded and can be used to find out the event which caused the modification in the book. The cumulated volume transacted is also recorded, as well as the price at which the last transaction takes place.
Dataset BASA contains information about the transactions in terms of volume, price and time occurred during the trading session disaggregated by orders.

The databases can be combined to yield information on events generating changes in the limit order book. That is, combining the information contained in the datasets we obtain for each side of the market the new orders

[1] See Pardo and Pascual [20] for a discussion of the role of hidden orders in the Spanish Stock Exchange.

placed with their price, volume, time of the placement and the transactions and cancellations occurred during the trading session.

We use an algorithm proposed by Abad [1] in order to classify the events in the SM dataset, and we construct a set of all the new orders placed in the trading session and another one composed of the executed and cancelled orders. In this way we construct a limit order dataset with the explanatory variables needed.

In the creation of the limit order dataset we consider only the orders whose development we can follow. In the case of the analysis of the best order to introduce we consider all the orders placed independently of their development, meanwhile in the second case we take into consideration all the orders we can follow. This way we obtain a dataset composed of the new orders placed during the period of analysis, their cancellation and execution times and the value of the explanatory variables at the moment of placement and at the moment of the cancellation or execution of the order. To the limit order dataset we need to aggregate all the market orders introduced in the market so we have a complete dataset of all the orders submitted.

The period considered is July–September 2000, and the assets are all the stocks belonging to the IBEX 35 except ZELTIA, since in September 2000 the company made a split.

3.3 Description of the Market

The assets belonging to IBEX 35 are very different in terms of trading activity, depth, volatility etc. We have divided the assets in three sub–samples: stocks with high, medium and low trading activity (see Appendix).

We start showing the information related to the proportion of market orders and limit orders divided in cancelled, executed and expired on both sides of the book. Our dataset has some limitations, since we only observe the first five levels of the LOB. This implies that when an order moves out of the fifth level our data consider it as expired. Nevertheless, since most of the orders are concentrated in the first five levels our dataset is still quite informative.

Table 1 shows the proportion of market and limit orders which are cancelled, executed and expired on both sides of the market. The proportion of orders executed and cancelled decreases when the trading activity increases. The opposite pattern is followed by expired and market orders.

Table 1: Proportion of limit and market orders on both sides.				
	Low	Medium	High	Total
	BUY			
Limit Orders: Executed	0.147	0.160	0.107	0.128
Limit Orders:Cancelled	0.186	0.114	0.052	0.087
Limit Orders: Expired	0.219	0.234	0.223	0.226
Market Orders	0.448	0.493	0.618	0.559
	SELL			
Limit Orders: Executed	0.146	0.142	0.109	0.124
Limit Orders:Cancelled	0.186	0.105	0.052	0.083
Limit Orders: Expired	0.227	0.239	0.254	0.246
Market Orders	0.441	0.514	0.585	0.547

In the low trading activity sample the proportion of orders cancelled is very high, and so is the proportion of executed orders. This is probably due to the fact that institutional traders are more likely to trade these stocks, and they use cancellation as an instrument to search for information. Non–institutional investors are probably not attracted by assets with low trading activity.

What characteristics do orders which are eventually cancelled have? Table 2 shows that, on the buy side[2], most of the orders cancelled are introduced at the first level, and this proportion decreases as trading activity increases. In the following levels (from the second to the fifth) the proportion increases as the trading activity increases. At the moment of cancellation most orders are still at the first level but the difference with other levels is not as high as before. Table 2 therefore shows that traders respond to changes in the level of the order, although this is not the only cause of cancellation (the percentage or orders remaining at the first level that are cancelled is quite high).

[2] From now on we present only the figures related with the buy side, since the sell side behaves in the same way.

Table 2: Distribution of canc. orders at placement (t) and moment of cancellation (t+1).										
	Level_1		Level_2		Level_3		Level_4		Level_5	
	t	t+1	t	t+1	t	t+1	t	t+1	t	t+1
Buy										
Low	0.848	0.454	0.100	0.322	0.034	0.143	0.014	0.060	0.004	0.021
Medium	0.797	0.419	0.124	0.322	0.047	0.160	0.022	0.072	0.009	0.028
High	0.681	0.330	0.190	0.345	0.077	0.196	0.037	0.093	0.015	0.036
Sell										
Low	0.829	0.410	0.111	0.350	0.040	0.155	0.016	0.063	0.005	0.022
Medium	0.789	0.408	0.133	0.336	0.050	0.162	0.021	0.068	0.008	0.026
High	0.677	0.331	0.193	0.350	0.079	0.193	0.037	0.091	0.014	0.035

For the low and medium activity samples the percentage of orders cancelled at the first level is higher than for the high activity sample. This is probably another signal that low and medium activity stocks are more likely to be traded by institutional investors.

Consider now the distribution of the orders cancelled and executed over the trading session (Figures 1, 2 and 3). For the high and medium activity groups executed orders are always more numerous than cancelled orders. For the low trading activity group the opposite is usually true. The low and medium trading activity samples show a special pattern: when the proportion of executed orders increases the proportion of orders cancelled decreases and vice-versa[3].

If cancellations are used to search for information, then they are likely to be used more often in periods of higher uncertainty. At the same time, during periods of higher uncertainty traders are less willing to execute orders; this may explain the negative correlation between cancellations and executions. The negative correlation is stronger for the low and medium trading activity samples, probably as a consequence of the stronger presence of professional traders.

Looking at the average and median times of the orders cancelled (Figures 4 and 5) over the trading session we see that the times for cancellation are shorter at the beginning and at the end of the trading session showing an inverse U-shaped pattern[4]. The duration is affected by the price-discovering

[3] The correlation coefficient between the proportion of orders executed and orders cancelled is negative for the medium and low trading activity samples (in both cases it is higher than 45%). In the case of high trading activity sample the correlation coefficient between orders executed and cancelled is positive and close to 70%.

[4] This pattern is more evident when the trading activity decreases.

Figure 1: Distribution of cancellations and executions over the trading session for the high trading activity sample on the buy side.

Figure 2: Distribution of cancellations and executions over the trading session for the medium trading activity sample on the buy side.

Figure 3: Distribution of cancellations and executions over the trading session for the low trading activity sample on the buy side.

process and the opening of the NYSE.

