Titulo: Un análisis de las cancelaciones en el mercado bursátil español

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Resumen:

La Bolsa de valores española es un mercado transparente dónde los agentes pueden observar el libro de órdenes y tienen la opción de cancelar las órdenes limitadas que aún permanecen en el libro a la espera de ser ejecutadas. La opción puede ser utilizada si las condiciones de mercado no son las esperadas o también como una forma de descubrir más información sobre el mercado en períodos de incertidumbre.
Vamos a estudiar los factores empíricos que afectan a las cancelaciones en el mercado español. En general, órdenes que se cancelan muy rápidamente después de su introducción en el mercado tienen probablemente el objetivo de recolectar información, mientras las cancelaciones de órdenes que tienen lugar tras períodos más largos están probablemente inspiradas por los cambios en las condiciones del mercado.
Estamos interesados en averiguar qué factores y de qué modo influencian la decisión de cancelar en ambos casos. En el primer caso usamos un modelo logit multinomial para testar la estrategia de introducción/cancelación de la orden, ya que cuando la orden se emite la decisión de cancelarla ya ha sido tomada. Parece que la probabilidad de introducir una orden exploratoria aumenta con la horquilla, la volatilidad, el nivel de actividad comercial, además de estar relacionada con el tipo de orden introducida anteriormente a la nueva orden.
En el caso de una cancelación determinada por el cambio en las condiciones de mercado vamos a utilizar un modelo de probabilidad tipo logit. Los resultados apuntan a que la decisión de cancelar está relacionada con la horquilla y la volatilidad calculada en el momento de la cancelación, el cambio en el número de negociaciones en el mercado, el movimiento del orden a lo largo de los niveles del libro así como el nivel en el que la orden se introduce.

Código JEL: G10, G14

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 market conditions, 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 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 each stock. The possible alternatives are not participating to the market, placing a market order, placing a 'serious' limit order and placing a 'fleeting' order. Following Hasbrouck and Saar [16], 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 market orders, limit orders and no activity confirm the ones provided by the theoretical and empirical literature summarized in Ellul et al. [10]. 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 at which the order is placed and the moment at 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 transactions outstanding in the market. We show that the cancellation decision is related to the spread and the volatility at the moment of cancellation, the change in the number of transactions, the movement of the order 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 [14] 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 [18] 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 [15] 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 orders 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 order 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 [16] have shown that the main motive for placing fleeting orders is to ‘fish’ for hidden orders placed inside the quotes.

Ellul et al. [10] analyze the determinants of electronic order submission strategy by using the New York Stock Exchange system order data using a multinomial logit model. 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 a minimum price variation (tick) 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 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 stocks experiencing an increase in the tick also have a higher number of cancellations.

Pascual and Veredas [21] analyze what pieces of book information are important in explaining the time between two consecutive trades, limit order submission and cancellations 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 [19] 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 orders 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. [10]. 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. [10]. This confirms that fleeting orders 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 [12]). 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 [16]) 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. 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 [12].

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

[1] See Pardo and Pascual [19] for a discussion of the role of hidden orders in the Spanish Stock Exchange.

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.

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 add 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 diverse 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 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).

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[2] (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

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

[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%.

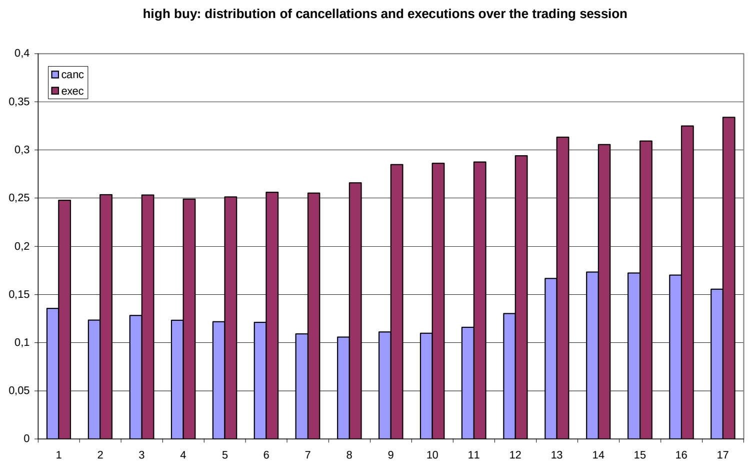

Figure 1: Distribution of cancellations and executions over the trading session for the high trading activity sample on the buy side.

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.

inverse U-shaped pattern[4]. The duration is affected by the price-discovering 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 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 cancellations belongs to the high

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

[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.

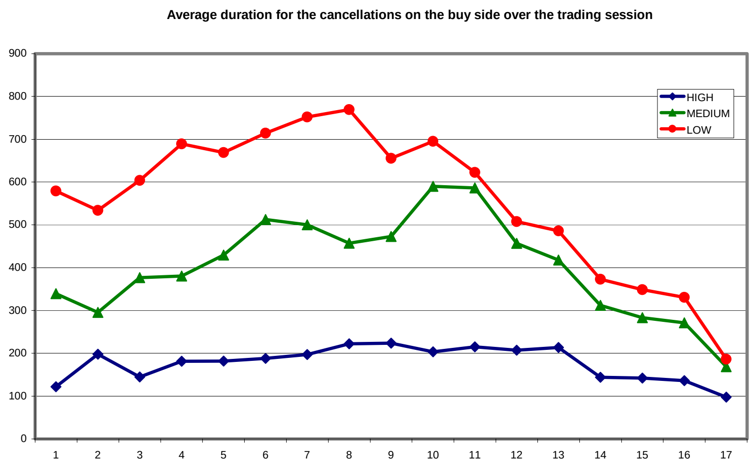

Figure 4: Average duration for cancellations along the trading session on the buy side for the three sub-samples.

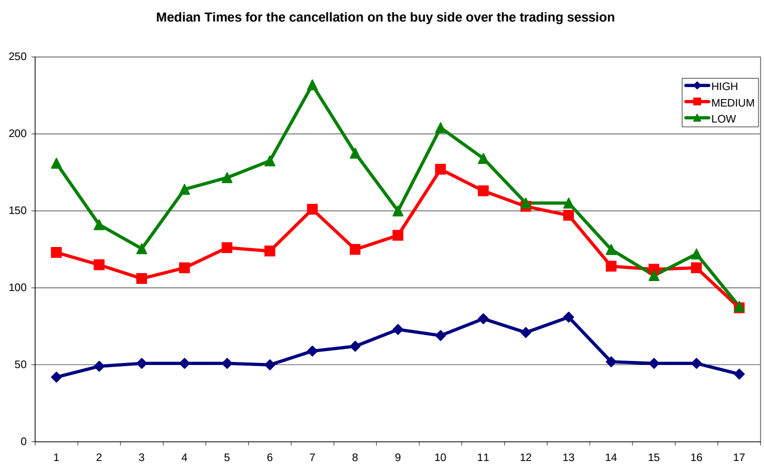

Figure 5: Median duration for cancellations along the trading session on the buy side for the three sub-samples.

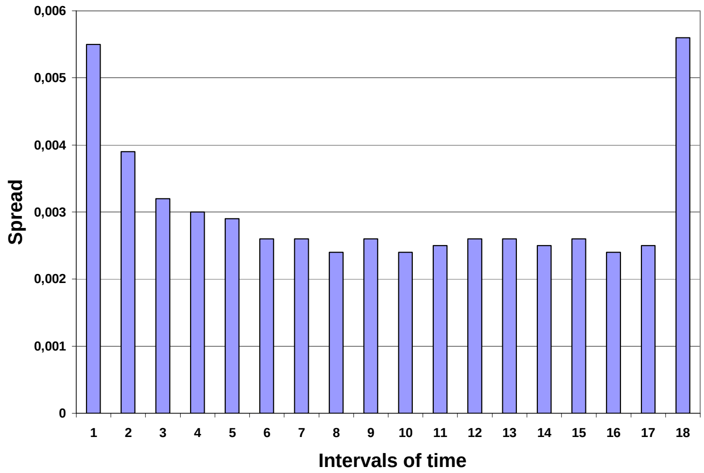

Figure 6: The relative inside spread over the trading session. The relative inside spread is equal to $\frac{best\ ask - best\ bid}{QMP}$, where $QMP = \frac{best\ ask + best\ bid}{2}$. The bars are the averages over the 65 days of the sample.