In fact Figures 6 and 7 show that the spread and volatility are higher at the beginning and the end of the trading session, confirming that these are periods of higher uncertainty.

Figure 8 shows the frequency of change of level over the three groups and the differences among them. We call dk, with $k \in \{0, 1, 2, 3, 4\}$ the set of orders which move up n levels from the moment of placement to the moment of cancellation, and dnj, with $j \in \{1, 2, 3, 4\}$ the set of orders which move down j levels[5]. Thus, $d0$ is the set of orders which do not change level, $d1$ is the set of orders moving up one level (e.g. from first to second level), $dn1$ is the set of orders moving down one level, and so on.

The proportion of orders which do not change their level ($d0$) is the highest in all cases. In the low trading activity group the proportion of $d0$ is the highest, and the proportion decreases as the trading activity increases. For orders which move up one level ($d1$) we have the highest proportion of orders cancelled for the assets with low trading activity, while, when the order loses one level ($dn1$) the highest proportion of cancellation belongs to the high trading activity group.

The proportion of orders which does not change level and are placed at

[5] An order can move down only if it is not placed at the first level. This is why j runs from 1 to 4.

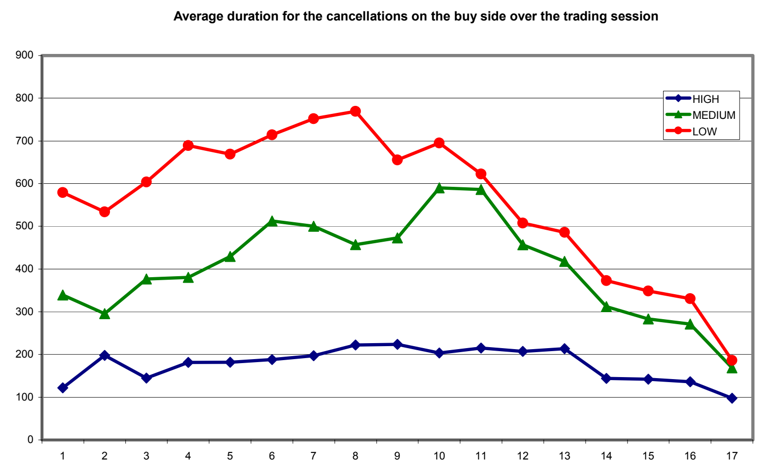

Figure 4: Average duration for cancellations along the trading session on the buy side for the three sub-samples.

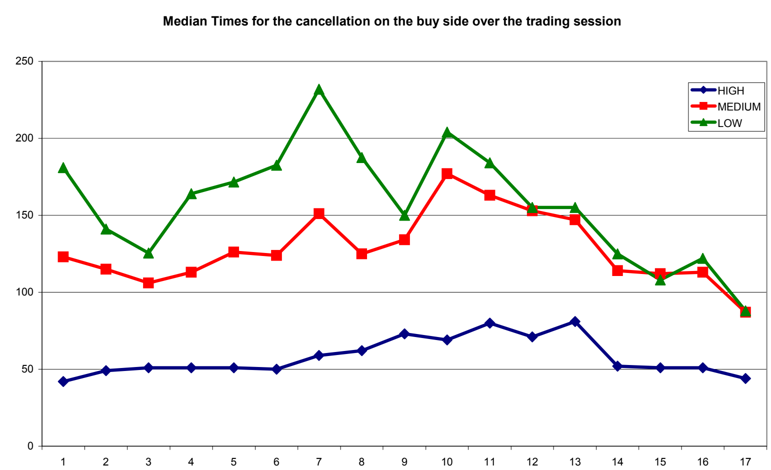

Figure 5: Median duration for cancellations along the trading session on the buy side for the three sub-samples.

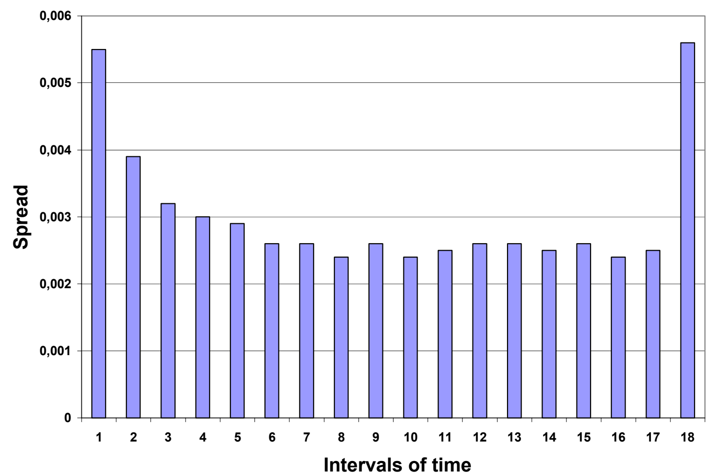

Figure 6: This figure reports the relative inside bid ask spread. The relative inside spread is equal to $\frac{best\ ask - best\ bid}{QMP}$, where $QMP = \frac{best\ ask + best\ bid}{2}$. The bars are the averages over the 65 days of the sample.

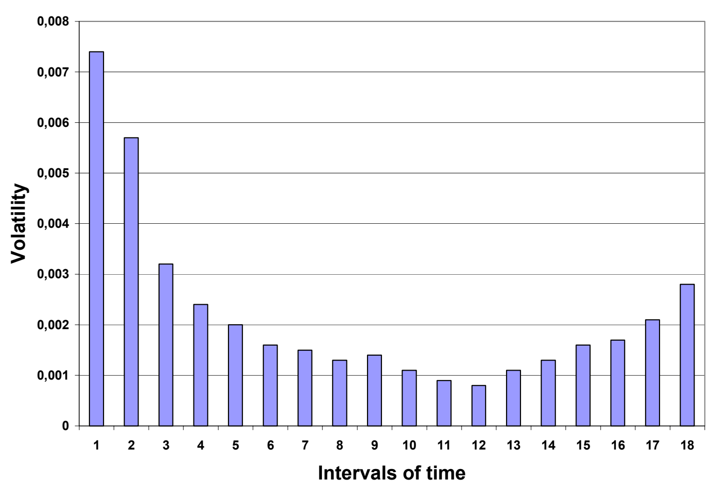

Figure 7: This figure reports the volatility computed as the squared quote midpoint returns. The quote midpoint return is computed as the ln(QMP$_t$)-ln(QMP$_{t-1}$). The bars are the averages over the 65 days of the sample.