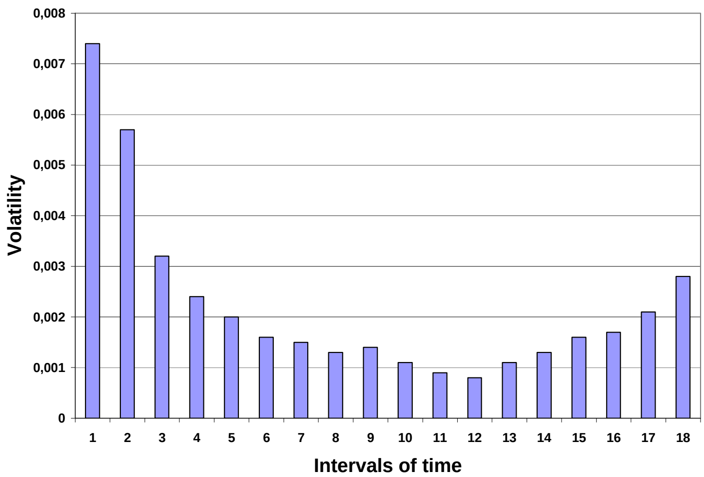

Figure 7: The volatility over the trading session. Volatility computed as the squared quote midpoint returns. The quote midpoint return is computed as the ln(QMP$_t$)-ln(QMP$_{t-1}$). The bars are the averages over the 65 days of the sample.

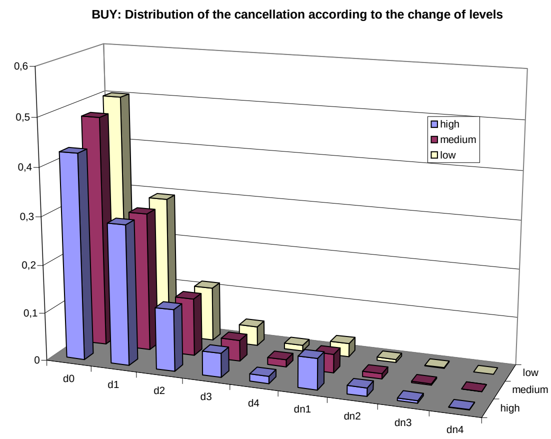

Figure 8: Distribution of the cancellations according to the change of levels for the three sub-samples. We define dk, with $k \in \{0, 1, 2, 3, 4\}$ the set of orders which move up n levels from the moment of placement to the moment of cancellation, and dnj, with $j \in \{1, 2, 3, 4\}$ the set of orders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

trading activity group.

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

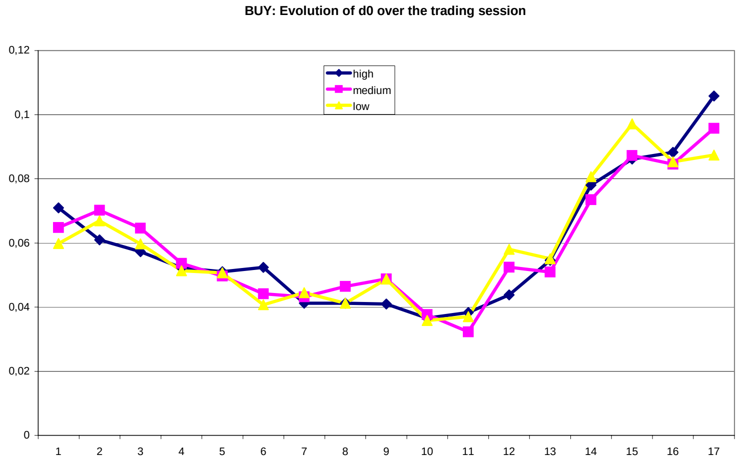

Figure 9: Distribution of d0 for the three sub-samples along the trading session.

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 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 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 low, differently from the U.S. market (in fact, Hasbrouck and Saar [15] and [16] 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.

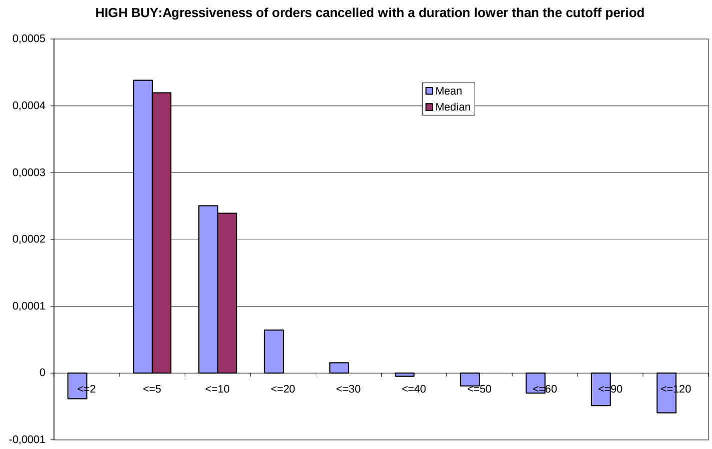

Figure 10: Average and median price aggressiveness (PA) of orders cancelled with a duration lower than a cutoff period (cutoff period i, i=2, 5, 10, 20, 30, 40, 50, 60, 90, 120 seconds) for the high trading activity sample on the buy side. The median value of the PA is equal to zero except when the duration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

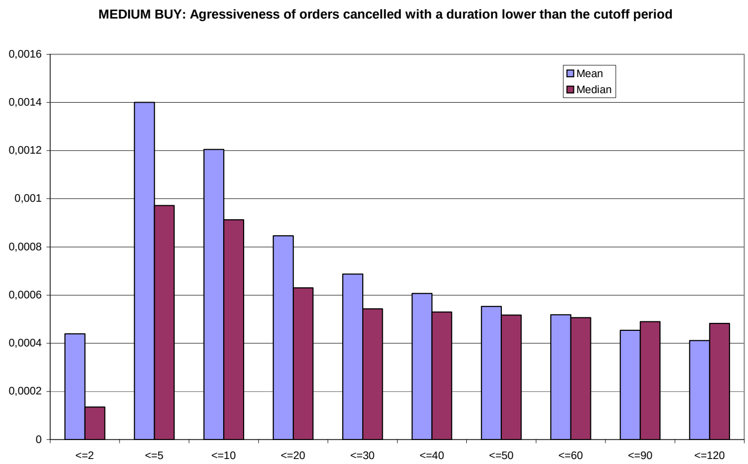

Figure 11: Average and median PA of orders cancelled with a duration lower than a cutoff period (cutoff period i, i=2, 5, 10, 20, 30, 40, 50, 60, 90, 120 seconds) for the medium trading activity sample on the buy side.

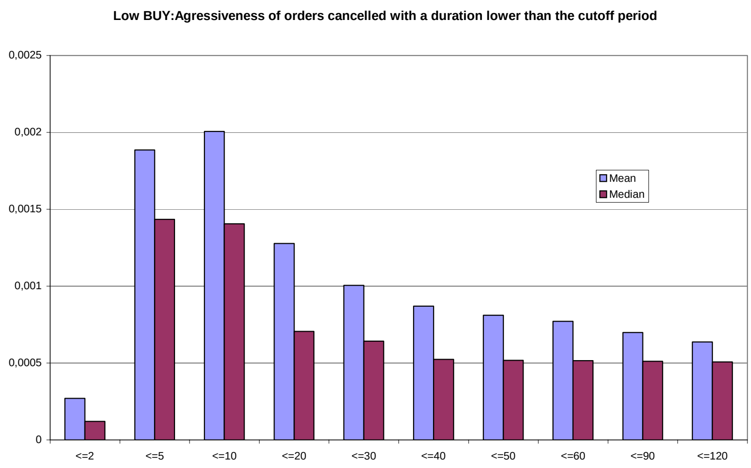

Figure 12: Average and median PA of orders cancelled with a duration lower than a cutoff period (cutoff period i, i=2, 5, 10, 20, 30, 40, 50, 60, 90, 120 seconds) for the low trading activity sample on the buy side.

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 cancellations depending on the price aggressiveness and the different periods of the trading session divided in morning (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 pay 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 the determinants of the cancellation decision.

4.1 Description of the Variables

The **relative inside spread** *(bidask)* 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 *(volat)* 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].

[6] The actual price is the price negotiated in the market at the moment of the placement

Number of transactions *(trades)* counts the transactions occurred in the market one hour before the event considered. This is a proxy for the number of traders present in the market.

Depth *(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 divided by the median number of shares outstanding at the best quote on the same side of the market, and **Opposite Depth** *(opdepth)* is the number of shares outstanding at the best quote on the opposite side of the book divided by the median number of shares outstanding at the best quote on the opposite side of the book.

We also insert dummy variables for the **level** *(level_i)* of the LOB at which the order is placed and cancelled or executed, and for the **type of the last order introduced** (*market* 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. Another set of dummy variables introduced is the **change of level** *(neg)*. 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. [10] analyze how the different explanatory variables affect the likelihood of placing a market order, 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.

---

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 very important. Given the relatively few observations available for this event for some assets with low trading activity, we have decided to aggregate the two sides of the book for all the stocks[7]. 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 we introduce a 'no activity' event t_m seconds before the latest order, inserting as many events as the time interval allows. 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 10:51:23. Then we introduce no–activity events at 10:51:17 and 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. [10]; 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 [9] use a similar definition of no activity event to model and estimate the passage of clock time without activity.