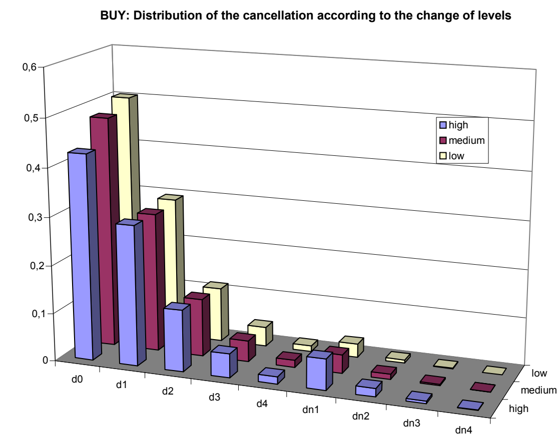

Figure 8: Distribution of the cancellations according to the change of levels for the three sub-samples. We define dk, with $k \in \{0, 1, 2, 3, 4\}$ the set of orders which move up n levels from the moment of placement to the moment of cancellation, and dnj, with $j \in \{1, 2, 3, 4\}$ the set of orders which move down j levels.

the first level changes over the trading session, showing a U shaped pattern as in Biais et al. [5] (see Figure 9).

Summing up, executions occur mostly as the consequence of movements in the market price. Cancellations may instead be due to various reasons. To start with, cancellations may be the consequence of adverse price movements, just like executions. A signal indicating that the conditions for execution of the order are not optimal can be given by the fact that the order is moving to higher order levels, so that the expected time of execution increases. In this case the trader may want to cancel the order and resubmit it at a better price.

Another possibility is that cancellation is a strategic decision taken by the trader at the moment of the placement of the order, with the goal of collecting information about the market. In this case the order is cancelled very quickly without moving to the following levels. As we have seen above this behavior seems to be common at the beginning and at the end of the day.

The key variables in order to distinguish between the two types of cancellations are the duration, the change of level and the placement at the

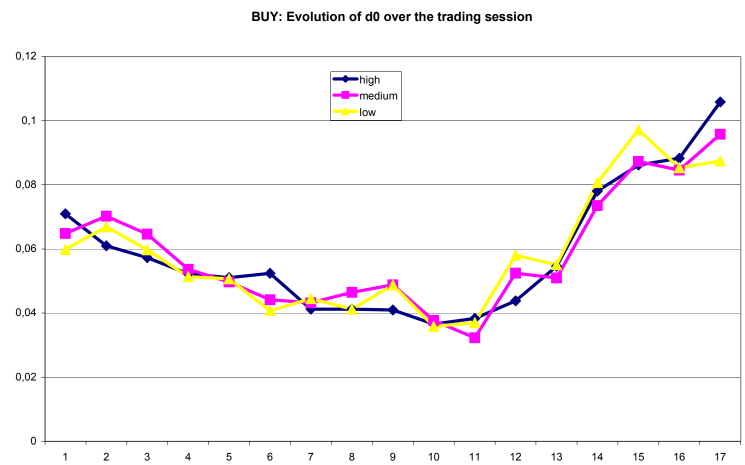

Figure 9: Distibution of d0 for the three sub-samples along the trading session.

first level. Orders placed with the goal of collecting information should be cancelled very quickly and should be aggressive (i.e. placed at the first level).

So, we have two different types of cancellation depending on the duration. In order to distinguish between them it is useful to find out a cut-off time, classifying the cancellation of an order as strategic if it occurs before the cut-off time.

In order to determine the cut-off period we look at the price aggressiveness of the orders cancelled. Remember that orders which are placed to collect information should be quickly cancelled *and* should be aggressive. Thus, when we select a cut-off period we would like to see that orders cancelled before the cut-off time are in fact aggressive.

We formally define price aggressiveness on the two sides as follows. Let limitprice_t be the price at which the limit order is placed and bidprice_{t-1}, askprice_{t-1} the existing best quotes on both sides at the moment of the order placement. For the ask side, we define the price aggressiveness of the limit order as:

$$\text{price agr}_t = \frac{\text{askprice}_{t-1} - \text{limitprice}_t}{\frac{\text{bidprice}_{t-1} + \text{askprice}_{t-1}}{2}}.$$

For the bid side, we define the price aggressiveness of the limit order as:

$$\text{price agr}_t = \frac{\text{limitprice}_t\text{- bidprice}_{t-1}}{\frac{\text{bidprice}_{t-1}+\text{askprice}_{t-1}}{2}}.$$

When the value of this variable is equal to 0 it means that the placement of the new order occurs at the same price of the best ask (bid) in the limit order book. If the value of this measure is positive it means that the trader is improving the price of the new order with respect to best quote, so the trader has placed a more aggressive order than the one placed at the quote or out of the quote. An increase in the value of this variable shows an increase in the aggressiveness, so the more aggressive an order is, the higher will be the value of this variable. If the price aggressiveness takes a negative value it means that the trader has placed the order out of the quote.

We have computed the average and the median price aggressiveness for different cut-off periods for the three groups. Orders are divided in two subsets: one containing cancellations with a duration lower than the cutoff period and another one with cancellation time higher than the cutoff period. Taking a quick look at the pictures (Figures 10, 11 and 12) we can see that, in the three groups, price aggressiveness achieves a maximum when the cutoff periods are either 5 or 10 seconds. It is interesting to observe that the values of price aggressiveness are the lowest for the high activity group: assets in this group have usually a narrower spread, which reduces the possibility of placing very aggressive orders.

However, the percentage of cancellations under a cutoff period of 5 or 10 seconds is very low, differently from the U.S. market (in fact, Hasbrouck and Saar [16] and [17] adopt a cutoff time of 2 seconds). We have selected a cutoff time of 10 seconds in order to have a sufficient number of fleeting orders.

Table 3 shows the different proportions of orders cancelled depending on the level of price aggressiveness and trading activity. The low activity group has the highest percentage of aggressive orders, and in general the proportion of orders cancelled which are introduced with positive price aggressiveness decreases as the trading activity of the assets increases. In the case of orders introduced at the quote the proportion of orders increases as the trading activity increases, and the same pattern is observed for cancellations with negative price aggressiveness.

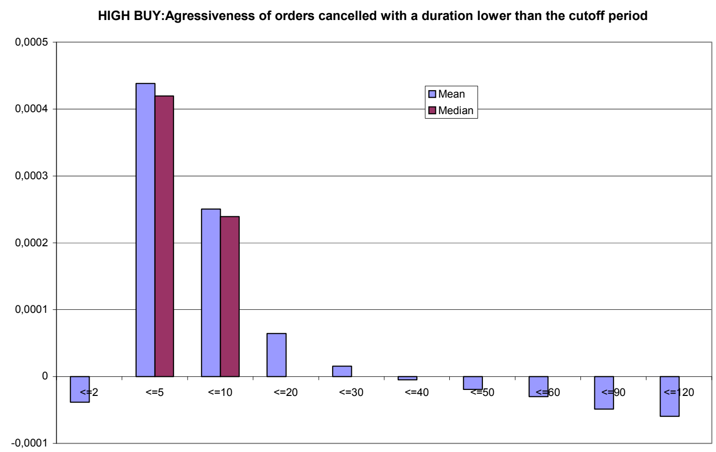

Figure 10: Average and median price aggressiveness of orders cancelled with a duration lower than a cutoff period (cutoff period i, i=2, 5, 10, 20, 30, 40, 50, 60, 90, 120 seconds) for the high trading activity sample on the buy side.

Figure 11: Average and median price aggressiveness of orders cancelled with a duration lower than a cutoff period (cutoff period i, i=2, 5, 10, 20, 30, 40, 50, 60, 90, 120 seconds) for the medium trading activity sample on the buy side.

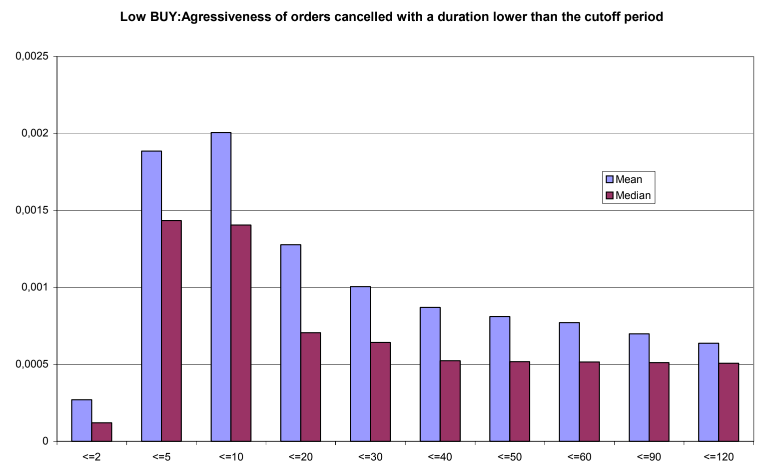

Figure 12: Average and median price aggressiveness of orders cancelled with a duration lower than a cutoff period (cutoff period i, i=2, 5, 10, 20, 30, 40, 50, 60, 90, 120 seconds) for the low trading activity sample on the buy side.

Table 3: Proportion of orders cancelled classified according to the trading activity and PA

	BUY			SELL		
	Low	Medium	High	Low	Medium	High
Total						
PA>0	0.691	0.622	0.444	0.677	0.621	0.454
PA=0	0.158	0.175	0.237	0.151	0.168	0.222
PA<0	0.152	0.203	0.319	0.171	0.211	0.323
Morning						
PA>0	0.712	0.631	0.470	0.686	0.631	0.473
PA=0	0.135	0.157	0.206	0.147	0.152	0.197
PA<0	0.154	0.212	0.324	0.166	0.217	0.330
Intermediate						
PA>0	0.682	0.617	0.443	0.668	0.620	0.454
PA=0	0.166	0.180	0.246	0.161	0.175	0.230
PA<0	0.152	0.204	0.311	0.171	0.205	0.316
Afternoon						
PA>0	0.683	0.622	0.425	0.679	0.613	0.440
PA=0	0.167	0.184	0.249	0.144	0.174	0.234
PA<0	0.150	0.193	0.325	0.176	0.213	0.326

We have also analyzed the behavior of the cancellation depending on the price aggressiveness and the different periods of the trading session divided in morning (it takes into account the period between 9:00-11:00); intermediate period (the period between 11:00-15:30) and afternoon (the period between 15:30-17:30).

In the morning we can observe the same pattern shown for the daily trading session, but in the intermediate period the proportion of orders cancelled with positive or negative price aggressiveness decreases in favor of the ones with price aggressiveness equal to zero. A possible explanation is that the price is discovered and the placement of aggressive orders is costly, so that people prefer to submit at the quote and not stand the cost of the price improvement.

4 Empirical Analysis

In this section we investigate empirically the determinants of order submission and cancellation strategies on the SIBE. We start describing the variables that we use in the analysis, and next proceed to estimate a multinomial logit model for the type of orders submitted by the traders. Here we distinguish, among others, between 'fleeting' limit orders and 'serious' limit orders (orders which are not cancelled almost immediately). Next, we focus our attention on the subset of 'serious' orders which are cancelled, and estimate a logistic model to find out the determinants of the cancellation decision.

4.1 Description of the Variables

In this section we define the variables used in the models and in the empirical analysis.

The **relative inside spread** for an order placed at time t is computed looking at the ask and bid prices existing right before the order is placed (i.e. the moment at which the trader makes the decision), and it is given by:

$$\text{Relative inside spread}_{t-1} = \frac{\text{askprice}_{t-1} - \text{bidprice}_{t-1}}{\frac{\text{bidprice}_{t-1} + \text{askprice}_{t-1}}{2}}$$

A wider spread implies a higher transaction cost which provides little incentive for market order traders to execute against the existing limit orders (see Al-Suhaibani and Kryzanowsky [4]).

Volatility is the sum of the absolute value of changes in transaction price in the last ten minutes before the placement of the order divided by the actual price[6].

Trading activity is the logarithm of the number of transactions occurred one hour before the event considered.