According to Focault [11] 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 [14] and Smith [23] 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 observe 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).

[7]Notice that when we do our regressions, some of the independent variable depend on the side of the book. For example, when an order is a 'sell', we use the depth of the sell side (and 'opposite depth' is the depth of the buy side). Thus what we are assuming is that the buy and sell sides are symmetric; for example, the impact of increased depth on the buy side on the decision to place a buy market order is the same as the impact on increased depth on the sell side on the decision to place a sell order.

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

Parlour [20] 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 [11] proposes a model of a dynamic market where increased volatility makes traders place limit orders at less competitive prices. In equilibrium the higher volatility makes market orders more costly leading to a higher proportion of limit orders. Handa and Schwartz [13] , Smith [23] Ahn, Bae and Chang [3], Hollifield, Miller, Sandas and Slive [17] and Ranaldo [22] find evidence of the direct relation between volatility and the placement of limit orders. Given the definition of fleeting orders they are more likely to be placed 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.*

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 the events and let j index the stock. We postulate the relationship:

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

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*), trading activity[8] ($\ln\_trades$), depth of the best quote on the same side of the book (*depth*), depth of the best quote on the opposite side of the book (*opdepth*). All these variables are computed at the moment of placement. We also include a set of dummy variables which represents the type of the last order introduced: *market* 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[9], and zero otherwise.

The regression we run is the following:

$$\begin{aligned}\text{Event type}_{i,t} \;=\;& \alpha + \beta_1\,(bidask)_{i,t} + \beta_2\,(volat)_{i,t} + \\ & + \beta_3\,(\ln\_trades)_{i,t} + \beta_4\,(depth)_{i,t} + \beta_5\,(opdepth)_{i,t} + \\ & + \beta_6\,(market)_{i,t} + \beta_7\,(limit)_{i,t} + e_{i,t}\end{aligned} \qquad (1)$$

We estimate the 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 significant at the 1% level.

[8] Trading activity is defined as the logarithm of the number of trades.

[9] In this case the limit order category is composed of serious limit orders and fleeting orders.

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.

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 significant for most of the assets, although it is negative and significant for all the subsamples.

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 it is significant 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. [10]). In fact, the coefficient for market and limit orders in the three sub–samples is usually positive. The probability of submitting fleeting orders also increases with the increase of trading activity, but it is not significant for a few assets belonging to the high trading activity group.

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.

When the last order introduced is a market order the probability of submission of a market order and limit order increases in all the samples. 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.

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[10].

Ellul et al. [10] 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 is losing priority in the 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 prices, waiting for an improvement in market conditions (see Focault [11]). Thus, the probability of cancellation decreases.

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

Large [18] 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 transactions as a proxy for the number of traders.

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

If we let $y = 1$ to denote cancellation, then 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 ($bidask_t$) and volatility ($volat_t$) computed right before the cancellation, the change in the number of transactions in the market, computed

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

as the difference between the variable *trades* computed at the time of cancellation and at the time of the introduction of the order (dif_trades), 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 also introduce the interaction between trading activity and relative inside spread computed at the moment of the cancellation ($effect$), since we suspect that the impact of the spread on the cancellation decision is weakened when trading activity is high. The regression we run is the following:

$$\begin{aligned} \text{Cancellation decision}_{i,t} &= \alpha + \gamma_1 (neg)_{i,t} + \gamma_2 (bidask_t)_{i,t} + \gamma_3 (effect)_{i,t} + \\ &\quad + \gamma_4 (volat_t)_{i,t} + \gamma_5 (dif\_trades)_{i,t} + \gamma_6 (level\_1)_{i,t} + \\ &\quad + \gamma_7 (level\_2)_{i,t} + \gamma_8 (level\_3)_{i,t} + \gamma_9 (level\_4)_{i,t} + e_{i,t} \end{aligned} \tag{2}$$

We estimate model (2) for each stock (i), 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; for the high trading activity sample, the results differ across assets, especially when we look at the impact of dif_trades. We provide more details below.

An increase of the relative inside spread increases the probability of cancellation for all the samples and assets, thus supporting Hypothesis 7.

When the order loses one or more levels after the placement, the probability of cancellation increases, as predicted in Hypothesis 8.