The number of transactions in the market one hour before the event considered. This is a proxy for the number of traders present in the market.

Depth is defined as the number of shares outstanding at the best quote at the same side of the book at the moment of the placement of the order, and **Opposite Depth** is the number of shares outstanding at the best quote on the opposite side of the book.

We also insert dummy variables for the **level** of the LOB at which the order is placed and cancelled or executed, and for the **type of the last order introduced** (marker or limit order).

When we study the determinants of cancellation we use dummy variables both for the level at which the order is placed and for the level at which the order is cancelled, executed or expired. We expect that an higher level of the LOB causes smaller expected probability of cancellation. Another set of dummy variables introduced is the **change of level**. These variables indicate that a cancelled order belongs to one of the sets dk or dnj, with $k \in \{0, 1, 2, 3, 4\}$ and $j \in \{1, 2, 3, 4\}$ as defined in subsection 3.3.

4.2 Order Submission Strategies

Given their information, traders have to decide whether or not to place an order and, if yes, what type of order to place. Elull et al [11] analyze how the different explanatory variables affect the likelihood of placing a market or a limit order or a cancellation. Another possibility however is to collect more information by placing a fleeting order. So, in our analysis of order submission strategies, we assume that a trader appearing on the market has 4 alternatives.

1. Avoid placing an order.
2. Place a market order.
3. Place a 'serious' limit order.
4. Place a 'fleeting' limit order.

[6] The actual price is the price negotiated in the market at the moment of the placement of the order. The definition of volatility without being divided by the actual price is due to Cho and Nelling [6]; we think it is better to divide by the actual price in order to normalize.

We don't distinguish between sell and buy side because we are interested particularly in studying the event 'fleeting order': given its nature of collecting information the side of the market is not important. Another reason is given by the relatively few observations available for this event for some assets with low trading activity, so we have decided to aggregate the two sides of the book for all the stocks. We classify a limit order as 'fleeting' if it is cancelled within ten seconds, and all remaining limit orders are considered 'serious' (we will call simply 'limit orders' the serious limit orders).

The event 'avoid placing an order' is defined as follows. First, we have computed the median time t_m between successive orders for each asset. Second, whenever the time between orders is higher than the median one we introduce a 'no activity' event t_m seconds before the latest order. For example, the median times between successive orders for REPSOL is 6 seconds. Suppose that we observe an order at 10:51:06, and another at 10:51:17. Then we introduce a no–activity events at 10:51:11. There is considerable variation across stocks in their no activity time interval.

This definition of 'no activity event' follows closely the one used in Ellul et al. [11]; the only difference is that in their case the no activity time interval is defined as the minimum between the median time between successive order events and five minutes. In our dataset all the median times between successive events are lower than 5 minutes, so we ignored this part. Easley, Kiefer and O'Hara [10] use a similar definition of no activity event to model and estimate the passage of clock time without activity.

According to Focault [12] the percentage of limit orders increases with the spread. In his model, in equilibrium, there is a positive relation between spread and limit orders and a negative relation between spread and market orders. Harris [15] and Smith [24] show empirically that the relative inside spread is positively related to the likelihood of limit orders and inversely related to the likelihood of market orders. The quoted bid–ask spread represents a potential cost to market orders and a potential benefit to limit orders. So if the relative inside spread increases it is more likely to introduce a limit or a fleeting order than a market order since the transaction costs are higher (see also Al-Suhaibani and Kryzanowsky [4] for a similar analysis).

Hypothesis 1 *Wider spreads make the placement of limit and fleeting orders more likely, and the placement of market orders less likely.*

Parlour [21] notes that the arrival of a limit buy (sell) order lengthens the queue at the bid (ask) side of the book and this reduces the attractiveness of submitting additional limit orders of the same kind. So, if the depth on one side of the book increases then it becomes more likely to observe a market order than a limit order on the same side since the chances of execution of the latter are low. Also, market and limit orders on the other side are more likely to be submitted. On the other hand fleeting orders should not be affected by the depth since their objective is not the execution.

Hypothesis 2 *An increase in depth on one side of the book increases the likelihood of introducing a market order rather than a limit order on the same side.*

Hypothesis 3 *An increase in depth on one side of the book increases the likelihood of market and limit orders on the other side.*

More trading activity in the recent past encourages traders to participate in the market, since they see better opportunities to complete the desired transactions.

Hypothesis 4 *A higher number of transactions in the recent past reduces the probability of no activity.*

Focault [12] proposes a model of a dynamic limit order market where increased volatility makes traders place limit orders at less competitive prices and market orders are less profitable. In equilibrium the higher volatility makes market order more costly leading to a higher proportion of limit orders. Handa and Schwartz [14] , Smith [24] Ahn, Bae and Chang [3], Hollifield, Miller, Sandas and Slive [18], Danielson and Payne [9] and Ranaldo [23] find evidence of the direct relation between the volatility and the placement of limit orders. Given the definition of fleeting orders they are more likely in volatile and uncertain periods.

Hypothesis 5 *An increase in volatility increases the probability of limit and fleeting orders, and reduces the probability of market orders.*

The effect of the last order introduced on the new order placed has been studied by Biais et al. [5] and Parlour [21]. Biais et al. [5] observe that the probability of a given type of order is larger after an order of the same type has been placed, and they refer to it as the *diagonal effect.* This may be due to order splitting or to the fact that traders reacts similarly, in sequence, to the same events. According to Parlour [21] the probability of observing a limit sell (buy) order given that the transaction in the previous period was a limit sell (buy) order is at most as large as the probability conditional on the previous time transaction being a market sell order. The transaction occurs on one side of the book and encourages the submission of the limit order on the same side of the book. Since we don't take into account the side of the market of the different events we have decided to do the same with the side of the last order introduced. By looking at Biais et al. [5] and Abad [1] we can observe that the probability of placing, for example, a market order after a market order of the same side or the opposite side of the book is high in both cases.

Hypothesis 6 *The probability of a given type of order increases after an order of the same type has been placed or executed.*

In order to test these hypotheses we use a multinomial logit specification.