According to Hypothesis 9 volatility is negatively related to the probability of cancellation. 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 transactions 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 some assets with high trading activity (SCH and BBVA) an increase in the number of traders increases the probability of cancelling . If we pool together the assets with high trading activity we obtain a negative coefficient as expected.

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.

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.

5 Conclusions

This work studies 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 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 and placing limit, market or fleeting orders, and we study the decision using a multinomial logit model. The results obtained for the Spanish market confirm the ones provided by the existing 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 change 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 that the cancellation decision is positively related to the spread and the loss of levels of the order after the placement and it is negatively related to the volatility, the change in the number of trades in the market and the interaction variable considering the bidask and the trading activity.

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 defined the low trading activity group as the set of 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 the stock belongs to 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	-57.5254	1.1337	-50.74
	volat	-9.4344	0.1170	-80.61
	ln_trades	0.6264	0.0038	164.78
	depth	0.00615	0.0011	5.73
	opdepth	0.0002	0.00009	2.16
	market	1.174	0.0079	146.87
	limit	0.9497	0.0072	132.14
	cons	-3.7180	0.0142	-260.81
2				
	bidask	64.455	0.8098	79.60
	volat	0.8360	0.0068	123.14
	ln_trades	0.3121	0.0033	94.69
	depth	-0.0143	0.0009	-15.59
	opdepth	-0.0029	0.0011	-2.57
	market	1.6989	0.0069	243.69
	limit	1.0587	0.0067	156.62
	cons	-3.3338	0.0124	-267.86
3				
	bidask	60.1979	6.8164	8.83
	volat	0.8507	0.0208	40.96
	ln_trades	0.5152	0.0319	16.15
	depth	-0.00983	0.0078	-1.26
	opdepth	-0.01317	0.01063	-1.24
	market	3.3854	0.0697	48.59
	limit	1.9849	0.0795	24.98
	cons	-9.7714	0.1313	-74.42

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	-66.4758	1.0571	-62.89
	volat	-7.0255	0.0458	-153.21
	ln_trades	0.6064	0.0022	281.06
	depth	0.129	0.00058	22.34
	opdepth	0.0008	0.00013	6.34
	market	0.8485	0.0045	186.20
	limit	0.7719	0.0043	177.07
	cons	-3.871	0.0099	-390.5
2				
	bidask	88.7306	0.8588	103.32
	volat	0.6004	0.0026	231.25
	ln_trades	0.2757	0.0021	131.09
	depth	-0.01267	0.0006	-21.81
	opdepth	-0.00244	0.00067	-3.63
	market	1.4933	0.0042	351.98
	limit	0.8457	0.0046	184.5
	cons	-3.4212	0.0097	-352.04
3				
	bidask	94.127	6.2699	15.01
	volat	0.6179	0.0082	75.41
	ln_trades	0.2701	0.0173	15.58
	depth	-0.01	0.00458	-2.18
	opdepth	0.0046	0.00436	1.06
	market	3.203	0.0439	72.84
	limit	2.0191	0.0499	40.40
	cons	-9.1964	0.0862	-106.64

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	-61.5282	1.9325	-31.84
	volat	-3.3124	0.0155	-212.74
	ln_trades	0.3318	0.0013	242.70
	depth	0.01259	0.00037	33.56
	opdepth	0.0046	0.00019	23.33
	market	1.0201	0.0028	362.32
	limit	0.8349	0.0032	256.81
	cons	-3.3130	0.0092	-361.98
2				
	bidask	239.543	1.8492	129.53
	volat	0.3489	0.0009	376.97
	ln_trades	0.0522	0.0016	32.84
	depth	-0.00726	0.0004	-16.16
	opdepth	0.0056	0.0005	11.53
	market	1.2962	0.0032	401.7
	limit	0.8468	0.0039	217.14
	cons	-2.7871	0.0105	-265.24
3				
	bidask	308.037	5.8145	52.98
	volat	0.3583	0.0030	124.99
	ln_trades	0.0278	0.0115	2.43
	depth	0.0045	0.00108	4.14
	opdepth	0.0101	0.00301	3.37
	market	1.8722	0.0268	69.87
	limit	1.6753	0.02924	57.30
	cons	-7.6323	0.0733	-104.07

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	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	-2.249	0.9028	-2.49	-0.0833	0.0109	-7.61
dif_trades	-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 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	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	-17.61	0.5884	-29.93	-0.2328	0.0063	-36.92
dif_trades	-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 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	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	-2.671	0.2755	-9.70	0.005	0.0025	1.94
dif_trades	-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 the decision of cancelling.

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