Let $i \in \{0, 1, 2, 3\}$ denote an index corresponding to these events and let j index the stock. We postulate the relationship:

$$\ln\left(\frac{\mathrm{Pr}_{i,j}}{\mathrm{Pr}_{0,j}}\right) = \beta_i X_j \qquad \text{for } i \in \{1, 2, 3\}\,.$$

where X_j is the vector of explanatory variables and β_i represents the vector of coefficients. We assign the value of zero for the dependent variable to the no activity event, so the probability for the other events is modeled relative to this event. We consider the following explanatory variables: relative inside spread (*bidask*), volatility (*volat*), the trading activity (TA), the depth of the best quote on the same side of the book (*depth*), the depth of the best quote on the opposite side of the book (*opdepth*). All these variables are computed at the moment of the placement. We include also a set of dummy variables which represents the type of the last order introduced: mk is equal to one if the last order introduced is a market order, and zero otherwise, while *limit* is equal to one if the last order introduced is a limit order, and zero otherwise.

We estimate the following model for each stock i and time t over which an event occur:

$$\begin{aligned} \text{Event type}_{i,t} \quad = \quad & \alpha + \beta_1 \left(bidask\right)_{i,t} + \beta_2 \left(volat\right)_{i,t} + \\ & + \beta_3 \left(TA\right)_{i,t} + \beta_4 \left(depth\right)_{i,t} + \beta_5 \left(opdepth\right)_{i,t} + \\ & + \beta_6 \left(mk\right)_{i,t} + \beta_7 \left(limit\right)_{i,t} + e_{i,t} \end{aligned} \tag{1}$$

We estimate this model for each stock and for the three subsamples classified according to the trading activity. When we run regressions for a single stock we keep i fixed and run regression (1). When we estimate, say, the low trading activity sample then we include in the regression all observations (i, t) such that stock i is a low trading stock.

Tables 4,5,6 Here.

In the analysis of the three subsamples almost all the coefficients of the independent variables are significative at 1%.

An increase of the spread reduces the probability of submitting a market order and increases the probability of introducing a limit or a fleeting order, as predicted in Hypothesis 1. The coefficient is higher for fleeting orders than for limit orders (in most of the cases) so in a period of wider spread the probability of placing a fleeting order is higher than the one for the limit order. The same results are obtained for all the assets and for the three subsamples.

In the case of depth on the same side of the book, an increase affects positively the probability of placing a market order and negatively the probability of a limit order, as predicted by Hypothesis 2. For the placement of fleeting orders this variable is not significative for most of the assets.

If the depth on the opposite side of the book grows the probability of placing a market order increases, as anticipated in Hypothesis 3. However, contrary to Hypothesis 3 the coefficient for limit orders is negative and sometimes not significant. In the same way this variable does not affect the placement of fleeting orders in most of the assets except the case of the three sub–samples where, except for the low group, it is significative and negative.

As conjectured in Hypothesis 4, trading activity is positively related to the probability of placing market and limit orders (as in Ellul et al. [11]). In fact, the coefficient for market and limit orders in the three sub–samples is usually positive. The only exception is for limit orders in the high trading activity sample. The probability of submitting fleeting orders also increases with the increase of trading activity, except in the case of TEF where the relative inside spread is narrow.

The volatility of the price affects negatively the probability of placing a market order and positively the probability of placing a limit or a fleeting orders, as predicted in Hypothesis 5. The results are obtained for all the assets and for the three sub–samples.

From the analysis of the last order introduced we can observe that this phenomenon affects the next choice. In the case the last order introduced is a limit order the probability of submission of a market order increases in the high and medium trading activity samples and decreases for the low trading activity sample. The limit order is more likely after a market order in all the cases. A fleeting order seems to be more likely after a market order than a limit order: when a transaction occurs at least a part of the volume outstanding at the best quote is executed so the spread could increase and the traders may want, in this case, to discover the new information. This confirms Hypothesis 6 where the last order introduced affects the next choice.

4.3 The Determinants of Cancellations

Once a 'serious' limit order is introduced it can be executed or remain outstanding in the LOB, and in this case the trader has the option to cancel it. The decision is taken looking at the evolution of market conditions. In this section we analyze the probability of cancelling the order by using a logistic probability model; notice that we exclude fleeting orders from our analysis[7].

Ellul et al. [11] observe that it is more likely to cancel orders when the prices at the quotes are wide.

Hypothesis 7 *If the spread is wider the probability of cancellation is higher.*

If the order placed in the market is losing priority in LOB then it is intuitive that the probability of cancellation should increase, while an improvement of its position in the book decreases the probability of cancellation.

Hypothesis 8 *When an order moves up in the levels of the book the probability of cancellation increases, and when an order moves down the probability of cancellation decreases.*

If volatility increases traders submit limit orders at less competitive price, waiting for an improvement in market conditions (see Focault [12]). Thus, the probability of cancellation decreases.

Hypothesis 9 *Higher volatility decreases the probability of cancellation.*

Large [19] predicts that when trading partners arrive at the market with low frequency it is preferable to cancel and eliminate the risk of no execution. So, an increase in the number of traders in the market reduces the probability of cancellation. We use the number of transaction as a proxy for the number of traders.

[7] When we include fleeting orders the results do not change. This is due to the fact that fleeting order are a small percentage of total limit orders.

Hypothesis 10 *A higher number of transactions reduces the probability of cancellation.*

We are convinced of the existence of a relationship between the interaction of trading activity and the relative inside spread ($effect$) and the probability of cancellation: a joint increase of the spread and the trading activity increases the likelihood of the order to be executed so the risk of no execution is reduced and the probability of cancelling is reduced too.

Hypothesis 11 *The interaction of trading activity and relative inside spread affects negatively the probability of cancellation.*

The dependent variable y is the cancellation indicator, taking value one if the order is cancelled and zero otherwise. The probability of cancellation is conditional on the vector of regressors $\mathbf{x}$ according to the relation

$$\Pr(y = 1|\mathbf{x}) = \Lambda(\gamma\mathbf{x})$$

where γ is a vector of coefficients and $\Lambda(.)$ is the logistic cumulative distribution function.

We include the following explanatory variables in the analysis: relative inside spread ($bidask_{t+1}$) and volatility ($volat_{t+1}$) computed right before the cancellation, the change in the number of traders present in the market computed between the time of cancellation and the time of the introduction of the order ($dif\_traders$), the interction between trading activity and relative inside spread ($effect$), a dummy variable (neg) taking value 1 if the order loses levels between the submission and the cancellation, and a set of dummy variables representing the level at which the order is introduced ($level\_i$, with $i = 1, 2, 3, 4, 5$).

We estimate the model for each stock and for each side (bid or ask) of the book. We also consider what happens when we aggregate stocks in subsamples according to the trading activity. The results of the aggregate estimates are displayed in Tables 7 to 9.

Tables 7,8,9 HERE.

For the low and medium trading activity samples we obtain the same results of the assets but in the case of the high trading activity sample the results differ from the ones of the assets.

An increase of the relative inside spread increases the probability of cancellation (Hypothesis 7) for all the samples and the assets. An increase of the distance between the best prices allows the placement of new limit orders so the outstanding ones lose their priority and they are more difficult to execute, so traders prefer to cancel them.

An increase in the interaction variable between spread and trading activity allows a quicker execution of the outstanding limit orders so the probability of cancellation decreases for all the assets and the three subsamples (Hypothesis 11).

When the order loses one or more levels the probability of cancellation increases, as predicted in Hypothesis 8, since the probability of execution decreases.

According to Hypothesis 9 volatility is negatively related to the probability of cancellation: in the period of uncertainty traders prefer to place orders out of the best quote so the probability of cancellation is reduced. In fact, the coefficient is negative in all regressions except for the sell side of the high activity group, where it is not significant.

An increase in the number of traders between submission and cancellation reduces the probability of cancellation for assets with low and medium trading activity, as suggested in Hypothesis 10. However, in the case of assets with high trading activity an increase in the number of traders increases the probability of cancelling. Probably the traders want to protect their orders from liquidity traders and speculators. If we pool together the assets with high trading activity we obtain a negative coefficient as expected.

Another interesting result is that orders introduced at the first level have a lower probability of cancelling than orders introduced at other levels for most of the assets belonging to the high and medium trading activity samples. Sometimes the trader wants to submit his/her order at a particular level but, given the degree of activity in the market, the order will be placed at a worse level so the trader decides immediately to cancel it. This variable is not always significant.

5 Conclusions

This work is a first attempt to study cancellations in the Spanish Stock Exchange. We distinguish two types of cancellation: one dedicated to collect information in the market and, for this reason, with a short duration (fleeting orders) and the other one determined by the characteristics of the market (cancelled orders) with a higher duration.

In our analysis of the order submission strategy, we assume that the trader has to decide among no activity, placing limit, market or fleeting orders and we study the decision by using a multinomial logit model. The results obtained for the market, limit orders and the no activity event confirm the ones provided by the theoretical and empirical literature. An important contribution of this work is provided by the results obtained for the fleeting orders: they are positively related with volatility, spread, trading activity and the prior submission of market orders while the depth does not seem to be important.

In the case of cancelled orders, the decision is taken after the placement as the conditions of the market have changed and the trader is not satisfied with the development of the order in the book. In this case we estimate a logistic probability model. We find out the variables involved in this process: volatility, spread, change in the number of traders, movement of the orders along the levels of the LOB and the level at which the order is introduced.

Over all the paper we confirm hypotheses we can find in the literature as well as intuitions that we have about the behavior of the traders, paying special attention to the cancellations and fleeting orders, in the Spanish Stock Exchange.

Appendix

In this section we describe the composition of the three subsamples according to the trading activity. We have computed the median trading activity of each asset and we have decided that the low trading activity group contains all the assets with a median trading activity lower than 3.8. When the median trading activity is between 3.8 and 5 the stock belongs to the Medium Trading Activity group. Finally, if the median trading activity is higher than 5 then we have the high trading activity sample

Low Trading Activity Group (assets with a median trading lower than 3.8).

1. Acesa (ACE).
2. Actividades Construccion Servicios (ACS).
3. Acerinox (ACX).
4. Aguas de Barcelona (AGS).
5. Corporacion Financiera Alba (ALB).
6. Acciona (ANA).
7. Hidrocantabrico (CAN).
8. Continente (CTE).
9. NH Hoteles (NHH).
10. Pryca (PRY).
11. Red Electrica de España (REE).
12. Grupo Vallehermoso (VAL).

Medium Trading Activity Group (assets with a median trading between 3.8 and 5).

1. Aceralia (ACR.)
2. Altadis (ALT).
3. Amadeus A Privilegiadas (AMS).
4. Bankinter (BKT).
5. Gas Natural (CTG).
6. Grupo Dragados (DRC).
7. Fomento de Construccion Contratas (FCC).
8. Ferrovial (FER).
9. Iberdrola (IBE).
10. Indra (IDR).
11. Banco Popular (POP).
12. Sogecable (SGC).
13. Sol Meliá (SOL).
14. Telefonica Publicidad e Informacion (TPI).
15. Telepizza (TPZ).
16. Union Fenosa (UNF).

High Trading Activity Group (assets with a median trading activity higher than 5).

1. Banco Bilbao Vizcaya Argentaria (BBVA).
2. Endesa (ELE).
3. Repsol (REP).
4. (Banco) Santander Central Hispano (SCH).

5. Telefónica (TEF).

6. Terra (TRR).

Table 4

Event		Coef	Std Err	z
1				
	bidask	-62.38	1.3127	-47.52
	opdepth	2.82e-06	8.02e-07	3.50
	depth	0.000011	1.97e-06	5.52
	lb	-0.07073	0.0073	-9.63
	TA	0.3825	0.0044	86.23
	volat	-18.55	0.1827	-101.5
	cons	-0.7993	0.0176	-45.42
2				
	bidask	50.25	1.0120	49.65
	opdepth	-2.69e-06	1.96e-06	-1.37
	depth	-0.00003	1.60e-0.6	-18.93
	lb	-0.3369	0.00683	-49.32
	TA	0.0871	0.00389	22.38
	volat	0.667	0.00852	78.19
	cons	-0.2979	0.01555	-19.17
3				
	bidask	51.44	6.769	7.60
	opdepth	-0.000049	0.000018	-2.73
	depth	-0.000021	0.0000122	-1.73
	lb	-1.1332	0.05166	-21.93
	TA	0.40446	0.03119	12.97
	volat	0.7129	0.02027	35.16
	cons	-5.7976	0.1254	-46.23

Table 4: Multinomial Logit for the Low trading activity group. Event=0 is the comparison group and represents the no activity event; event=1 represents the event placing a market order; event=2 represents the event placing a limit order and event=3 represents the event placing a fleeting order.

Table 5

Event		Coef	Std Err	z
1				
	bidask	-74.167	1.2603	-58.85
	opdepth	3.21e-06	3.91e-07	8.21
	depth	8.11e-06	6.16e-07	13.16
	lb	0.1132	0.00437	25.91
	TA	0.39079	0.00253	154.19
	volat	-13.821	0.0707	-195.49
	cons	-1.08032	0.01212	-89.15
2				
	bidask	73.3168	1.0474	70.00
	opdepth	-2.32e-06	6.34e-07	-3.66
	depth	-1.44e-05	5.97e-07	-24.05
	lb	-0.3759	0.00427	88.01
	TA	0.08378	0.00236	35.56
	volat	0.52717	0.00333	158.01
	cons	-0.52772	0.01133	-46.59
3				
	bidask	82.15	6.118	13.43
	opdepth	-0.000019	5.71e-06	-3.30
	depth	-0.000046	6.39e-06	-7.23
	lb	-0.9664	0.03181	-30.38
	TA	0.2077	0.0171	12.15
	volat	0.5659	0.00819	69.04
	cons	-5.460	0.0818	-66.74

Table 5: Multinomial Logit for the Medium trading activity group. Event=0 is the comparison group and represents the no activity event; event=1 represents the event placing a market order; event=2 represents the event placing a limit order and event=3 represents the event placing a fleeting order.

Table 6

Event		Coef	Std Err	z
1				
	bidask	-23.16	2.458	-9.42
	opdepth	2.19e-07	8.31e-08	26.42
	depth	4.68e-06	6.85e-08	6.82
	lb	0.1676	0.00318	52.70
	TA	0.2677	0.00168	159.27
	volat	-6.737	0.02494	-270.09
	cons	-0.978	0.01138	-85.94
2				
	bidask	185.65	2.2720	81.71
	opdepth	-2.76e-07	8.81e-08	-3.14
	depth	-1.65e-06	9.77e-08	-16.94
	lb	-0.3044	0.00343	-88.56
	TA	-0.0270	0.001796	-15.06
	volat	0.3804	0.001346	282.50
	cons	-0.40598	0.01199	-33.83
3				
	bidask	258.458	6.031	42.85
	opdepth	-0.000017	1.41e-06	-12.42
	depth	-0.000024	1.59e-06	-15.07
	lb	-0.1656	0.0224	-7.39
	TA	0.03606	0.01159	3.11
	volat	0.3871	0.003174	121.95
	cons	-5.160	0.07346	-70.25

Table 6: Multinomial Logit for the High trading activity group. Event=0 is the comparison group and represents the no activity event; event=1 represents the event placing a market order; event=2 represents the event placing a limit order and event=3 represents the event placing a fleeting order.

Table 7

Low	Buy			Sell		
	Coef.	Std Err	z	Coef	Std Err	z
neg	3.0009	0.0316	94.92	3.1176	0.0345	90.28
bidask_{t+1}	330.73	7.9277	41.72	346.56	9.284	37.33
effect	-69.043	2.255	-30.62	-63.98	2.656	-24.09
level_1	-0.5204	0.1358	-3.83	-0.1621	0.13	-1.25
level_2	-0.103	0.1391	-0.74	0.2973	0.1342	2.22
level_3	-0.0283	0.1445	-0.20	0.3058	0.1404	2.18
level_4	-0.0883	0.1543	-0.57	0.2441	0.1533	1.59
level_5		dropped			dropped	
volat_{t+1}	-2.249	0.9028	-2.49	-0.0833	0.0109	-7.61
dif_traders	-0.021	0.0005	-39.29	-0.0246	0.0006	-42.81
cons	-3.0947	0.1377	-22.47	-3.51	0.133	-26.38

Table 7: Logistic Probability model for the Low trading activity group. The dependent variable is represented by the decision of cancelling.

Table 8

Medium	Buy			Sell		
	Coef.	Std Err	z	Coef	Std Err	z
neg	2.7857	0.0209	132.88	2.6763	0.0228	117.53
bidask_{t+1}	529.24	11.416	46.36	517.96	12.112	42.76
effect	-104.98	2.7868	-37.67	-88.22	2.922	-30.19
level_1	-0.3546	0.0683	-5.19	-0.514	0.077	-6.68
level_2	0.0085	0.0708	0.12	0.0028	0.079	0.04
level_3	0.0705	0.0747	0.94	0.0881	0.0835	1.06
level_4	0.17102	0.0808	2.12	0.0204	0.090	0.23
level_5		dropped			dropped	
volat_{t+1}	-17.61	0.5884	-29.93	-0.2328	0.0063	-36.92
dif_traders	-0.0037	0.0001	-32.61	-0.0023	8.46e-05	-26.99
cons	3.094	0.0705	-43.88	-3.0151	0.0793	-38.02

Table 8: Logistic Probability model for the Medium trading activity group. The dependent variable is represented by the decision of cancelling.

Table 9

high	Buy			Sell		
	Coef.	Std Err	z	Coef	Std Err	z
neg	2.0115	0.0178	112.82	1.8528	0.0186	99.45
bidask_{t+1}	1382.16	35.053	39.43	1877.3	38.4	48.88
effect	-236.76	6.362	-37.21	-314.08	6.905	-45.49
level_1	-1.232	0.0539	-22.83	-0.4854	0.0535	-9.08
level_2	-0.5688	0.0559	-10.18	-0.0627	0.0554	-1.13
level_3	-0.3249	0.0589	-5.51	-0.0296	0.0583	-0.51
level_4	-0.1938	0.0637	-3.04	-0.0793	0.0629	-1.26
level_5		dropped			dropped	
volat_{t+1}	-2.671	0.2755	-9.70	0.005	0.0025	1.94
dif_traders	-9.59e-05	1.61e-05	-5.94	-7.89e-05	1.53e-05	-5.16
cons	-2.0771	0.05584	-37.20	-2.859	0.05591	-51.13

Table 9: Logistic Probability model for the High trading activity group. The dependent variable is represented by the decision of cancelling.

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